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November 13, 2025

Via E-Filing

Ms. Lisa Felice
Executive Secretary
Michigan Public Service Commission
7109 West Saginaw Highway
Lansing, MI 48917

RE: MPSC Case No. U-21870

Dear Ms. Felice:

Please find enclosed the Official Exhibits of Tabitha Williams on Behalf of Urban Core Collective, UCC-101 to UCC-112, along with proof of service for electronic filing in the above-referenced matter.

Please do not hesitate to contact my office with any questions or comments.

Sincerely,

Mark N. Templeton, *pro hac vice*
6020 S. University Avenue
Chicago, IL 60637
Phone: (773) 702-9611
Email: templeton@uchicago.edu

xc: Parties to Case No. U-21870

Research

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Disparities in Air Pollution Exposure in the United States by Race/Ethnicity and Income, 1990–2010

Jiawen Liu,[1] *Lara P. Clark,*[1] *Matthew J. Bechle,*[1] *Anjum Hajat,*[2] *Sun-Young Kim,*[3] *Allen L. Robinson,*[4] *Lianne Sheppard,*[5,6] *Adam A. Szpiro,*[5] *and Julian D. Marshall*[1]

[1]Department of Civil & Environmental Engineering, University of Washington, Seattle, Washington, USA
[2]Department of Epidemiology, University of Washington, Seattle, Washington, USA
[3]Department of Cancer Control and Population Health, Graduate School of Cancer Science and Policy, National Cancer Center, Goyang-si, Gyeonggi-do, Korea
[4]Department of Mechanical Engineering & Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA
[5]Department of Biostatistics, University of Washington, Seattle, Washington, USA
[6]Department of Environmental and Occupational Health Sciences, University of Washington, Seattle, Washington, USA

Background: Few studies have investigated air pollution exposure disparities by race/ethnicity and income across criteria air pollutants, locations, or time.

Objective: The objective of this study was to quantify exposure disparities by race/ethnicity and income throughout the contiguous United States for six criteria air pollutants, during the period 1990 to 2010.

Methods: We quantified exposure disparities among racial/ethnic groups (non-Hispanic White, non-Hispanic Black, Hispanic (any race), non-Hispanic Asian) and by income for multiple spatial units (contiguous United States, states, urban vs. rural areas) and years (1990, 2000, 2010) for carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), particulate matter with aerodynamic diameter ≤ 2.5 μm ($PM_{2.5}$; excluding year-1990), particulate matter with aerodynamic diameter ≤ 10 μm (PM_{10}), and sulfur dioxide (SO_2). We used census data for demographic information and a national empirical model for ambient air pollution levels.

Results: For all years and pollutants, the racial/ethnic group with the highest national average exposure was a racial/ethnic minority group. In 2010, the disparity between the racial/ethnic group with the highest vs. lowest national-average exposure was largest for NO_2 [54% (4.6 ppb)], smallest for O_3 [3.6% (1.6 ppb)], and intermediate for the remaining pollutants (13%–19%). The disparities varied by U.S. state; for example, for $PM_{2.5}$ in 2010, exposures were at least 5% higher than average in 63% of states for non-Hispanic Black populations; in 33% and 26% of states for Hispanic and for non-Hispanic Asian populations, respectively; and in no states for non-Hispanic White populations. Absolute exposure disparities were larger among racial/ethnic groups than among income categories (range among pollutants: between 1.1 and 21 times larger). Over the period studied, national absolute racial/ethnic exposure disparities declined by between 35% (0.66 $\mu g/m^3$; $PM_{2.5}$) and 88% (0.35 ppm; CO); relative disparities declined to between $0.99\times$ ($PM_{2.5}$; i.e., nearly zero change) and $0.71\times$ (CO; i.e., a $\sim 29\%$ reduction).

Discussion: As air pollution concentrations declined during the period 1990 to 2010, absolute (and to a lesser extent, relative) racial/ethnic exposure disparities also declined. However, in 2010, racial/ethnic exposure disparities remained across income levels, in urban and rural areas, and in all states, for multiple pollutants. https://doi.org/10.1289/EHP8584

Introduction

Air pollution is associated with ~100,000 annual premature deaths in the United States in 2017 (Stanaway et al. 2018) and has been linked to cardiovascular disease, respiratory disease, cancers, adverse birth outcomes, cognitive decline, and other health impacts (Cohen et al. 2017; Darrow et al. 2011; Lelieveld et al. 2015; Paul et al. 2019; Pope et al. 2009; Rivas et al. 2019; Stieb et al. 2012; Underwood 2017). Air pollution and its associated health impacts are not equitably distributed by race/ethnicity or income. Previous research has documented higher-than-average air pollution exposures for racial/ethnic minority populations and lower-income populations in the United States (Brulle and Pellow 2006; Evans and Kantrowitz 2002; Mohai et al. 2009), leading to disparities in attributable health impacts (Bowe et al. 2019; Fann et al. 2019; Gee and Payne-Sturges 2004). Most investigations of disparities in air pollution exposure involve a single pollutant, location, and/or time point [see, e.g., literature reviews by Hajat et al. (2015) and Marshall et al. (2014); see Table S2]. Evidence from broader investigations suggests that exposure disparities by race/ethnicity and/or income can vary by pollutant (Rosofsky et al. 2018), location [e.g., by state (Bullock et al. 2018; Salazar et al. 2019), urbanicity (Mikati et al. 2018), metropolitan area (Zwickl et al. 2014; Downey et al. 2008)], and time point (Ard 2015; Clark et al. 2017; Kravitz-Wirtz et al. 2016; Colmer et al. 2020). However, to our knowledge, broad patterns in exposure disparities have not yet been investigated, using consistent methods, across pollutants, locations, and time points, for the contiguous U.S. population.

The objective of our research was to comprehensively and consistently investigate disparities in exposure to U.S. Environmental Protection Agency (U.S. EPA) criteria air pollutants for the two decades following the 1990 Clean Air Act Amendments in the United States. Specifically, we investigated the following questions regarding disparities in exposure to six criteria air pollutants: *a*) How do exposures vary by race/ethnicity and income? *b*) How do racial/ethnic exposure disparities vary by pollutant? *c*) How do racial/ethnic exposure disparities vary by location (state, urban vs. rural areas)? *d*) How have racial/ethnic exposure disparities changed over time? To address these questions, we combined demographic data from the U.S. Census (Manson et al. 2019) with predictions of outdoor average levels of six criteria air pollutants from a publicly available national empirical model derived from satellite, measurement, and other types of data (Kim et al. 2020) at the spatial scale of census block groups and census tracts. We then analyzed disparities in exposure to six criteria air pollutants [all criteria air pollutants except lead (Pb); i.e., carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), fine and respirable suspended particulate matter with an aerodynamic diameter ≤ 2.5 μm

Address correspondence to Julian Marshall, Department of Civil & Environmental Engineering, University of Washington, 201 More Hall, Seattle, WA 98195 USA. Telephone: (206) 685-2591. Email: jdmarsh@uw.edu

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($PM_{2.5}$), particulate matter with aerodynamic diameter $\leq 10\ \mu m$ (PM_{10}), and sulfur dioxide (SO_2)] by race/ethnicity (four racial/ethnic groups: non-Hispanic White, non-Hispanic Black, Hispanic (any race), non-Hispanic Asian) and income (16 household income categories) across time points (decennial census years: 1990, 2000, and 2010) and spatial units (contiguous United States, state, urban vs. rural areas).

Methods

Demographic and Air Pollution Datasets

We obtained demographic data (i.e., population estimates by race/ethnicity, household income, and household income disaggregated by race/ethnicity) and map boundaries (e.g., states, census tracts, and census block groups) for the contiguous United States from the 1990, 2000, and 2010 decennial censuses from the IPUMS National Historic Geographic Information System (NHGIS) (Manson et al. 2019).

NHGIS provides, for each census block group, and for 1990, 2000, and 2010 (standardized to 2010 spatial boundaries), population estimates for six census self-reported racial groups: *a*) White alone, *b*) Black or African American alone, *c*) American Indian and Alaska Native alone, *d*) Asian and Pacific Islander alone, *e*) some other race alone, and *f*) two or more races. NHGIS reports population estimates for two census self-reported ethnic groups: *a*) Hispanic or Latino and *b*) not Hispanic or Latino. Thus, there are a total of 12 combined racial/ethnic groups in NHGIS (six racial groups, two ethnic groups). Our main analyses of racial/ethnic exposure disparities included the four largest racial/ethnic groups, which in total covered 307 million people (97.2% of the population) in the contiguous United States in 2010: *a*) not Hispanic or Latino, White alone (64% of the population; hereafter, "non-Hispanic White"), *b*) Hispanic or Latino of any race(s) (16%; hereafter, "Hispanic"), *c*) not Hispanic or Latino, Black or African American alone (12%; hereafter, "non-Hispanic Black"), and *d*) not Hispanic or Latino, Asian and Pacific Islander alone (4.6%; hereafter, "non-Hispanic Asian").

For analyses by income in 2010, we used 2010 NHGIS household income estimates. For each block group, NHGIS reports the number of households in 16 annual household income categories (total covered in 2010: 114 million households) (in 2010 inflation-adjusted U.S. dollars): <10,000 , 10,000–15,000, 15,000–20,000, 20,000–25,000, 25,000–30,000, 30,000–35,000, 35,000–40,000, 40,000–45,000, 45,000–50,000, 50,000–60,000, 60,000–75,000, 75,000–100,000, 100,000–125,000, 125,000–150,000, 150,000–200,000, and >200,000.

For analyses by income disaggregated by race/ethnicity in 2010, data from the 2010 NHGIS were available at the census tract level. For each census tract, NHGIS reports householder data for eight predefined race and/or ethnicity categories within each of the 16 census income categories, including one category based on both race and ethnicity (non-Hispanic White), one based on ethnicity regardless of race (Hispanic or Latino), and six based on race regardless of ethnicity (Black or African American alone, American Indian and Alaska Native alone, Asian alone, Native Hawaiian or Other Pacific Islander alone, some other race alone, and two or more race). To best match demographic variables used in race/ethnicity analysis at the census block group level, we reported results for four largest racial/ethnic groups (total covered in 2010: 113 million census householders, 98.5% of householders with data on income by race/ethnicity): not Hispanic or Latino, White alone (71% of householders; hereafter, "non-Hispanic White"), Hispanic or Latino (12%; hereafter, "Hispanic"), Black or African American alone (12%; hereafter, "Black"), and Asian alone (3.8%; hereafter, "Asian"). Thus, for the data used for the household income by race/ethnicity analysis (but not for other analyses), Black and Asian categories included both Hispanic and non-Hispanic individuals; for these analyses (but not others), Hispanic Black populations ($\sim 0.40\%$ of the population) would be included in results for Hispanic and for Black populations, and Hispanic Asian populations ($\sim 0.08\%$) would be included in results for Hispanic and for Asian populations. Additionally, for the data used for the household income by race/ethnicity analysis (but not for other analyses), the Asian category does not also include Pacific Islander populations.

The U.S. Census Bureau defined census blocks as "urban" or "rural" based on population density and other characteristics (Ratcliffe et al. 2016). We used 2010 census urban/rural block definitions to define a 2010 census block group for all 3 y (1990, 2000, and 2010) as rural if all blocks inside it were rural, and we defined the remaining block groups as urban (i.e., each census block group and urban/rural designation was the same in 1990, 2000, and 2010).

Average estimates of ambient air pollution levels for U.S. EPA criteria pollutants were obtained from the Center for Air, Climate, and Energy Solutions (CACES) empirical models for the contiguous United States (www.caces.us/data). These models incorporate satellite-derived estimates of air pollution, satellite-derived land cover data, land use data, U.S. EPA monitoring station data, and universal Kriging (Kim et al. 2020); estimated pollution levels were available by census block at block centroids based on 2010 census boundaries for the years from 1990 to 2010 for all pollutants except $PM_{2.5}$ (for which monitoring data and exposure models were only available starting in 1999). Estimated levels of O_3 from the CACES empirical model are 5-month summer averages (specifically, the average during May–September of the daily maximum 8-h moving average); for the remaining pollutants pollutants, estimated levels are annual averages.

CACES model performance during the years studied here (2000, 2010 for $PM_{2.5}$; 1990, 2000, 2010 for the other pollutants), as measured by cross-validated R^2, was 0.84–0.89 for NO_2, 0.85 for $PM_{2.5}$, 0.62–0.82 for O_3, 0.56–0.62 for PM_{10}, 0.32–0.66 for SO_2, and 0.34–0.57 for CO (Kim et al. 2020). Mean error (ME) across the census years studied was between -0.02 and 0 ppm for CO, -0.04 to 0 ppb for O_3, -0.09 to -0.06 ppb for NO_2, -0.17 to -0.13 ppb for SO_2, -0.31 to $-0.26\ \mu g\ m^{-3}$ for PM_{10}, and -0.05 to $-0.02\ \mu g\ m^{-3}$ for $PM_{2.5}$. Mean bias (MB) was 13%–22% for SO_2, and $<10\%$ for the other pollutants (Table S1); further details about the models and model performance are in Kim et al. (2020) and Liu (2021).

Combining Demographic and Air Pollution Data

We matched the CACES empirical model results and the U.S. census demographic data using the 2010 census spatial boundary definitions (from finest to coarsest spatial resolution: block, block group, and tract boundaries) for the three census years (1990, 2000, 2010). We matched census block–level CACES model predictions for criteria air pollutants (blocks in 2010 in the contiguous United States: $n = \sim 7$ million; average: ~ 44 residents per block) to census block group–level demographic data (block groups: $n = \sim 220{,}000$; average: ~ 1400 residents per block group) by calculating population-weighted mean of the block-level predictions, for all blocks in that block-group. Similarly, to match census tract–level demographic data (tracts: $n = \sim 74{,}000$; ~ 4200 residents per tract), we calculated the population-weighted mean air pollution levels for all census block groups located within that tract.

Estimating Exposures to Pollutants

We estimated annual pollutant-specific exposures for 1990 (excluding $PM_{2.5}$), 2000, and 2010 based on population-weighted mean predicted ambient air pollution levels for each demographic group [race/ethnicity, income, and income by race/ethnicity; results for additional groups (income poverty ratio, age, language, mobility, travel time) are described in the Supplemental Material (SM)]. The data for the five additional groups (income poverty ratio, age, language, mobility, travel time) were extracted from NHGIS (i.e., we are directly employing values calculated by NHGIS; the values employed do not reflect our own data or calculations) (Manson et al. 2019). For all five additional groups, the rationale for including them is to explore whether exposures vary univariately for that demographic attribute. For all five additional groups, the categories used follow NHGIS categories and/or natural breaks in the data [e.g., for a ratio, separating values at, e.g., 0.5, 1.0, 1.5, 2.0; for age, separating young children as age 4 y or below, other children (who, typically, attend K12 education) as age 5–17 y, adults as age 18–64 y, and older adults as age 65+ y (reflecting an assumed retirement age)]. Income poverty ratio is defined by the U.S. Census as the ratio of income to poverty level in the past 12 months (Manson et al. 2019). The poverty level varies by number of people in the family and their ages; poverty level does not vary geographically (i.e., the same threshold is used throughout the United States) (U.S. Census Bureau 2021). In results shown in the SM for income to poverty ratio, we bin this ratio into five categories: <0.5, 0.5–1, 1–1.5, 1.5–2, and >2. The motivation for this analysis is to investigate income relative to the U.S. Census-defined poverty level. Age is binned into four categories: <5 y old, 5–17 y old, 18–64 y old, and 65+ y old. Language refers to language(s) spoken in the home. For households in which language(s) other than English are spoken, the U.S. Census subdivides household counts into *a*) households in which no one age 14 y and over speaks English only, and *b*) households in which one or more people age 14 y and over speaks English "very well." We bin the NHGIS household language data into nine categories: English only, Spanish language and no English, English and a Spanish language, Asian language and no English, English and an Asian language, European language and no English, English and a European language, other language and no English, English and other language. Mobility refers to geographical mobility in the past year for current residence, based on metropolitan statistical areas (MSAs). We bin mobility into six categories: *a*) same house 1 y ago, *b*) different house: moved from same metropolitan, *c*) different house: moved from different metropolitan, *d*) different house: moved from micropolitan, *e*) different house: moved from not metropolitan nor micropolitan, and *f*) abroad 1 y ago. Travel time refers to travel time to work for workers age 16+ y who did not work at home. We divide the data into seven categories: <10 min, 10–20 min, 20–30 min, 30–40 min, 40–60 min, 60–90 min, and >90 min. This approach (average ambient air pollution level at residential census block group or tract) is broadly consistent with many examples in research and practice, including U.S. EPA monitors (Office of Air Quality Planning and Standards 2008), the National Ambient Air Quality Standards (e.g., Clean Air Scientific Advisory Committee 2010; Independent Particulate Matter Review Panel 2020; U.S. EPA 2019, 2020), many influential epidemiological studies (e.g., Di et al. 2017; Laden et al. 2006; Pope et al. 2009, 2020; Shi et al. 2016; Zanobetti and Schwartz 2009), and national empirical models for air pollution in the United States (e.g., Bechle et al. 2015; Di et al. 2020; Goldberg et al. 2019; Kim et al. 2020; Novotny et al. 2011; U.S. EPA 2016; Van Donkelaar et al. 2019; Young et al. 2016). We used the finest publicly available census spatial boundary data to estimate exposures for each analysis (income by race/ethnicity: tracts; all other analyses: block groups) based on availability of census demographic data.

The national annual (for O_3, 5-month average; for remaining pollutants, annual average) exposure (e_i) for demographic group i was calculated for a given pollutant and year as:

$$e_i = \frac{\sum_{j=1}^{n} c_j p_{ij}}{\sum_{j=1}^{n} p_{ij}}, \tag{1}$$

where c_j is the predicted average ambient pollution level for census block group or census tract j [here and after, we use c to represent ambient pollution level (observed or predicted) and e to represent population-weighted value for c), p_{ij} is the population of demographic group i in census block group or census tract j, and n is the number of census block groups or census tracts in the analyzed spatial level [the contiguous United States, each of the 49 "states" (including the District of Columbia plus the 48 contiguous states), and urban vs. rural areas].

National Exposure Disparities Analyses

Our primary exposure disparity metrics are based on absolute and relative differences in population-weighted mean air pollution exposures. We selected metrics based on mean pollution levels for consistency with our focus on broad national average patterns in exposure disparities among multiple pollutants. Absolute disparity metrics are often connect to pollutant-specific health impacts (Harper et al. 2013) (the present article focuses on pollution levels rather than health outcomes). Relative disparity metrics (e.g., ratios, relative percent differences) are relevant for quantifying disproportionality in exposure burdens, in a way that can be compared or summarized among different pollutants. An important limitation of these metrics (based on differences in mean exposures) is that they do not include information about disparities across the full exposure distributions (Harper et al. 2013). To address this limitation, we conducted supplemental analyses using inequality metrics accounting for full exposure distributions (Gini Coefficient and between-group Atkinson Index), as described in the SM, as well as sensitivity analyses comparing metrics based on other specific points of the exposure distribution (i.e., comparing specific exposure percentiles) as described below.

We calculated the absolute and relative exposure disparity metrics using two different approaches nationally: *a*) by race/ethnicity group and/or income category (i.e., the unit of analysis is a national subpopulation defined by race/ethnicity and/or income) and *b*) by local demographic characteristics (i.e., the unit of analysis is a set of census block groups defined based on proportion of racial/ethnic minority residents).

National exposure disparity metrics based on racial/ethnic group and/or income category. Our primary absolute disparity metric for quantifying national racial/ethnic exposure disparities is the pollutant-specific absolute difference in population-weighted average pollution level, as calculated using Equation 1 with block group–level data, between the racial/ethnic group with the highest national mean exposure ("most-exposed group") and the racial/ethnic group with the lowest national mean exposure ("least-exposed group") among the four racial/ethnic groups (non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, Hispanic); here, the unit of analysis is a racial/ethnic group. In addition, we derived the percent difference relative to the model-predicted national mean exposure level for that pollutant $\{[(\text{population-weighted mean in most exposed} - \text{population-weighted mean in least exposed})/\text{national mean exposure}] \times 100\%\}$. We also included relative exposure disparity metric as the pollutant-specific exposure ratio (i.e., population-weighted mean of most-exposed group/population-weighted mean of least-exposed group). Both the absolute and relative exposure disparity metrics are constructed based on differences between most- and least-exposed racial/ethnic groups, to provide a measure of overall racial/ethnic disparities that avoids preselecting two specific groups for comparison and accounts for exposure disparities across multiple groups, in a consistent way for each pollutant (accounting for potential differences in the most- and least-exposed racial/ethnic groups by pollutant). We also report averages in relative disparities across pollutants as a representation of overall average inequalities in exposure to multiple pollutants, not as a representation of inequalities in health risks, which are pollutant-specific and depend on absolute levels of pollution exposure. Last, as a supplemental comparison among pollutants, we also calculated inequality metrics that account for the full exposure distributions: Gini coefficients by race/ethnicity and between-group Atkinson Indices.

To quantify national income-based exposure disparities, we calculated the pollutant-specific absolute difference in population-weighted average pollution level, using Equation 1 with block group–level data, between the lowest (<\$10,000) and the highest (>\$200,000) household income categories (of the 16 census categories). Additionally, as a relative disparity metric, we calculated the relative percent difference in mean exposures between the lowest and highest income categories. As a supplementary analysis, we calculated similar absolute and relative exposure disparity metrics between the income categories containing the 25th percentile (\$20,000–\$25,000) and the 75th percentile (\$75,000–\$100,000) of the income distribution.

To quantify national exposure disparities by race/ethnicity and income, we first calculated the absolute difference in population-weighted average pollution level between the most- and least-exposed racial/ethnic group (among the four racial/ethnic groups, not mutually exclusive with four racial/ethnic groups in racial/ethnic disparity, as described in "Demographic and Air Pollution Data Sets" in the "Methods" section) within each of the 16 census income categories, and then averaged that income category-specific racial/ethnic exposure disparity across all 16 income categories, for each pollutant. In the analyses for both race/ethnicity and income, we used census data for householders to calculate exposures for the four racial/ethnic groups using Equation 1 with tract-level data. Reflecting publicly available census data for racial/ethnic groups by income category, for this section only, the Black and Asian groups include Hispanic and non-Hispanic individuals, and the Asian group does not include Pacific Islander individuals. As a relative disparity metric, we divided the absolute exposure disparity metric by the national mean pollution level, for each of the pollutants.

National exposure disparity metrics based on local demographic characteristics (i.e., block group bins by proportion of racial/ethnic minority residents). We also investigated exposure disparities based on racial/ethnic minority resident percentages; here, the unit of analysis is bin of census block groups. Each block group bin was defined as single percentile (i.e., 1%) of all block groups stratified by the proportion of racial/ethnic minority residents. There were approximately 215,000 block groups in 2010, so each block group bin contained approximately 2,150 block groups. To investigate racial/ethnic disparities among block group bins, we rank ordered all census block group bins based on percent of racial/ethnic minority residents (i.e., people self-reporting any race/ethnicity other than non-Hispanic White alone). For example, the first block group bin was the first percentile and consisted of all block groups with between 0% and 0.67% racial/ethnic minority residents; the second block group bin was the second percentile, consisting of all block groups with 0.67%–0.97% racial/ethnic minority residents; the third block group bin consisted of all block groups with 0.97%–1.2% racial/ethnic minority residents, and so on through all 100 block group bins. The last block group bin consisted of all block groups with 99.1%–99.6% racial/ethnic minority residents. The annual exposure (e_{ig}) for demographic group i for the gth percentile census block group bin (i.e., the average exposure across all block groups in the gth percentile for proportion of residents that belong to a racial/ethnic minority group) was calculated for a given pollutant and year as:

$$e_{ig} = \frac{\sum_{j=1}^{n_g} c_j p_{ij}}{\sum_{j=1}^{n_g} p_{ij}}, \tag{2}$$

where c_j is the predicted average ambient pollution level for census block group j, p_{ij} is the population of demographic group i in census block group j, and n_g is the number of census block groups in the gth percentile block group bin. The absolute disparity is calculated as the exposure difference between block groups with the highest vs. lowest deciles of proportion racial/ethnic minority residents, and, similarly, the relative disparity is calculated as the exposure ratio between block groups with the highest vs. lowest deciles of proportion racial/ethnic minority residents.

Sensitivity Analysis on Robustness of National Exposure Disparity Estimates

We conducted three sensitivity tests to investigate the robustness of conclusions based on estimated exposure disparities. First, as a sensitivity test for conclusions based on comparisons of mean values' rank order for exposures between groups, we calculated disparities using different metrics of the exposure distribution (10th, 25th, 50th, 75th, 90th percentiles).

The remaining two sensitivity tests investigated whether conclusions here are robust to uncertainty in empirical model predictions. Specifically, in the second sensitivity test, we repeated the analysis of national mean exposures by racial/ethnic group, but for only the population living in a census block group with a U.S. EPA monitor in 2010. In this sensitivity test, for the pollution levels, we employ the monitor observations rather than the empirical model results. We then calculated Spearman rank order correlation of relative disparities by pollutant (between the most- and least-exposed group) between base case and sensitivity test.

In the third sensitivity test, we compared the magnitude of uncertainties in the estimated racial/ethnic exposure disparities with the magnitude of the estimated racial/ethnic exposure disparities. To assess the potential impact of model error on racial/ethnic disparities, we first calculated population-weighted mean error (ME_i) for each racial/ethnic group, i, using Equation 3:

$$ME_i = \frac{\sum_{j=1}^{n_o} (c_{jm} - c_{jo}) p_{ij}}{\sum_{j=1}^{n_o} p_{ij}}, \tag{3}$$

where c_{jm} is the predicted average ambient pollution level for census block group j, c_{jo} is the measured average ambient pollution level across all reporting U.S. EPA monitors within census block group j, p_{ij} is the population of demographic group i in block group j, and n_o is the total number of census block groups with EPA monitors. For each pollutant, the ME of disparity between two racial/ethnic groups i_1 and i_2 induced by the model was calculated as the difference between populated-weighted ME for the most- and least-exposed racial/ethnic groups i_1 and i_2. Calculated uncertainties are based on comparison with U.S. EPA measured pollution level in 2010. We then derived the ratio between the uncertainty due to exposure model error (i.e., the difference in population-weighted mean errors between racial/ethnic groups) and the estimated disparity in mean annual exposures between the most- and least-exposed racial/ethnic groups.

National Analysis of High-End Exposure Disparities in 2010

To quantify racial/ethnic disparities at the highest exposure levels, we analyzed the racial/ethnic composition of census block groups above the 90th percentiles of the pollution level among all census block groups. This analysis was done separately for each pollutant. First, for each of the four largest racial/ethnic groups, we estimated the proportion of that group's national population who lived in a high-exposure block group; here, our unit of analysis is a racial/ethnic group. This calculation reflects the proportion of a racial/ethnic group's total U.S. population who lived in heavily polluted (above the 90th percentile) block groups. We performed this calculation for each pollutant and each racial/ethnic group, using Equation 4.

$$\mathrm{a_i} = \frac{\sum_{j=1}^{n_{90}} p_{ij}}{p_{total\_national_i}} \times 100\%, \tag{4}$$

where a_i is the percent of racial/ethnic group i living in a block group with concentration above the 90th percentile for that pollutant, p_{ij} is the population of group i in census block group j, $p_{total\_national_i}$ is the total population for demographic group i in the United States, and n_{90} is the number of census block groups with mean pollutant concentration >90th percentile.

In the second analysis, which was the converse of the first, we investigated the racial/ethnic composition of block groups above the 90th percentile for average pollution level. Here, our unit of analysis is all block groups above the 90th percentile. This calculation reflects the demographics of only people that lived in heavily polluted block groups. We completed this calculation for each pollutant and each racial/ethnic group using Equation 5.

$$\mathrm{b_i} = \frac{\sum_{j=1}^{n_{90}} p_{ij}}{p_{total\_block\,group}} \times 100\%, \tag{5}$$

where b_i is (when considering only the people counted toward $P_{total\_block\,group}$) the percent of people who are in demographic group i, and $p_{total\_\mathrm{block\,group}}$ is the total population of census block groups above the 90th percentile for that pollutant.

In addition, we explored differences in exposures to multiple pollutants by race/ethnicity by using data for 2010 and Equation 3 to estimate the proportion of each major race/ethnicity group's total U.S. population living in block groups with mean exposure levels above the 90th percentile for 0, 1, 2, 3, and ≥4 pollutants, respectively.

Counterfactual Analysis of Migration

We investigated whether changes in racial/ethnic exposure disparities over time were mainly attributable to changes in air pollution levels ("air pollution") or changes in where people lived (abbreviated as "migration", but also including immigration and other shifts in demographic patterns) as a sensitivity analysis. To do so, we employed two counterfactual scenarios (Clark et al. 2017) during two decades (1990 to 2000; 2000 to 2010). For each scenario and year, we calculated exposures for the four largest racial/ethnic groups for the contiguous U.S. population using Equation 1 based on census block group data. We then calculated the absolute racial/ethnic exposure disparity between the most- and least-exposed racial/ethnic groups (referred to in this section as "disparity") for all pollutants with available data (i.e., all except $PM_{2.5}$ in 1990). To analyze the period 1990 to 2000, we calculated the change in disparity attributable to air pollution changing from 1990 to 2000 levels but with demographics remained constant at 1990 values (counterfactual scenario A—i.e., "counterfactual" because it includes consideration of year-2000 pollution levels with year-1990 demographics) and, separately, used 1990 air pollution levels with demographic data changing from 1990 to 2000 values (counterfactual scenario B—includes consideration of year-1990 pollution levels with year-2000 demographics). To estimate the separate contribution of changes in *air pollution* during the period 1990 to 2000, we divided the disparity-changes from counterfactual scenario A by the "true" calculated disparity changes between 1990 and 2000 (i.e., using 1990 air pollution levels with 1990 demographic data, and using 2000 air pollution levels with 2000 demographic data). Similarly, to estimate the separate contribution of *migration* during 1990 to 2000, we divided the disparity changes from counterfactual scenario B by the "true" calculated disparity change between 1990 and 2000. Last, we used an analogous approach to analyze the next decade: 2000 to 2010.

Exposure Disparities Comparison Metrics for States

We investigated patterns among the 48 states of the contiguous United States plus the District of Columbia (DC) (hereafter, "states" refers to 48 states and DC, a total of 49 geographic units in state-level related calculations) using two metrics for absolute exposure disparity by race/ethnicity. First, for each state, pollutant, and race/ethnicity group, we calculated the normalized population-weighted disparity ($d1_i$) as the absolute difference in the annual exposure for racial/ethnic group i in the state (e_i) and the annual exposure for the state population as a whole (e_{state}) relative to the annual exposure across the contiguous United States ($e_{national}$):

$$d1_i = \frac{e_i - e_{state}}{e_{national}}. \tag{6}$$

Second, for each state, we used Equation 7 to calculate a normalized population-weighted disparity ($d2_m$) between the annual exposure for all non-Hispanic Black, non-Hispanic Asian, and Hispanic people combined (e_m), and for the non-Hispanic White population (e_{NHW}). This metric has the advantage of consistently comparing, for each state, exposures between racial/ethnic minority populations and the majority racial/ethnic group population (non-Hispanic White, 64% of the population).

$$d2_m = \frac{e_m - e_{NHW}}{e_{national}}. \tag{7}$$

Last, for each state, we averaged both metrics across the six pollutants.

Results

National Exposure Disparities by Race/Ethnicity and Income in 2010

By race/ethnicity. To investigate national disparities in exposure to criteria air pollution by race/ethnicity, we first compared national population-weighted mean exposures by U.S. Census self-reported race/ethnicity in 2010, the most recent decennial census year with available data. We first present results for differences among subpopulations (unit of analysis: racial/ethnic group), then we present differences among locations, depending on the proportion of each racial/ethnic group residents in that location (unit of analysis: census block groups binned by proportion of racial/ethnic minority residents).

Estimated national mean air pollution exposures for 2010 were higher for all three racial/ethnic minority groups than for the non-Hispanic White group for four of the six criteria pollutants (CO, NO_2, $PM_{2.5}$, and PM_{10}) (Table 1; Table S2–S3; Figure 1). For all six pollutants, the most-exposed group was a racial/ethnic

Table 1. Population distribution and population-weighted exposure distribution for six criteria pollutants for four main racial/ethnic groups and the national average in year 2010.

Demographic	Non-Hispanic White	Non-Hispanic Black	Hispanic	Non-Hispanic Asian	Entire population
Proportion of population	64%	12%	16%	4.6%	100%
$PM_{2.5}$ ($\mu g/m^3$)					
10th percentile	6.1	7.9	6.5	6.7	6.3
25th percentile	7.7	9.2	7.7	8.2	7.9
50th percentile	9.3	10	9.6	9.7	9.5
Mean (SD)	9.1 (2.2)	10 (1.8)	9.4 (2.2)	9.4 (1.9)	9.3 (2.2)
75th percentile	11	11	11	11	11
90th percentile	12	13	12	12	12
NO_2 (ppb)					
10th percentile	3.1	3.8	4.6	5.4	3.4
25th percentile	4.3	5.8	6.6	7.5	4.9
50th percentile	6.2	8.7	9.5	10	7.4
Mean (SD)	7.2 (4.1)	9.7 (5.3)	11 (6.1)	12 (5.9)	8.7 (5.1)
75th percentile	8.9	12	15	15	11
90th percentile	12.5	18	21	21	16
O_3 (ppb)					
10th percentile	38	39	33	39	38
25th percentile	43	43	42	44	43
50th percentile	47	47	46	47	47
Mean (SD)	46 (6.0)	46 (6.1)	45 (7.2)	46 (5.9)	46 (6.2)
75th percentile	50	50	49	50	50
90th percentile	52	53	52	53	52
SO_2 (ppb)					
10th percentile	0.91	1.0	0.83	0.79	0.95
25th percentile	1.1	1.2	1.0	1.0	1.2
50th percentile	1.5	1.6	1.3	1.2	1.5
Mean (SD)	1.6 (0.65)	1.7 (0.63)	1.4 (0.55)	1.4 (0.58)	1.6 (0.64)
75th percentile	1.9	2.1	1.7	1.7	2.0
90th percentile	2.4	2.5	2.2	2.3	2.5
PM_{10} ($\mu g/m^3$)					
10th percentile	12	14	15	14	13
25th percentile	14	16	17	16	15
50th percentile	17	19	20	19	18
Mean (SD)	18 (4.4)	19 (3.7)	21 (4.9)	20 (4.5)	18 (4.6)
75th percentile	21	21	23	22	22
90th percentile	23	23	28	25	24
CO (ppm)					
10th percentile	0.23	0.25	0.26	0.27	0.24
25th percentile	0.27	0.29	0.30	0.30	0.28
50th percentile	0.31	0.32	0.34	0.34	0.31
Mean (SD)	0.30 (0.057)	0.32 (0.067)	0.35 (0.079)	0.35 (0.071)	0.31 (0.066)
75th percentile	0.33	0.35	0.39	0.38	0.35
90th percentile	0.37	0.40	0.45	0.45	0.39

Note: CO, carbon monoxide; NO_2, nitrogen dioxide; O_3, ozone; $PM_{2.5}$, fine particulate matter with aerodynamic diameter less than or equal to 2.5 micrometers; PM_{10} 10 micrometers, SD, standard deviation; SO_2, sulfur dioxide.

minority group: for $PM_{2.5}$ and SO_2, national mean exposures were highest for the non-Hispanic Black population; for CO, NO_2, and O_3, the non-Hispanic Asian population; and for PM_{10}, the Hispanic population. For CO, NO_2, $PM_{2.5}$, and PM_{10}, national mean exposures were lowest for non-Hispanic White population; for O_3, Hispanic population; and for SO_2, non-Hispanic Asian population. Disparities between the most- and least-exposed racial/ethnic groups were largest (based on the relative disparity ratio) for NO_2 [absolute disparity: 4.6 ppb (54%), relative disparity (ratio): 1.6]; intermediate for SO_2 [0.29 ppb (19%), 1.2], PM_{10} [3.0 $\mu g/m^3$ (17%), 1.2], CO [0.044 ppm (16%), 1.1], and $PM_{2.5}$ [1.2 $\mu g/m^3$ (13%), 1.1]; and lowest for O_3 [1.6 ppb (3.6%), 1.0] (Table S4). Across the five pollutants, normalized disparities were also largest for NO_2 and smallest for O_3 for all the additional demographic groups considered (income poverty ratio, age, language, mobility, and travel time) (Table S5). Among those additional demographic groups, disparities that stand out as comparatively larger are income poverty ratio (NO_2), mobility (NO_2, CO), and travel time (NO_2) (see Figure S1; Table S5).

Sensitivity tests on robustness of conclusions based on mean values showed that, for all pollutants, the rank order (i.e., most- to least-exposed racial/ethnic group, among the four racial/ethnic groups) was consistent throughout the exposure distributions (Figure 1). Results for the supplemental inequality metrics (Gini coefficient; between-group Atkinson Index) indicate that exposure inequality was largest for NO_2 and smallest for O_3 (Tables S6 and S7). This finding is consistent with the findings based on our primary metrics. The remaining two sensitivity tests investigated whether conclusions here are robust to uncertainty in exposure model predictions. Results reveal that the conclusions are robust to exposure model uncertainty. Results for analyzing only the population living in a census block group with a U.S. EPA monitor in 2010 were essentially the same as results using exposure model predictions: the non-Hispanic White group was the least-exposed group on average for most pollutants (CO, NO_2, $PM_{2.5}$, PM_{10}, and O_3), and the relative disparities by pollutant (between the most- and least-exposed group on average) were highly correlated (Spearman rank order correlation between base case and sensitivity test: 0.89) (Tables S8 and S9). The ratio between the uncertainties in estimated racial/ethnic exposure disparities and the estimated racial/ethnic disparities between the most- and least-exposed racial/ethnic groups were small: on

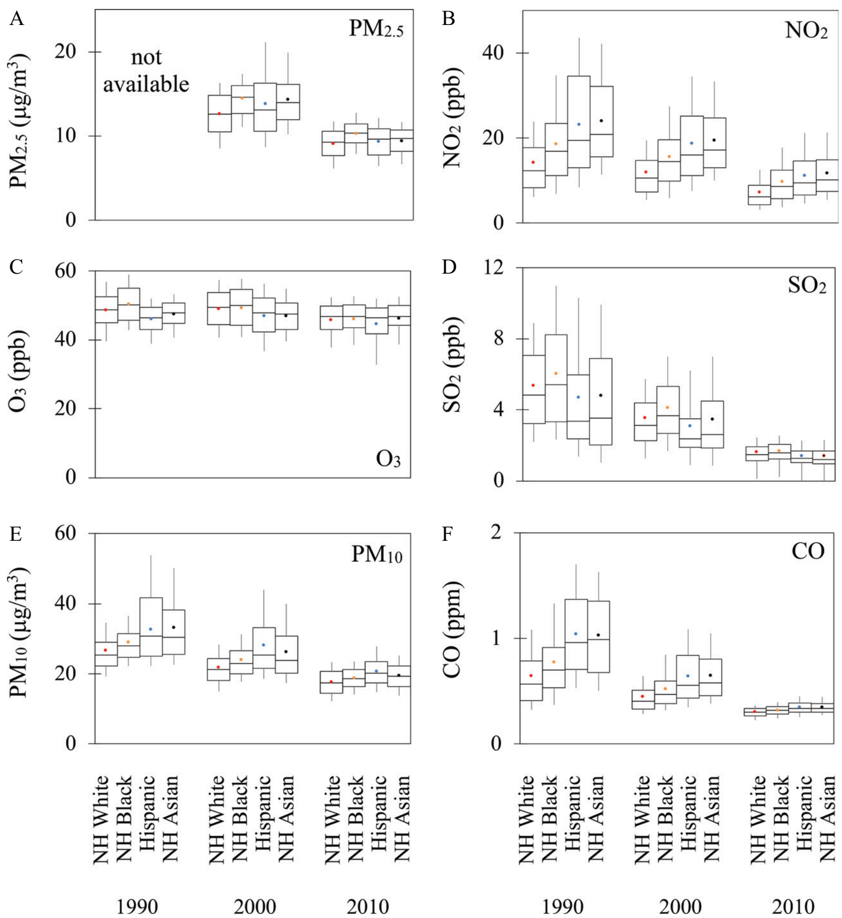

Figure 1. Distribution of exposure to pollutants in years 1990, 2000, and 2010, stratified by racial/ethnic group, for (A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO. For all panels, the highest/lowest bound represents the 90th/10th percentile value, the box shows the 25th and 75th percentiles, and the horizontal line in the box represents the median. Color circles indicate the national population-weighted mean. $PM_{2.5}$ has no estimates in 1990 because of a lack of monitoring data prior to 1999. Note: CO, carbon monoxide; Hispanic, Hispanic people of any race(s); NH, non-Hispanic; NO_2, nitrogen dioxide; O_3, ozone; $PM_{2.5}$, fine particulate matter with aerodynamic diameter less than or equal to 2.5 micrometers; PM_{10} 10 micrometers; SO_2, sulfur dioxide.

average across the six pollutants, 0.0073 (if using absolute values of the ratio, 0.083). The largest absolute ratio was −0.17 (O_3). That result indicated that the uncertainty in the exposure model predictions was always small in comparison with the predicted racial/ethnic exposure disparities (Tables S10 and S11).

We also performed an analysis to determine whether average air pollution levels varied based on the racial/ethnic composition of a given census block group. For CO, NO_2, $PM_{2.5}$, and PM_{10}, average pollution levels were higher in census block groups with higher proportions of racial/ethnic minority residents (Figure 2). For O_3, estimated average levels were approximately equal across census block group bins, regardless of census block group racial/ethnic characteristics (Figure 2). For SO_2, estimated average levels were generally higher in census block group bins with the highest and lowest proportions of racial/ethnic minority residents (i.e., higher in more racially segregated census block groups) (Figure 2). This approach also reveals that the disparities were much larger for NO_2 than for other pollutants. The disparity in average air pollution levels between block groups with the highest vs. lowest deciles of proportion racial/ethnic minority residents (block groups with >88% vs. <4% racial/ethnic minority residents) was larger for NO_2 [absolute disparity: 9.4 ppb, relative disparity (ratio): 3.1] than for other pollutants [relative disparity (ratio) range: 0.8–1.4, median: 1.1] (Table S12).

Last, we investigated racial/ethnic disparities in exposure to the highest air pollution levels. First, for each racial/ethnic group we calculated the proportion of people nationally who lived in a block group with air pollution levels above the 90th percentile for each pollutant. Averaged across all pollutants, the proportion of people nationally who lived in those highest-exposure block groups was: 9.6% for the overall population, 17% for the Hispanic population, 15% for the non-Hispanic Asian population, 12% for the non-Hispanic Black population, and 7.2% for the non-Hispanic White population. Racial/ethnic minority populations were more likely than non-Hispanic White populations to live in a census block group with air pollution levels above the 90th percentile, for all pollutants (range: 1.0× to 4.1×, median: 2.1×) except SO_2 (0.88×) (Figure S2; Table S13). Next, we calculated the racial-ethnic composition of the block groups with air pollution levels above the 90th percentile for each pollutants; the proportion of the population in those block groups that is non-Hispanic White is less than the national average, for all pollutants except SO_2 (Figure S3; Table S14). Racial/ethnic minority populations were also disproportionately likely to live in a census block group having *multiple* pollutants with levels above the 90th percentile. For example, the proportion of population living in a census block group with levels above the 90th percentile for four or more criteria pollutants was 5.2% for the Hispanic population (3.6 times the national population average proportion), 2.2% for the non-Hispanic Asian population (1.5 times the average), 1.9% for the non-Hispanic Black population (1.3 times the average), and 0.36% for the non-Hispanic White population (0.25 times the

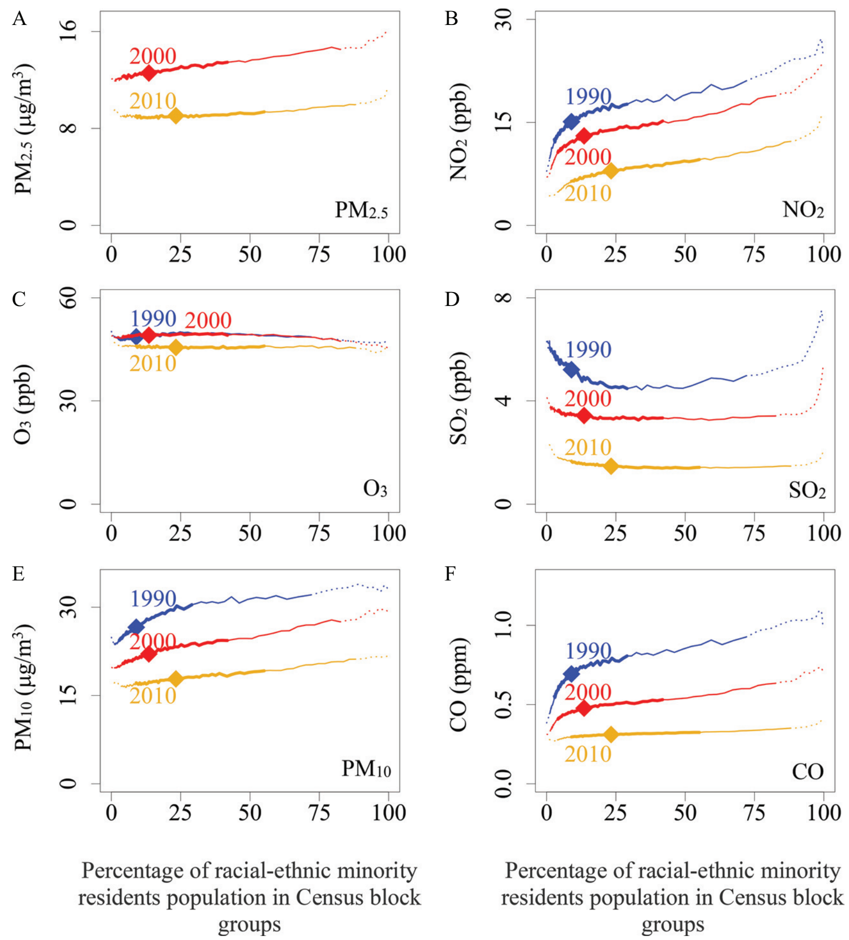

Figure 2. Relationship between the proportion of racial/ethnic minority residents in census block groups and average criteria air pollution concentrations in the years 1990, 2000, and 2010 for (A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO. For each panel, the thicker portion of the line indicates the 25th to 75th percentile of census block groups, the thin line indicates the 10th to 90th percentiles, the dashed line indicates the 1st to 99th percentiles, and the diamond icon indicates the median. Note: CO, carbon monoxide; Hispanic, Hispanic people of any race(s); NH, non-Hispanic; NO_2, nitrogen dioxide; O_3, ozone; $PM_{2.5}$, fine particulate matter with aerodynamic diameter less than or equal to 2.5 micrometers; PM_{10} 10 micrometers; SO_2, sulfur dioxide.

average) (for comparison: 1.4% for the overall U.S. population) (Table S14). The ratio of the non-Hispanic White population relative to the national population average in each block group category declined monotonically as the number of pollutants above the 90th percentile increased from 0 to ≥4 (ratios from 1.1 to 0.25), whereas corresponding ratios increased monotonically for non-Hispanic Black (from 0.88 to 1.3) and for Hispanic populations (from 0.84 to 3.6) and increased nonmonotonically for non-Hispanic Asian populations (from 0.88 for 0 pollutants to 2.3 and 1.5 for 3 and ≥4 pollutants >90th percentile, respectively) (Figure S4; Table S15).

By income. To investigate national exposure disparities by income, we first compared national mean exposures to criteria air pollution by census income category in 2010. For all pollutants except O_3, national mean exposures were higher for lowest-income (<\$10,000; 7.2% of the households with income data) than for highest-income (>\$200,000; 4.2%) households, with all pollutants except NO_2 (and, to a lesser extent, CO and O_3) exhibiting a monotonic trend (Figure S5). (Consistent with those findings, we also found that for the remaining three pollutants (SO_2, $PM_{2.5}$, PM_{10}), but not for O_3, NO_2, and CO, the most-exposed income category is the lowest-income category and the least-exposed income category is the highest-income category; see Table S16). Relative to the overall population-weighted mean exposure for all households in 2010, the absolute difference between mean exposures among those in the lowest- vs. highest-income category households were 16% (relative to national mean exposure) higher for SO_2, 6.6% higher for $PM_{2.5}$, and 5.2% higher for PM_{10}. For NO_2, CO, and O_3, exposures for lowest- and highest-income households were similar ($\sim \pm 2\%$) (Table S17). (For comparison, for NO_2, CO, and O_3, exposure differences between the most- and least-exposed income categories were 2.5% to 9.4%; see Table S16.)

Based on differences in average exposures between the approximate 25th and 75th percentiles for income [\$20,000–\$25,000 (midpoint: \$22,500) and \$75,000–\$100,000 (midpoint: \$87,500)], a \$10,000 increase in income was associated with an average reduction in concentration (expressed as a percent of the national mean concentration) of 0.90% for SO_2, 0.41% for $PM_{2.5}$, 0.36% for NO_2, and 0.22% for PM_{10} and CO, and an increase of 0.16% for O_3. For NO_2, the change in average exposure per \$10,000 increase in income was 0.59% between the 25th and 50th [\$40,000–\$45,000 (midpoint: \$42,500)] percentiles, and 0.26% between the 50th and 75th percentile (Table S18).

By both race/ethnicity and income. In this section, we present exposure disparities accounting for both race/ethnicity and income together for census householders (hereafter, "households"). For all six pollutants in 2010, the absolute exposure disparity between the most- and least-exposed racial/ethnic groups was larger [on average, ~6 times larger; 1.1 times (i.e., 10% larger) for SO_2, 21 times for NO_2, and 1.4 (i.e., 40% larger) to 6.8 times for the remaining

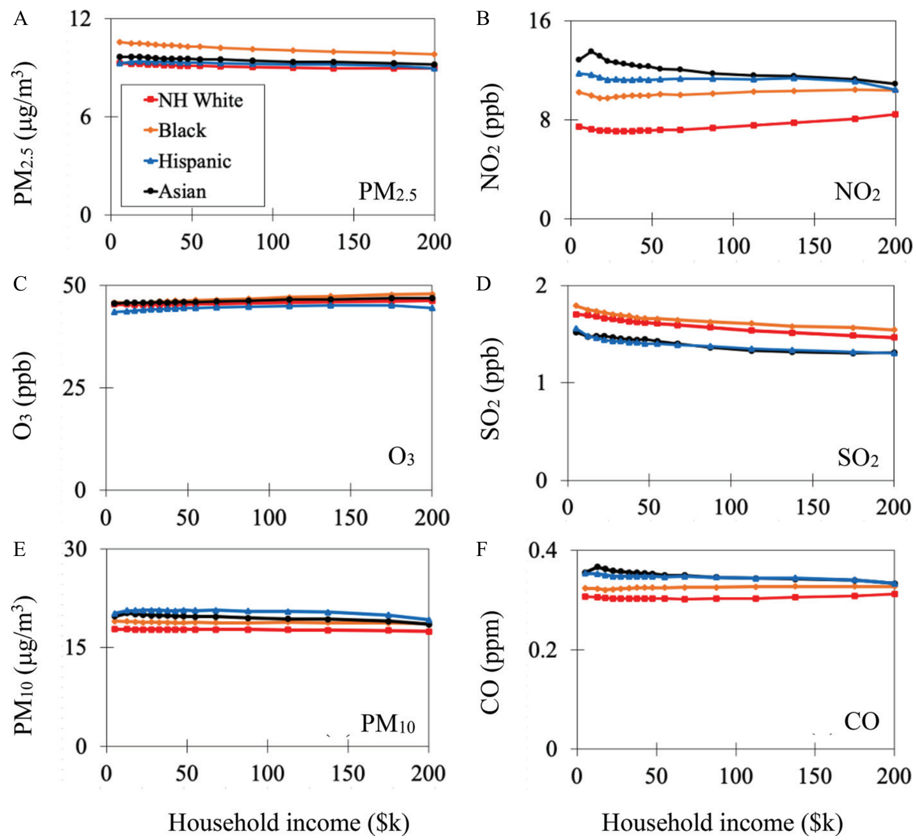

Figure 3. Population-weighted criteria air pollution concentration in 2010 for 16 household income groups, stratified by race/ethnicity, for (A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO. For all panels, each data point represents pollution exposure for one income category and racial/ethnic group. Values plotted for household income are, for values below $200,000 (i.e., for the first 15 income categories), the midpoint value; for the highest income category (">$200,000"), the value plotted is the low end of the range ($200,000). Note: Asian, Hispanic and non-Hispanic Asian people; Black, Hispanic and non-Hispanic Black people; CO, carbon monoxide; Hispanic, Hispanic people of any race(s); NH White, non-Hispanic White people; NO_2, nitrogen dioxide; O_3, ozone; $PM_{2.5}$, fine particulate matter with aerodynamic diameter less than or equal to 2.5 micrometers; PM_{10} 10 micrometers; SO_2, sulfur dioxide.

pollutants] than the absolute exposure disparity between the lowest- and highest-income categories [relative disparity: on average, ~1.2 times (i.e., 20% larger)]. The absolute exposure disparity between the most- and least-exposed racial/ethnic groups is 5.8 times for NO_2, 1.1 times (i.e., 10% larger) for SO_2, and 1.4 to 4.4 times for remaining pollutants than the absolute exposure disparity between the most- and least-exposed income categories (Table S19). For all income levels and pollutants, the most-exposed racial/ethnic group was a racial/ethnic minority group (Figure 3; Table S20). For five of the six pollutants (not SO_2; Figure 3), average exposures were higher on average for Black households at the approximate 75th percentile for income (income category midpoint: $87,500) than for non-Hispanic White households at the approximate 25th percentile for income (midpoint: $22,500). Racial/ethnic exposure disparities tended to be comparatively smaller at higher incomes than at lower incomes (except for O_3), but the size of that effect was modest. For example, the absolute exposure disparity between the most- and least-exposed racial/ethnic groups (Figure 3) was, on average, 9.5% lower for households at the approximate 75th percentile than at the approximate 25th percentile of income.

Income distributions varied by racial/ethnic group. For example, non-Hispanic White households represented 61% of the lowest income category (<$10,000) and 85% of the highest income category (>$200,000), vs. 23% and 3.5%, respectively, for Black households, 13% and 4.3% for Hispanic households, and 3.5% and 6.9% for Asian households (Table S21). To quantify racial/ethnic exposure disparities after accounting for racial/ethnic income distribution variation, we calculated the absolute exposure disparity between the most- and least-exposed racial/ethnic groups within each income category in 2010 and then averaged across all 16 income categories. The resulting national absolute exposure disparity between most- and least-exposed racial/ethnic groups averaged across income categories and normalized to national mean exposure (i.e., expressed as a percent of the national mean concentration) was 58% for NO_2, 4.5% for O_3, 12%–17% for the remaining pollutants. Conversely, to quantify income exposure disparities after accounting for race/ethnicity, we calculated the absolute income disparity within each racial/ethnic group and averaged across the four racial/ethnic groups. The resulting national absolute exposure disparity between lowest and highest income categories normalized to national mean exposure was 15% for SO_2, −2.9% for O_3, and 2.7%–6.3% for the remaining pollutants (Table S22). In conclusion, the results given here, consistent with Liu (2021), indicate that racial/ethnic exposure disparities were distinct from, and larger than, exposure disparities by income.

Racial/ethnic Exposure Disparities by State and by Urbanicity in 2010

By state. We explored how exposures varied by state, pollutant, and racial/ethnic group in 2010 (Figure 4). The analysis separately considers the District of Columbia (DC) plus the 48 states of the contiguous United States (hereafter, "states" refers to 48 states and DC, a total of 49 geographic units in state-level related calculations). There are 294 pollutant-state combinations (6 pollutants × 49 units) and

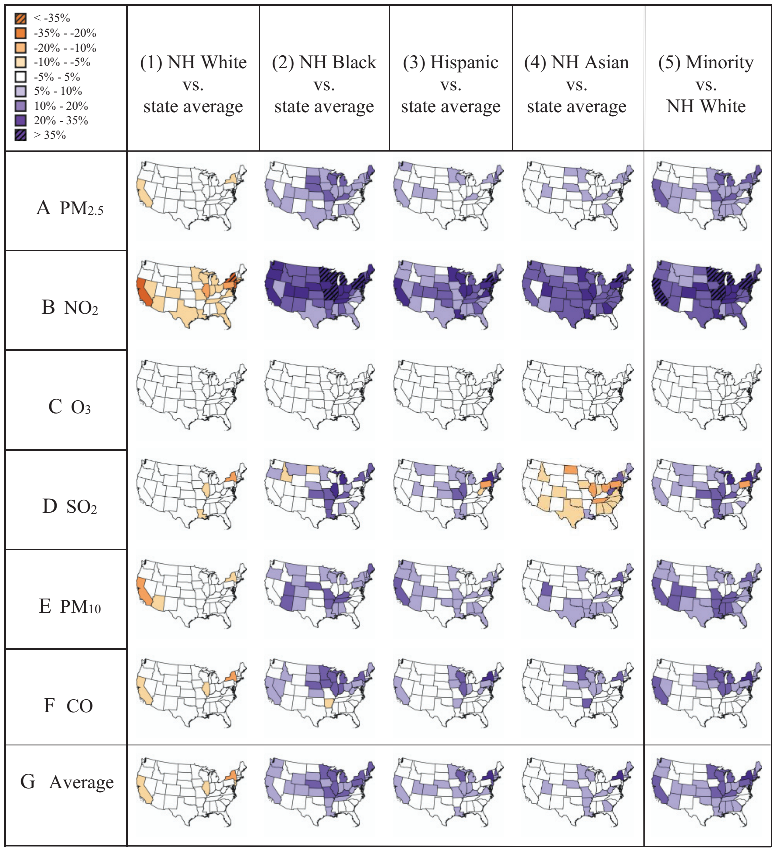

Figure 4. State racial/ethnic disparities in pollution exposure in 2010, showing the difference between (1) NH White vs. state average, (2) NH Black vs. state average, (3) Hispanic vs. state average, (4) NH Asian vs. state average, and (5) Minority vs. NH White for the six pollutants. (A) $PM_{2.5}$, (B) NO_2, (C) O_3, (D) SO_2, (E) PM_{10}, and (F) CO, and (G) average across the six pollutants. Columns 1–4: exposure disparity relative to state average; calculated as mean exposure for a racial/ethnic group in that state minus the overall mean for that state, then divided by the national overall mean. Column 5: exposure disparity for racial/ethnic minorities relative to the racial/ethnic majority group; calculated as mean exposure for racial/ethnic minorities minus mean exposure for non-Hispanic White people, then divided by the national overall mean. Mean values are population-weighted. States displayed in white indicate that the disparity is within $\pm 5\%$ of the national overall mean. Purple shading indicates that mean exposures are higher than average by more than 5% of the national overall mean (columns 1–4) or that mean exposures are higher for racial/ethnic minorities than for non-Hispanic White people, by more than 5% of the national overall mean (column 5). Orange shading indicates the reverse: mean exposures are lower than average for that group (columns 1–4) or mean exposures are lower for racial/ethnic minorities than for non-Hispanic White people (column 5), and the disparity is greater than 5% of the national overall mean. See Excel Table S1 for corresponding numeric data. Note: CO, carbon monoxide; Hispanic, Hispanic people of any race(s); NH, non-Hispanic; NO_2, nitrogen dioxide; O_3, ozone; $PM_{2.5}$, fine particulate matter with aerodynamic diameter less than or equal to 2.5 micrometers; PM_{10} 10 micrometers; SO_2, sulfur dioxide.

1,176 pollutant-state-group combinations (294 pollutant-states × 4 racial/ethnic groups). For this section, we define $\pm 5\%$ (all percentages used in this section were expressed as a percent of the national mean exposure in 2010) as "similar to" and therefore report examples where exposures differ from the average by >5% (or, in a sensitivity test, >20%). For example, ">5% lower-than-average" means the exposure is lower than state average by an amount greater than 5% of the pollutant's national mean.

Overall, several spatial patterns emerge across states. First, racial/ethnic exposure disparities were ubiquitous among U.S. states. In all 48 states and DC in 2010, one or more racial/ethnic groups experienced exposures disparities >5% of the pollutant's national mean. Second, racial/ethnic minority populations within states were much more likely to have been more exposed vs. less exposed than the state average; in contrast, none of the non-Hispanic White populations within states experienced exposures >5% above the state average. Third, having exposures >5% lower than average within a state was much more likely to happen for non-Hispanic White populations than for racial/ethnic minority (non-Hispanic Black, non-Hispanic Asian, and Hispanic populations combined) populations (Figure 4, right column). Fourth, racial/ethnic exposure disparities were most pronounced (in magnitude and with regard to the number of states affected) for NO_2, whereas mean O_3 exposures were similar among all racial/ethnic groups in all states.

Those findings reflect underlying trends across states, pollutants, and racial/ethnic groups. For example, for the non-Hispanic White group, 87% of the 294 pollutant-states had exposures that were similar ($\pm 5\%$) to the average, 13% had exposures >5% less than average, and none were >5% greater than average. In contrast, for exposures for the three racial/ethnic minority groups, 42% (of 882 pollutant-state-group combinations) were >5% greater than average, 55% were $\pm 5\%$ of the average, and only 4% were >5% lower than average. Thus, within individual states, the non-Hispanic White group was exposed to pollution levels that were similar to or cleaner than average, whereas the three racial/ethnic minority groups were more likely to be exposed to dirtier rather than cleaner pollution levels. For example, averaged across pollutants, the proportion of the states for which exposures were >5% greater than average is 73% for non-Hispanic Black populations, 57% for Hispanic populations, 35% for non-Hispanic Asian populations, and zero for non-Hispanic White populations.

The three racial/ethnic minority groups were disproportionately *likely* to be the *most*-exposed group, and disproportionately *unlikely* to be the *least*-exposed group of the four racial/ethnic groups across states. For example, the most-exposed group (for all cases, not just cases >5% greater than average) was the non-Hispanic Black group for 45% of the 294 pollutant-states, the Hispanic group for 29%, the non-Hispanic Asian group for 18%, and non-Hispanic White group for 7.5%. In contrast, the least-exposed group was rarely a racial/ethnic minority group (of the 294 pollutant-states, ~8%, each for the non-Hispanic Black and the Hispanic groups, 15% for the non-Hispanic Asian group) and was usually (70% of 294 pollutant-states) the non-Hispanic White group.

In a sensitivity test, we changed the analysis threshold to exposures >20% (rather than >5%) greater than average and similarly found that the air pollution disproportionately impacted racial/ethnic minority groups. For example, exposure disparities >20% of national mean exposure for one or more pollutant-groups occurred for 67% of states (Figure 4, left four columns for six pollutants, darkest two purple shades), further emphasizing that disparities were widespread across states in 2010.

Figure 4 reveals differences among states. For example, the four most populous states (California, Florida, New York, and Texas), all have large, racially/ethnically diverse urban areas. However, average disparities between racial/ethnic minority populations and non-Hispanic White populations (Figure 4, bottom right) were notably larger (on average, 6 times larger) for California and New York than for Florida and Texas (Excel Table S1). Some small, relatively rural states also had substantial exposure disparities; examples include NO_2 in Nebraska (19%) and $PM_{2.5}$ in Nebraska (8.1%).

By urbanicity. We investigated racial/ethnic and income-based exposure disparities in 2010 separately for block groups that were defined as urban (89% of the population) vs. rural (11% of the population). Overall, urban populations experienced larger exposure than that of rural populations for all pollutants (Table S23).

The most- and least-exposed of the four racial/ethnic groups differed between urban and rural areas for SO_2 and O_3. For SO_2, the most-exposed racial/ethnic group was the non-Hispanic Black group in urban areas and the non-Hispanic White group in rural areas. For O_3, the most-exposed racial/ethnic group was the non-Hispanic Asian group in urban areas and the non-Hispanic White group in rural areas. For the remaining four pollutants, the most-exposed group was a racial/ethnic minority group in both urban and rural areas (Table S24).

The racial/ethnic exposure disparities were generally larger for urban than for rural block groups. Specifically, the average exposure disparity between the most- and least-exposed racial/ethnic group was 5.5 times larger for absolute disparity [1.2 times for relative disparity (ratio between relative disparity in urban areas and relative disparity in rural areas)] for urban block groups than for rural block groups for NO_2, 3.1 times (1.0 times) larger for O_3, 2.4 times (1.1 times) larger for CO, 1.3 times (1.0 times) larger for SO_2, and 1.2 times (1.0 times) larger for PM_{10}. [Here, 1.2 times larger would indicate 20% larger, and 1.0 times larger would indicate 0% larger (i.e., not larger).] In contrast, for $PM_{2.5}$, the average racial/ethnic exposure disparity was 1.2 times (1.0 times) larger for rural block groups than for urban block groups (Table S24).

Exposure disparities by income category were also larger in urban than in rural areas. Absolute exposure disparities between lowest and highest income category were 1.1 times ($PM_{2.5}$) to 25 times (O_3) (median: 3.5 times) greater [for relative disparity (ratio), range: 0.98–1.1 times; median: 1.0 times] in urban than in rural areas (Table S25). Of the 12 pollutant-urbanicity categories (6 pollutants × 2 urbanicities), exposures were higher for the lowest-income category than for the highest-income category in all cases except for O_3 in urban areas and NO_2 in rural areas (Table S25).

Changes in National Exposures and Exposure Disparities from 1990 to 2010

Criteria air pollution levels have declined in the United States in the decades following the 1990 Clean Air Act amendments (U.S. EPA 2020) (Table S26). To investigate whether these reductions have led to reductions in racial/ethnic exposure disparities, we compared average exposures by racial/ethnic group from 1990 to 2010, for five of the pollutants. Exposure model results for $PM_{2.5}$ were available only from 2000 to 2010, so those results are presented separately.

National mean pollution levels for all six pollutants fell over the study period. For example, from 1990 to 2010, the national mean exposures decreased for all five pollutants by an average of 40% relative to national mean exposures in 1990 [range: −6% (O_3) to −71% (SO_2); −34% to −55% for remaining three pollutants]. $PM_{2.5}$ exposures decreased 29% from 2000 to 2010 (Table S27).

Average racial/ethnic exposure disparities also declined from 1990 to 2010. The amount of change depends in part on whether one considers *absolute* or *relative* disparities. In terms of *absolute* disparities, the disparities between the most- and least-exposed racial/ethnic groups decreased on average by 69% relative to absolute disparity in 1990 across the five pollutants. The largest change was an 88% decrease for CO disparities [0.40 ppm in 1990, 0.044 ppm in 2010, a 0.35 ppm (i.e., 88%) change], and the smallest change was a 54% decrease for NO_2 [9.8 ppb (1990), 4.6 ppb (2010), a 5.3 ppb (54%) change]. From 2000 to 2010, $PM_{2.5}$ disparities decreased by 35% [1.9 $\mu g/m^3$ (2000), 1.2 $\mu g/m^3$ (2010), a 0.66 $\mu g/m^3$ change] (Table S28).

In terms of *relative* disparities, the greatest change during the period 1990–2010 was a decrease for CO [disparities: 1.63 (1990), 1.15 (2010), 0.71 times (i.e., 29% reduction)], and the smallest was a decrease for O_3 [1.10 (1990), 1.04 (2010), 0.95 times (i.e., 5% reduction)]; remaining three pollutants (NO_2, PM_{10}, SO_2) were between 0.94 times and 0.95 times (i.e., 5%–6% reduction in relative disparity). $PM_{2.5}$ relative disparity remained nearly constant (0.99 times) during the period 2000–2010 (Table S28).

Absolute disparities between census block group bins with the highest vs. lowest deciles of proportions of racial/ethnic minority residents (90th–100th vs. 1st–10th percentiles in Figure 2) decreased for CO, NO_2, PM_{10}, and SO_2 [by 10% (SO_2) to 164% (CO)] and decreased by 17% from 2000 to 2010 for $PM_{2.5}$ (Table S29). For O_3, absolute disparities increased slightly, from −1.7 ppb in 1990 to −1.3 ppb (which is 0.74% of the national mean exposure) in 2010.

In addition to national changes, we investigated changes in absolute racial/ethnic exposure disparities from 1990 to 2010 by state and by urban vs. rural areas. Most states (>75%) experienced a reduction in racial/ethnic exposure disparities for pollutants, except for PM_{10} (and, except for $PM_{2.5}$ during the period 2000–2010) (Figure S6; Table S30). Urban areas experienced larger reductions in racial/ethnic exposure disparities than did rural areas for NO_2 and PM_{10} (13 times larger reductions in urban areas, for both pollutants), CO (2.4 times), and SO_2 (1.2 times). Conversely, $PM_{2.5}$ (during the period 2000–2010) and O_3 (during the period 1990–2010) had larger reductions in absolute racial/ethnic disparities for rural than for urban (2.4 times and 3.4 times larger in rural areas, respectively) (Figure S7; Table S31).

Finally, we investigated whether the changes in absolute racial/ethnic exposure disparities from 1990 to 2010 were more attributable to changes in air pollution levels or to changes in demographic patterns (migration, immigration, and other factors). Based on a counterfactual analysis, reductions in racial/ethnic exposure disparities between the most- and least-exposed racial/ethnic groups were mainly attributable to changes in air pollution levels rather than to changes in demographic patterns. On average across all pollutants, 87% of the reduction in the absolute racial/ethnic disparity metric was attributable to changes in air pollution levels from 1990 to 2000 (excluding $PM_{2.5}$ based on lack of available data), and 97% from 2000 to 2010 (Tables S32 and S33).

Discussion

Our research provides the first national investigation of air pollution exposure disparities by income and race/ethnicity for all criteria pollutants (except lead). Our results reveal trends by pollutant and across time and space.

In 2010, on average nationally, racial/ethnic minority populations were exposed to higher average levels of transportation-related air pollution (CO, NO_2) and particulate matter ($PM_{2.5}$, PM_{10}) than were non-Hispanic White populations. This finding, which holds even after accounting for uncertainties in the predictions from exposure models, is consistent with prior national studies of NO_2, $PM_{2.5}$, and PM_{10} (Clark et al. 2017; Kravitz-Wirtz et al. 2016; Mikati et al. 2018; Tessum et al. 2019; Colmer et al. 2020). Disparities for the remaining pollutants (CO, O_3, and SO_2) had not been previously studied in detail for the national population, and few studies have considered how disparities for any pollutant have changed across 20 y (Kravitz-Wirtz et al. 2016; Bullard et al. 2008).

Our findings on "which group was most exposed over time?" (on average, nationally) varied by pollutant, but in all six cases the most exposed group was a racial/ethnic minority group. That result is consistent with prior national studies, which have reported, for example, highest average NO_2 exposures for Hispanic Black and non-Hispanic Asian populations (Clark et al. 2017) and highest average proximities to industrial $PM_{2.5}$ emissions (Mikati et al. 2018) and highest average exposures to industrial air toxins (Ard 2015) for non-Hispanic Black populations.

We found that racial/ethnic minority populations were more than two times as likely than non-Hispanic white populations to live in a census block group with highest air pollution levels (above 90th percentile) on average. Those results are consistent with existing literature on disproportionate environmental risks for racial/ethnic minority populations (Collins 2016) and on groups or locations with higher risks for one environmental factor having higher risks for other factors, too (Morello-Frosch and Lopez 2006; Su et al. 2012).

We found that air pollution exposures were generally higher for lower-income than for higher-income households (for all pollutants except O_3). This finding is consistent with previous national research [e.g., for industrial $PM_{2.5}$ emissions (Mikati et al. 2018), industrial air toxins (Ard 2015), and $PM_{2.5}$ and NO_2 (Clark et al. 2014; Kravitz-Wirtz et al. 2016)]. Additionally, we found that, in 2010, absolute racial/ethnic exposure disparities were distinct from and were larger than (on average, ~ 6 times larger than) absolute exposure disparities by income. The findings here are *inconsistent* with the idea that racial/ethnic exposure disparities can be explained by, or are "merely" a reflection of, income disparities among racial/ethnic groups (Liu 2021).

The findings from this study can be used to compare relative exposure disparities for different criteria air pollutants in a consistent way, providing additional context for previous studies of single pollutant. We found that in 2010, relative racial/ethnic exposure disparities (i.e., ratios of average exposures between the most- and least-exposed groups) were largest for NO_2 and smallest for O_3. Relative income-based exposure disparities (i.e., ratios of average exposures between the lowest and highest income groups), although smaller than racial/ethnic exposure disparities for each pollutant, were largest for SO_2 and smallest (and similar) for NO_2, CO, and O_3. (These results provide information on the rank order of relative disparities in air pollution levels by pollutant; information on the rank order of relative disparities in associated health impacts by pollutant would require further analysis, as discussed next.)

Exposure disparities often connect with health disparities. Based on the magnitude of exposure disparities (e.g., 2010 national average $PM_{2.5}$ exposures for non-Hispanic Black people were 1.0 $\mu g/m^3$ higher than average), the resulting health disparities may be substantial (Liu 2021). Future research could usefully extend our exposure disparity results to provide rigorous, comprehensive investigation of the associated health impacts.

State-level results may be especially useful given the important role that states play in air pollution and environmental policy making (Abel et al. 2015). Exposures $>5\%$ greater than the national mean exposure within states were common for racial/ethnic minority populations, but not for non-Hispanic White populations. Indeed, we found no case (no state and no pollutant) for which the non-Hispanic White group experiences exposures $>5\%$ greater than the state average. This finding reflects disparity in exposure as well as non-Hispanic White populations representing a large percentage of states' populations. Exposure disparities varied substantially among states, even among states with similar characteristics (e.g., urbanicity, population, region). Our results emphasize differences among states in the level and makeup of exposure disparities, yet also demonstrate that exposure disparities were ubiquitous, including both large and small states, and states in all regions of the United States, in 2010.

Our analyses by urbanicity were in part motivated by and reflect urban–rural differences in demographics and air pollution levels (Clark et al. 2017; Mikati et al. 2018; Rosofsky et al. 2018). Racial/ethnic disparities were larger for urban block groups for all pollutants except $PM_{2.5}$. Of the six pollutants, the largest ratio between urban and rural racial/ethnic absolute disparities (5.5 times larger) was for NO_2 (Table S24). The NO_2 results are consistent with prior research (Clark et al. 2014, 2017). Over our study period, reductions in absolute racial/ethnic exposure disparities for $PM_{2.5}$ and O_3 were larger for rural than for urban areas. Analyzing urban and rural block groups separately, exposures were mostly higher for the lowest income category than the highest. Absolute income-based exposure disparities were also 7.5 times larger on average in urban than in rural areas.

The results by state and by urbanicity reflect that exposure disparities differ by spatial units (e.g., urban/rural, and by state); future research could explore these aspects further, for example, through a spatial decomposition of national exposure disparities.

Regulations such as the 1990 Clean Air Act Amendments have achieved substantial reductions in the concentrations of many pollutants. Our analysis reveals that, as a concomitant benefit, falling pollution levels have reduced absolute exposure disparities among racial/ethnic groups. These findings are consistent with previous national research for NO_2, $PM_{2.5}$, and industrial air toxins (Ard 2015; Clark et al. 2017; Kravitz-Wirtz et al. 2016; Colmer et al. 2020). We found that a larger share of the racial/ethnic exposure disparity reduction was attributable to air pollution level reduction rather than changes in demographic and residential patterns.

Our study described patterns in exposure disparities but did not investigate aspects such as underlying causes or ethical or legal aspects. Systemic racism and racial segregation are two major causes discussed in multiple previous studies (Jones et al. 2014; Morello-Frosch and Lopez 2006; Schell et al. 2020). Future longitudinal research could further investigate the underlying causes of exposure disparities. One important dimension not considered here is responsibility for generating pollution. Recent analysis suggests that Hispanic and Black populations have disproportionately lower consumption of goods and services whose emissions lead to $PM_{2.5}$ air pollution (Tessum et al. 2019).

Our study has several limitations. The finest spatial scale of publicly available census demographic data for race/ethnicity and income, at consistent spatial geographies across time (Manson et al. 2019), is at the census block group level; race/ethnicity across income data is at census tract level with slightly different categories (see "Methods" section); we were unable to assess disparities at finer spatial scales than publicly available census data; we only included the four main racial/ethnic groups. Our analysis of exposures by income is based on national-level income distribution data and does not account for spatial variations in income distributions (e.g., among states). Our disparity estimates do not account for *a*) daily mobility for work, shopping, recreation, and other activities; *b*) direct indoor exposure to indoor sources such as cigarette smoke, cooking, or incense; *c*) indoor–outdoor relationships in pollution levels, such as particle losses during airflow in ducts or ozone losses to indoor surfaces; or *d*) occupational exposures. Our exposure disparity estimates were limited by uncertainties in the CACES exposure model predictions and in census demographic data. Our uncertainty analysis (but not our main analysis) was limited to U.S. EPA monitoring locations; we were not able to test potential exposure errors at locations without monitors on the national scale. However, sensitivity analyses (Results section) indicate that the general results are robust to model uncertainty.

To our knowledge, our study provides the first national analysis of air pollution exposure disparities among income and racial/ethnic groups, for all criteria pollutants (except Pb), including trends across time (by decade, 1990–2010) and spatial location (by state and for urban vs. rural areas). On average, exposures were generally higher for racial/ethnic minority populations than for non-Hispanic White populations. Among pollutants, national racial/ethnic exposure disparities were largest for NO_2 and smallest for O_3. Exposures were also, on average, higher for the lowest-income households than for the highest-income households. However, exposure disparities by race/ethnicity were not explained by disparities in income. Racial/ethnic exposure disparities declined from 1990 to 2010 (on an absolute basis, and to a lesser extent, on a relative basis), but still existed in all states in 2010.

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References

Abel TD, Salazar DJ, Robert P. 2015. States of environmental justice: redistributive politics across the United States, 1993–2004. Rev Policy Res 32(2):200–225, https://doi.org/10.1111/ropr.12119.

Ard K. 2015. Trends in exposure to industrial air toxins for different racial and socioeconomic groups: a spatial and temporal examination of environmental inequality in the U.S. from 1995 to 2004. Soc Sci Res 53:375–390, PMID: 26188461, https://doi.org/10.1016/j.ssresearch.2015.06.019.

Bechle MJ, Millet DB, Marshall JD. 2015. National spatiotemporal exposure surface for NO2: monthly scaling of a satellite-derived land-use regression, 2000–2010. Environ Sci Technol 49(20):12297–12305, PMID: 26397123, https://doi.org/10.1021/acs.est.5b02882.

Bowe B, Xie Y, Yan Y, Al-Aly Z. 2019. Burden of cause-specific mortality associated with $PM_{2.5}$ air pollution in the United States. JAMA Netw Open 2(11):e1915834, PMID: 31747037, https://doi.org/10.1001/jamanetworkopen.2019.15834.

Brulle RJ, Pellow DN. 2006. Environmental justice: human health and environmental inequalities. Annu Rev Public Health 27(1):103–124, PMID: 16533111, https://doi.org/10.1146/annurev.publhealth.27.021405.102124.

Bullard RD, Mohai P, Saha R, Wright B. 2008. Toxic wastes and race at twenty: why race still matters after all of these years. Environ Law 38(2):371–411. http://www.jstor.org/stable/43267204.

Bullock C, Ard K, Saalman G. 2018. Measuring the relationship between state environmental justice action and air pollution inequality, 1990–2009. Rev Policy Res 35(3):466–490, https://doi.org/10.1111/ropr.12292.

Clark LP, Millet DB, Marshall JD. 2014. National patterns in environmental injustice and inequality: outdoor NO_2 air pollution in the United States. PLoS One 9(4): e94431, PMID: 24736569, https://doi.org/10.1371/journal.pone.0094431.

Clark LP, Millet DB, Marshall JD. 2017. Changes in transportation-related air pollution exposures by race-ethnicity and socioeconomic status: outdoor nitrogen dioxide in the United States in 2000 and 2010. Environ Health Perspect 125(9):097012, PMID: 28930515, https://doi.org/10.1289/EHP959.

Clean Air Scientific Advisory Committee. 2010. Letter to Hon. Lisa P. Jackson, administrator, Environmental Protection Agency, Re: CASAC Review of Policy Assessment for the Review of the PM NAAQS – Second external review draft. https://yosemite.epa.gov/sab/sabproduct.nsf/CCF9F4C0500C500F8525779D0073C593/$File/EPA-CASAC-10-015-unsigned.pdf [accessed 18 October 2021].

Cohen AJ, Brauer M, Burnett R, Anderson HR, Frostad J, Estep K, et al. 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. Lancet 389(10082):1907–1918, PMID: 28408086, https://doi.org/10.1016/S0140-6736(17)30505-6.

Collins MB, Munoz I, Jaja J. 2016. Linking "toxic outliers" to environmental justice communities. Environ Res Lett 11(1):015004, https://doi.org/10.1088/1748-9326/11/1/015004.

Colmer J, Hardman I, Shimshack J, Voorheis J. 2020. Disparities in $PM_{2.5}$ air pollution in the United States. Science 369(6503):575–578, PMID: 32732425, https://doi.org/10.1126/science.aaz9353.

Darrow LA, Klein M, Strickland MJ, Mulholland JA, Tolbert PE. 2011. Ambient air pollution and birth weight in full-term infants in Atlanta, 1994–2004. Environ Health Perspect 119(5):731–737, PMID: 21156397, https://doi.org/10.1289/ehp.1002785.

Di Q, Amini H, Shi L, Kloog I, Silvern R, Kelly J, et al. 2020. Assessing NO_2 concentration and model uncertainty with high spatiotemporal resolution across the contiguous United States using ensemble model averaging. Environ Sci Technol 54(3):1372–1384, PMID: 31851499, https://doi.org/10.1021/acs.est.9b03358.

Di Q, Wang Y, Zanobetti A, Wang Y, Koutrakis P, Choirat C, et al. 2017. Air pollution and mortality in the Medicare population. N Engl J Med 376(26):2513–2522, PMID: 28657878, https://doi.org/10.1056/NEJMoa1702747.

Downey L, Dubois S, Hawkins B, Walker M. 2008. Environmental inequality in metropolitan America. Organ Environ 21(3):270–294, PMID: 19960094, https://doi.org/10.1177/1086026608321327.

Evans GW, Kantrowitz E. 2002. Socioeconomic status and health: the potential role of environmental risk exposure. Annu Rev Public Health 23(1):303–331, PMID: 11910065, https://doi.org/10.1146/annurev.publhealth.23.112001.112349.

Fann N, Coffman E, Hajat A, Kim SY. 2019. Change in fine particle-related premature deaths among US population subgroups between 1980 and 2010. Air Qual Atmos Health 12(6):673–682, https://doi.org/10.1007/s11869-019-00686-9.

Gee GC, Payne-Sturges DC. 2004. Environmental health disparities: a framework integrating psychosocial and environmental concepts. Environ Health Perspect 112(17):1645–1653, PMID: 15579407, https://doi.org/10.1289/ehp.7074.

Goldberg DL, Gupta P, Wang K, Jena C, Zhang Y, Lu Z, et al. 2019. Using gap-filled MAIAC AOD and WRF-Chem to estimate daily PM2.5 concentrations at 1 km resolution in the Eastern United States. Atmos Environ 199:443–452, https://doi.org/10.1016/j.atmosenv.2018.11.049.

Hajat A, Hsia C, O'Neill MS. 2015. Socioeconomic disparities and air pollution exposure: a global review. Curr Environ Health Rep 2(4):440–450, PMID: 26381684, https://doi.org/10.1007/s40572-015-0069-5.

Harper S, Ruder E, Roman HA, Geggel A, Nweke O, Payne-Sturges D, et al. 2013. Using inequality measures to incorporate environmental justice into regulatory analyses. Int J Environ Res Public Health 10(9):4039–4059, PMID: 23999551, https://doi.org/10.3390/ijerph10094039.

Independent Particulate Matter Review Panel. 2020. The need for a tighter particulate-matter air-quality standard. N Engl J Med 383:680–683, PMID: 32521130, https://doi.org/10.1056/NEJMsb2011009.

Jones MR, Diez-Roux AV, Hajat A, Kershaw KN, O'Neill MS, Guallar E, et al. 2014. Race/ethnicity, residential segregation, and exposure to ambient air pollution: the Multi-Ethnic Study of Atherosclerosis (MESA). Am J Public Health 104(11):2130–2137, PMID: 25211756, https://doi.org/10.2105/AJPH.2014.302135.

Kim SY, Bechle M, Hankey S, Sheppard L, Szpiro AA, Marshall JD. 2020. Concentrations of criteria pollutants in the contiguous U.S., 1979–2015: role of prediction model parsimony in integrated empirical geographic regression. PLoS One 15(2):e0228535, PMID: 32069301, https://doi.org/10.1371/journal.pone.0228535.

Kravitz-Wirtz N, Crowder K, Hajat A, Sass V. 2016. The long-term dynamics of racial/ethnic inequality in neighborhood air pollution exposure, 1990–2009. Du Bois Rev 13(2):237–259, PMID: 28989341, https://doi.org/10.1017/S1742058X16000205.

Laden F, Schwartz J, Speizer FE, Dockery DW. 2006. Reduction in fine particulate air pollution and mortality: extended follow-up of the Harvard Six Cities study. Am J Respir Crit Care Med 173(6):667–672, PMID: 16424447, https://doi.org/10.1164/rccm.200503-443OC.

Lelieveld J, Evans JS, Fnais M, Giannadaki D, Pozzer A. 2015. The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature 525(7569):367–371, PMID: 26381985, https://doi.org/10.1038/nature15371.

Liu J. 2021. Auxiliary Analysis of Air Pollution Disparities in the U.S. https://bit.ly/3B4PhKa. [accessed 20 October 2021].

Manson S, Schroeder J, Van Riper D, Ruggles S. 2019. IPUMS National Historical Geographic Information System: Version 14.0 [Database]. http://doi.org/10.18128/D050.V14.0 [accessed 24 May 2020].

Marshall JD, Swor KR, Nguyen NP. 2014. Prioritizing environmental justice and equality: diesel emissions in Southern California. Environ Sci Technol 48(7):4063–4068, PMID: 24559220, https://doi.org/10.1021/es405167f.

Mikati I, Benson AF, Luben TJ, Sacks JD, Richmond-Bryant J. 2018. Disparities in distribution of particulate matter emission sources by race and poverty status. Am J Public Health 108(4):480–485, PMID: 29470121, https://doi.org/10.2105/AJPH.2017.304297.

Mohai P, Pellow D, Roberts JT. 2009. Environmental justice. Annu Rev Environ Resour 34(1):405–430, https://doi.org/10.1146/annurev-environ-082508-094348.

Morello-Frosch R, Lopez R. 2006. The riskscape and the color line: examining the role of segregation in environmental health disparities. Environ Res 102(2):181–196, PMID: 16828737, https://doi.org/10.1016/j.envres.2006.05.007.

Novotny EV, Bechle MJ, Millet DB, Marshall JD. 2011. National satellite-based land-use regression: NO_2 in the United States. Environ Sci Technol 45(10):4407–4414, PMID: 21520942, https://doi.org/10.1021/es103578x.

Office of Air Quality Planning and Standards. 2008. Ambient Air Monitoring Strategy for State, Local, and Tribal Air Agencies. https://www.epa.gov/amtic/ambient-air-monitoring-strategy-state-local-and-tribal-air-agencies. [accessed 01 December 2021].

Paul KC, Haan M, Mayeda ER, Ritz BR. 2019. Ambient air pollution, noise, and late-life cognitive decline and dementia risk. Annu Rev Public Health 40:203–220, PMID: 30935305, https://doi.org/10.1146/annurev-publhealth-040218-044058.

Pope CA, Coleman N, Pond ZA, Burnett RT. 2020. Fine particulate air pollution and human mortality: 25+ years of cohort studies. Environ Res 183:108924, PMID: 31831155, https://doi.org/10.1016/j.envres.2019.108924.

Pope CA 3rd, Ezzati M, Dockery DW. 2009. Fine-particulate air pollution and life expectancy in the United States. N Engl J Med 360(4):376–386, PMID: 19164188, https://doi.org/10.1056/NEJMsa0805646.

Ratcliffe M, Burd C, Holder K, Fields A. 2016. Defining Rural at the U.S. Census Bureau (U.S. Census Bureau). https://www2.census.gov/geo/pdfs/reference/ua/Defining_Rural.pdf [accessed 7 July 2020].

Rivas I, Basagaña X, Cirach M, López-Vicente M, Suades-González E, Garcia-Esteban R, et al. 2019. Association between early life exposure to air pollution and working memory and attention. Environ Health Perspect 127(5):57002, PMID: 31070940, https://doi.org/10.1289/EHP3169.

Rosofsky A, Levy JI, Zanobetti A, Janulewicz P, Fabian MP. 2018. Temporal trends in air pollution exposure inequality in Massachusetts. Environ Res 161(2018):76–86, PMID: 29101831, https://doi.org/10.1016/j.envres.2017.10.028.

Salazar DJ, Clauson S, Abel TD, Clauson A. 2019. Race, income, and environmental inequality in the U.S. states, 1990–2014. Soc Sci Q 100(3):592–603, https://doi.org/10.1111/ssqu.12608.

Schell CJ, Dyson K, Fuentes TL, Des Roches S, Harris NC, Miller DS, et al. 2020. The ecological and evolutionary consequences of systemic racism in urban environments. Science 369(6510):, PMID: 32792461, https://doi.org/10.1126/science.aay4497.

Shi L, Zanobetti A, Kloog I, Coull BA, Koutrakis P, Melly SJ, et al. 2016. Low-concentration PM2.5 and mortality: estimating acute and chronic effects in a population-based study. Environ Health Perspect 124(1):46–52, PMID: 26038801, https://doi.org/10.1289/ehp.1409111.

Stanaway JD, Afshin A, Gakidou E, Lim SS, Abate D, Abate KH, et al. 2018. Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet 392(10159):1923–1994, PMID: 30496105, https://doi.org/10.1016/S0140-6736(18)32225-6.

Stieb DM, Chen L, Eshoul M, Judek S. 2012. Ambient air pollution, birth weight and preterm birth: a systematic review and meta-analysis. Environ Res 117(2012):100–111, PMID: 22726801, https://doi.org/10.1016/j.envres.2012.05.007.

Su JG, Jerrett M, Morello-Frosch R, Jesdale BM, Kyle AD. 2012. Inequalities in cumulative environmental burdens among three urbanized counties in California. Environ Int 40:79–87, PMID: 22280931, https://doi.org/10.1016/j.envint.2011.11.003.

Tessum CW, Apte JS, Goodkind AL, Muller NZ, Mullins KA, Paolella DA, et al. 2019. Inequity in consumption of goods and services adds to racial-ethnic disparities in air pollution exposure. Proc Natl Acad Sci U S A 116(13):6001–6006, PMID: 30858319, https://doi.org/10.1073/pnas.1818859116.

Underwood E. 2017. The polluted brain. Science 355(6323):342–345, PMID: 28126768, https://doi.org/10.1126/science.355.6323.342.

U.S. Census Bureau. 2021. Poverty Thresholds. https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html [accessed 5 November 2021].

U.S. EPA (U.S. Environmental Protection Agency). 2016. EPA Downscalar Model for Predicting Daily Air Pollution. https://19january2017snapshot.epa.gov/air-research/downscaler-model-predicting-daily-air-pollution_.html. [accessed 20 October 2021].

U.S. EPA. 2019. Integrated Science Assessment (ISA) for Particulate Matter (Final Report, December 2019). https://cfpub.epa.gov/ncea/isa/recordisplay.cfm?deid=347534. [accessed 13 October 2021].

U.S. EPA. 2020. Our Nation's Air: Status and Trends through 2019. https://gispub.epa.gov/air/trendsreport/2020/ [accessed 7 July 2020].

U.S. EPA. 2020. Review of the National Ambient Air Quality Standards for Particulate Matter. https://www.federalregister.gov/documents/2020/04/30/2020-08143/review-of-the-national-ambient-air-quality-standards-for-particulate-matter. [accessed 18 October 2021].

Van Donkelaar A, Martin RV, Li C, Burnett RT. 2019. Regional estimates of chemical composition of fine particulate matter using a combined geoscience-statistical method with information from satellites, models, and monitors. Environ Sci Technol 53(5):2595–2611, PMID: 30698001, https://doi.org/10.1021/acs.est.8b06392.

Young MT, Bechle MJ, Sampson PD, Szpiro AA, Marshall JD, Sheppard L, et al. 2016. Satellite-based NO_2 and model validation in a national prediction model based on universal kriging and land-use regression. Environ Sci Technol 50(7):3686–3694, PMID: 26927327, https://doi.org/10.1021/acs.est.5b05099.

Zanobetti A, Schwartz J. 2009. The effect of fine and coarse particulate air pollution on mortality: a national analysis. Environ Health Perspect 117(6):898–903, PMID: 19590680, https://doi.org/10.1289/ehp.0800108.

Zwickl K, Ash M, Boyce JK. 2014. Regional variation in environmental inequality: industrial air toxics exposure in U.S. cities. Ecol Econ 107:494–509, https://doi.org/10.1016/j.ecolecon.2014.09.013.

[redacted]

Consumers Energy
Count on Us®

Questions:
Visit: **ConsumersEnergy.com**
Call us: **800-477-5050**

Amount Due:	**$150.27**
Please pay by:	**May 21, 2025**

Thank You - We received your last payment of **$222.98** on **April 14, 2025**

Service Address:
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

TABITHA WILLIAMS
1128 JEFFERSON AVE SE
GRAND RAPIDS MI 49507-1154

May Energy Bill

Service dates: March 27, 2025 - April 28, 2025 (33 days)

Total Electric Use (kWh - kilowatt-hour)

kWh = A 100-watt bulb burning for 10 hours uses 1 kilowatt-hour.

ACTUAL

May Electric Use

714 kWh

Cost per day: **$4.38**

kWh per day: **22**

STAY SAFE: Call 9-1-1 and 800-477-5050. We'll respond day or night.

Downed power lines. Stay 25 feet away. Call from a safe location.

If you smell natural gas. If the "rotten egg" odor of gas is apparent, call from a safe location.

How to Plan for Trees and Reliable Service

To keep your service reliable, please plant as many feet away from overhead and underground lines as the expected mature height and width of the plant. Visit www.MISSDIG811.org or call 8-1-1 at least three working days before digging to have underground lines marked.

For existing trees and plants, we clear our lines within our easements. The clearance distance and our maintenance schedule follow safety standards for the voltage and tree type. We clean up debris from our planned work. Debris from other requested and emergent work is your property, and we're unable to clean it up. If a tree or branch is causing pressure on an electric wire, stay at least 25 feet away from the wire or anything touching it and call us at 800-477-5050. Learn more: www.ConsumersEnergy.com/Forestry

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Consumers Energy
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See reverse side for more information

[redacted]

Amount Due:	**$150.27**
Please pay by:	**May 21, 2025**
Enclosed:	

Service Address:
TABITHA WILLIAMS
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

[redacted]

03 05/25

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE, Grand Ra

[redacted]

Account Information

Bill Month: May

May Energy Bill

[redacted]

1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

Enclosed:

[redacted]

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE; Grand Rapids MI 49507-1154

[redacted]

Account Information

Bill Month: May
Service Dates: 03/27/2025 - 04/28/2025
Days Billed: 33
Portion: 03 05/25

A Home Heating Credit can help if you use electricity as your primary source of heat for your household. To complete the form, here are your 2024 heating costs for 12 months: $2,127.77.

Rate Information

Electric Residential Service
Rate Code: 1001

Meter Information

Your next scheduled meter read date is on or around 05/28/2025

Electric Service: Smart Meter
[redacted]
Beginning Read Date: 03-27
Ending Read Date: 04-28
Beginning Read: 84471
Ending Read: 85185 (Actual)
Usage: 714.000 kWh
Interval Usage: 714.303 kWh

Your meter records electric energy use in hourly intervals. Your bill is the total of all hourly intervals recorded during your billing period.

End and start date kWh meter readings are provided for information purposes only. Please visit Energy Use Details at ConsumersEnergy.com to view your energy use data.

May Energy Bill [redacted]

Account Summary

Last Month's Account Balance	$222.98
Payment on April 14, 2025	$222.98-
Balance Forward	**$0.00**

Payments applied after Apr 29, 2025 are not included.

Electric Charges

Non-Summer(Billed 03/27/2025 - 04/28/2025)

03/27/2025 - 04/03/2025		
Energy Charges	209.927@ 0.087554	$18.38
04/04/2025 - 04/28/2025		
Energy Charges	504.376@ 0.085252	$43.00
Other Charges		
PSCR	714.303@ 0.013440	$9.60
System Access		$8.00
Deferral Surcharge	504.376@ 0.001090	$0.55
IRM Surcharge	209.927@ 0.000424	$0.09
IRM Surcharge	504.376@ 0.000259	$0.13
Distribution	209.927@ 0.074267	$15.59
Distribution	504.376@ 0.078955	$39.82
FCM Incentive	70.466@ 0.000293	$0.02
Other Surcharges	714.303@ 0.004529	$3.24
Power Plant Securitization	714.303@ 0.001187	$0.85
Karn 1&2 Securitization Charge	714.303@ 0.004556	$3.25
DR Surcharge	504.376@ 0.002250	$1.13
Low-Income Assist Fund		$0.87
Total Electric		**$144.52**
State Sales Tax		$5.75
Total Energy Charges		**$150.27**

Amount Due: **$150.27**
by May 21, 2025
If you pay after the due date, a 2% late payment charge will be added to your next bill.

Please make any inquiry or complaint about this bill before the due date listed on the front. Visit **ConsumersEnergy.com/aboutmybill** for details about the above charges.

NEWS AND INFORMATION

Summer Pricing is in effect from 6/1 to 9/30. Use energy off-peak to save. Learn more at www.ConsumersEnergy.com/SummerRate

For information on safety and customer rights: www.ConsumersEnergy.com/CustomerGuides

Consumers Energy is regulated by the Michigan Public Service Commission, Lansing, Michigan

Ways to pay your energy bill

How: Checking or savings account, credit or debit card, cash, check or money order.

Where: Mobile app, ConsumersEnergy.com, mail (see front), phone (800-371-9811) or authorized in-person locations.

Automatic and one-time payment options are available. Payment methods accepted and transaction fee may vary.

Need help with your bill?

Payment plans, budgeting programs and more: 800-477-5050 or www.ConsumersEnergy.com/Assistance

Save money and energy: www.ConsumersEnergy.com/Save
Sign-up for billing alerts: www.ConsumersEnergy.com/MyLogin

More payment options and details:
www.ConsumersEnergy.com/WaysToPay

[redacted]

Consumers Energy
Count on Us®

Questions:
Visit: **ConsumersEnergy.com**
Call us: **800-477-5050**

Amount Due:	**$270.28**
Please pay by:	**June 20, 2025**

Reminder - Please pay previous amount due from 05/21/25. Thank you.

TABITHA WILLIAMS
1128 JEFFERSON AVE SE
GRAND RAPIDS MI 49507-1154

Service Address:
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

June Energy Bill

Service dates: April 29, 2025 - May 28, 2025 (30 days)

Total Electric Use (kWh - kilowatt-hour)

kWh = A 100-watt bulb burning for 10 hours uses 1 kilowatt-hour.

June Electric Use

548 kWh

Cost per day:
$3.76

kWh per day:
18

STAY SAFE: Call 9-1-1 and 800-477-5050. We'll respond day or night.

Downed power lines. Stay 25 feet away. Call from a safe location.

If you smell natural gas. If the "rotten egg" odor of gas is apparent, call from a safe location.

Want to know what we're doing to keep service reliable?
Make sure your email, phone number and mailing address are up to date so we can notify you about work affecting your service. Update your information in the Consumers Energy App or visit: www.ConsumersEnergy.com/UpdateMyInfo

Did you know you may have already experienced the benefits of recent upgrades? If your power has blinked or been restored within a few minutes, you're probably experiencing one of the many new technologies that quickly detect issues and remotely restore or reroute power to prevent longer outages. These benefits extend to keeping the energy flowing through our natural gas system.

Want more information on what's happening now? Follow us on social media and read the latest news at: www.ConsumersEnergy.com/Reliable

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Count on Us®

You can pay your bill by mail, by phone or online
See reverse side for more information

[redacted]

Service Address:
TABITHA WILLIAMS
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

Amount Due:	**$270.28**
Please pay by:	**June 20, 2025**
Enclosed:	

[redacted]

03 06/25

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE, Grand Ra

[redacted]

Account Information
Bill Month: June

June Energy Bill

[redacted]

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1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

Enclosed:

[redacted]

03 06/25

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE; Grand Rapids MI 49507-1154

[redacted]

Account Information

Bill Month: June
Service Dates: 04/29/2025 - 05/28/2025
Days Billed: 30
Portion: 03 06/25

A Home Heating Credit can help if you use electricity as your primary source of heat for your household. To complete the form, here are your 2024 heating costs for 12 months: $2,127.77.

Rate Information

Electric Residential Service
Rate Code: 1001

Meter Information

Your next scheduled meter read date is on or around 06/26/2025

Electric Service: Smart Meter
[redacted]
Beginning Read Date: 04-29
Ending Read Date: 05-28
Beginning Read: 85185
Ending Read: 85734 (Actual)
Usage: 549.000 kWh
Interval Usage: 548.494 kWh

Your meter records electric energy use in hourly intervals. Your bill is the total of all hourly intervals recorded during your billing period.

End and start date kWh meter readings are provided for information purposes only. Please visit Energy Use Details at ConsumersEnergy.com to view your energy use data.

June Energy Bill [redacted]

Account Summary

Last Month's Account Balance	$150.27
Balance Forward	**$150.27**
Late Payment Charge	$2.89

Reminder - Please pay previous amount due from 05/21/25. Thank you.
Payments applied after May 29, 2025 are not included.

Electric Charges

Non-Summer(Billed 04/29/2025 - 05/28/2025)

Energy Charges	548.494@ 0.085252	$46.76
Other Charges		
PSCR	548.494@ 0.010840	$5.95
System Access		$8.00
Deferral Surcharge	548.494@ 0.001090	$0.60
IRM Surcharge	548.494@ 0.000259	$0.14
Distribution	548.494@ 0.078955	$43.31
FCM Incentive	548.494@ 0.000293	$0.16
Other Surcharges	548.494@ 0.004529	$2.48
Power Plant Securitization	548.494@ 0.001187	$0.65
Karn 1&2 Securitization Charge	548.494@ 0.004556	$2.50
DR Surcharge	548.494@ 0.002250	$1.23
Low-Income Assist Fund		$0.87
Total Electric		**$112.65**
State Sales Tax		$4.47
Total Energy Charges		**$117.12**

Amount Due: $270.28
by June 20, 2025

If you pay after the due date, a 2% late payment charge will be added to your next bill.

Please make any inquiry or complaint about this bill before the due date listed on the front. Visit **ConsumersEnergy.com/aboutmybill** for details about the above charges.

NEWS AND INFORMATION

Safety first! Review the Electric Safety Guide tips on downed wires, power outages, and more at: www.ConsumersEnergy.com/ElectricSafetyGuide

Summer Pricing is in effect from 6/1 to 9/30. Use energy off-peak to save. Learn more at www.ConsumersEnergy.com/SummerRate

For information on safety and customer rights: www.ConsumersEnergy.com/CustomerGuides

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Ways to pay your energy bill

How: Checking or savings account, credit or debit card, cash, check or money order.

Where: Mobile app, ConsumersEnergy.com, mail (see front), phone (800-371-9811) or authorized in-person locations.

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Save money and energy: www.ConsumersEnergy.com/Save
Sign-up for billing alerts: www.ConsumersEnergy.com/MyLogin

More payment options and details: www.ConsumersEnergy.com/WaysToPay

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consumersenergy.com

[redacted]

Consumers Energy
Count on Us®

Questions:
Visit: **ConsumersEnergy.com**
Call us: **800-477-5050**

Amount Due:	$346.78
Please pay by:	August 20, 2025

Thank You - We received your last payment of **$204.18** on **July 23, 2025**

Service Address:
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

TABITHA WILLIAMS
1128 JEFFERSON AVE SE
GRAND RAPIDS MI 49507-1154

August Energy Bill

Service dates: June 27, 2025 - July 28, 2025 (32 days)

Total Electric Use (kWh - kilowatt-hour)

kWh = A 100-watt bulb burning for 10 hours uses 1 kilowatt-hour. **ACTUAL**

August Electric Use
1,537 kWh

Cost per day:
$10.42

kWh per day:
48

STAY SAFE: Call 9-1-1 and 800-477-5050. We'll respond day or night.

Downed power lines. Stay 25 feet away. Call from a safe location.

If you smell natural gas. If the "rotten egg" odor of gas is apparent, call from a safe location.

Your safety is our top priority. Scam tactics are changing fast.
Use caution before responding to incoming phone calls, emails, or text messages. When in doubt, call us. Always pay your bill using our secure payment options. See the bottom, backside of this bill for more information.

Before we visit, we try to provide notice by mailed postcards or letters, door hangers, emails or phone calls. Keep your contract information up to date: www.ConsumersEnergy.com/UpdateMyInfo

We'll never ask for your bill, or threaten to shut off your service if you don't let us in. Always ask for company identification before sharing account information or allowing anyone into your home or business. Call us at 800-760-3295 to confirm visitors claiming to work on behalf of Consumers Energy. Learn more at: www.ConsumersEnergy.com/Scams

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Consumers Energy
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You can pay your bill by mail, by phone or online
See reverse side for more information

[redacted]

Amount Due:	$346.78
Please pay by:	August 20, 2025
Enclosed:	

Service Address:
TABITHA WILLIAMS
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

[redacted]

03 08/25

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE; Grand Rapids MI 49507-1154

[redacted]

Account Information

Bill Month: August
Service Dates: 06/27/2025 - 07/28/2025
Days Billed: 32
Portion: 03 08/25

August Energy Bill

[redacted]

Account Summary

Last Month's Account Balance	$204.18

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1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

Enclosed:

[redacted]

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE; Grand Rapids MI 49507-1154

[redacted]

Account Information

Bill Month: August
Service Dates: 06/27/2025 - 07/28/2025
Days Billed: 32
Portion: 03 08/25

Rate Information

Electric Residential Service
Rate Code: 1001

Meter Information

Your next scheduled meter read date is on or around 08/26/2025

Electric Service: Smart Meter
[redacted]
Beginning Read Date: 06-27
Ending Read Date: 07-28
Beginning Read: 86625
Ending Read: 88162 (Actual)
Usage: 1537.000 kWh
Interval Usage: 1537.413 kWh

Your meter records electric energy use in hourly intervals. Your bill is the total of all hourly intervals recorded during your billing period.

End and start date kWh meter readings are provided for information purposes only. Please visit Energy Use Details at ConsumersEnergy.com to view your energy use data.

August Energy Bill

[redacted]

Account Summary

Last Month's Account Balance	$204.18
Payment on July 23, 2025	$204.18-
Balance Forward	**$0.00**

Payments applied after Jul 29, 2025 are not included.

Electric Charges

Summer(Billed 06/27/2025 - 07/28/2025)

On-Peak Energy (2pm- 7pm)	226.743@	0.150563	$34.14
Off Peak Energy	1310.670@	[illegible]	$130.05

Other Charges

PSCR	1537.413@	0.011270	$17.33
System Access			$8.00
Deferral Surcharge	1537.413@	0.001090	$1.68
IRM Surcharge	1537.413@	0.000259	$0.40
Distribution	1537.413@	0.078955	$121.39
FCM Incentive	1537.413@	0.000293	$0.45
Other Surcharges	1537.413@	0.004529	$6.97
Power Plant Securitization	1537.413@	0.001131	$1.74
Karn 1&2 Securitization Charge	1537.413@	0.004556	$7.00
DR Surcharge	1537.413@	0.002250	$3.46
Low-Income Assist Fund			$0.87
Total Electric			**$333.48**
State Sales Tax			$13.30
Total Energy Charges			**$346.78**

Amount Due: $346.78
by August 20, 2025

If you pay after the due date, a 2% late payment charge will be added to your next bill.

Please make any inquiry or complaint about this bill before the due date listed on the front.
Visit **ConsumersEnergy.com/aboutmybill** for details about the above charges.

NEWS AND INFORMATION

If you have questions or would like information about your energy use or weather-adjusted costs, call 800-477-5050 or visit: www.ConsumersEnergy.com/AboutMyBill

For information on safety and customer rights: www.ConsumersEnergy.com/CustomerGuides

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Save money and energy: www.ConsumersEnergy.com/Save
Sign-up for billing alerts: www.ConsumersEnergy.com/MyLogin

More payment options and details:
www.ConsumersEnergy.com/WaysToPay

2:21 5G UC

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consumersenergy.com

[redacted]

Consumers Energy
Count on Us®

Questions:
Visit: **ConsumersEnergy.com**
Call us: **800-477-5050**

Amount Due:	**$255.81**
Please pay by:	**September 18, 2025**

Thank You - We received your last payment of **$346.78** on **August 15, 2025**

TABITHA WILLIAMS
1128 JEFFERSON AVE SE
GRAND RAPIDS MI 49507-1154

Service Address:
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

September Energy Bill

Service dates: July 29, 2025 - August 26, 2025 (29 days)

Total Electric Use (kWh - kilowatt-hour)

kWh = A 100-watt bulb burning for 10 hours uses 1 kilowatt-hour.

ACTUAL

September Electric Use
1,128 kWh

Cost per day:
$8.48

kWh per day:
39

STAY SAFE: Call 9-1-1 and 800-477-5050. We'll respond day or night.

Downed power lines. Stay 25 feet away. Call from a safe location.

If you smell natural gas. If the "rotten egg" odor of gas is apparent, call from a safe location.

Michiganders have been counting on us for over 130 years.

Every day our top priority continues to be providing safe and reliable energy to 6.8 million Michiganders using our electric and/or natural gas service. Over the years, we've evolved our strategy, improved our standards, and served the growing energy needs of Michigan homes and businesses.

Multi-year investments in new technologies and industry materials with greater durability provide for your current and future energy needs with service you can rely on. Want more information on what's happening now? Follow us on social media and read the latest news at:
www.ConsumersEnergy.com/Reliable

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Consumers Energy
Count on Us®

You can pay your bill by mail, by phone or online
See reverse side for more information

[redacted]

Amount Due:	**$255.81**
Please pay by:	**September 18, 2025**
Enclosed:	

Service Address:
TABITHA WILLIAMS
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

[redacted]

01 09/25

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE, Grand Ra

[redacted]

Account Information
Bill Month: September

September Energy Bill

[redacted]

Downed power lines. Stay 25 feet away. Call from a safe location.

If you smell natural gas. If the "rotten egg" odor of gas is apparent, call from a safe location.

Every day our top priority continues to be providing safe and reliable energy to 6.8 million Michiganders using our electric and/or natural gas service. Over the years, we've evolved our strategy, improved our standards, and served the growing energy needs of Michigan homes and businesses.

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[redacted]

Amount Due:	$255.81
Please pay by:	September 18, 2025
Enclosed:	

Service Address:
TABITHA WILLIAMS
1128 Jefferson Ave SE
Grand Rapids MI 49507-1154

PAYMENT CENTER
PO BOX 740309
CINCINNATI OH 45274-0309

[redacted]

03 09/25

Need to talk to us? Visit **ConsumersEnergy.com** or call **800-477-5050**
Telecommunications Relay Services: Call 7-1-1

Service Address:
1128 Jefferson Ave SE; Grand Rapids MI 49507-1154

[redacted]

Account Information

Bill Month: September
Service Dates: 07/29/2025 - 08/26/2025
Days Billed: 29
Portion: 03 09/25

Rate Information

Electric Residential Service
Rate Code: 1001

Meter Information

Your next scheduled meter read date is on or around 09/25/2025

Electric Service: Smart Meter

[redacted]

Beginning Read Date: 07-29
Ending Read Date: 08-26
Beginning Read: 88162
Ending Read: 89290 (Actual)
Usage: 1128.000 kWh
Interval Usage: 1127.904 kWh

Your meter records electric energy use in hourly intervals. Your bill is the total of all hourly intervals recorded during your billing period.

End and start date kWh meter readings are provided for information purposes only. Please visit Energy Use Details at ConsumersEnergy.com to view your energy use data.

September Energy Bill

[redacted]

Account Summary

Last Month's Account Balance	$346.78
Payment on August 15, 2025	$346.78-
Balance Forward	**$0.00**

Payments applied after Aug 27, 2025 are not included.

Electric Charges

Summer(Billed 07/29/2025 - 08/26/2025)		
On-Peak Energy (2pm- 7pm)	162.531@ 0.150563	$24.47
Off-Peak Energy	965.373@ 0.099222	$95.79
Other Charges		
PSCR	1127.904@ 0.010230	$11.54
System Access		$8.00
Deferral Surcharge	1127.904@ 0.001090	$1.23
IRM Surcharge	1127.904@ 0.000259	$0.29
Distribution	1127.904@ 0.078955	$89.05
FCM Incentive	1127.904@ 0.000293	$0.33
Other Surcharges	1127.904@ 0.004529	$5.11
Power Plant Securitization	1127.904@ 0.001131	$1.28
Karn 1&2 Securitization Charge	1127.904@ 0.004556	$5.14
DR Surcharge	1127.904@ 0.002250	$2.54
Low-Income Assist Fund		$1.25
Total Electric		**$246.02**
State Sales Tax		$9.79
Total Energy Charges		**$255.81**

Amount Due: $255.81
by September 18, 2025
If you pay after the due date, a 2% late payment charge will be added to your next bill.

Please make any inquiry or complaint about this bill before the due date listed on the front. Visit **ConsumersEnergy.com/aboutmybill** for details about the above charges.

NEWS AND INFORMATION

Beware of unauthorized payment centers or phone and email scams regarding utility payments. We never demand payment using only a prepaid card. Find a payment center near you or choose from many other secure payment options at www.ConsumersEnergy.com/WaysToPay

For information on safety and customer rights: www.ConsumersEnergy.com/CustomerGuides

U.S. DEPARTMENT OF ENERGY | Energy Efficiency & Renewable Energy

BUILDING TECHNOLOGIES OFFICE

Building America Case Study:
Technology Solutions for Existing Homes

A Homeowner's Guide to Window Air Conditioner Installation for Efficiency and Comfort

PROJECT INFORMATION

Building Component: HVAC

Application: Retrofit; single and/or multi-family

Year Tested: 2012

Applicable Climate Zone(s): All

PERFORMANCE DATA

Cost of Window A/C unit: $150–$600

Cost of Materials for Improved Installation: $10–$15

Energy Savings: up to 7% cooling savings, or up to 280 kWh/year

Electricity Bill Savings: up to $31/year; enough to pay for the cost of the unit over its lifetime

FOR MORE INFORMATION

Read the full report, Laboratory Performance Testing of Residential Window Air Conditioners, NREL/TP-5500-57617, February 2013. *www.nrel.gov/docs/fy13osti/57617.pdf*

Watch the YouTube video:
http://www.youtube.com/watch?v=78AGFmGGjVY&feature=youtu.be

Building America SM
U.S. Department of Energy

Homeowners in the United States spend one out of every eight dollars of utility costs on cooling their living space. Window air conditioners (A/Cs) are an inexpensive alternative to central systems, and are sold in greater numbers each year than all other residential cooling systems. They are purchased to cool a specific room and are easy for anyone to install. In contrast to these benefits, window A/Cs come at a cost—they operate less efficiently (using more energy to do the same cooling) than most other residential A/C systems.

Researchers at the National Renewable Energy Laboratory (NREL) studied window A/Cs on behalf of the U.S. Department of Energy's Building America program, to understand how they perform and how they could be improved.

The study showed that window A/C installation resulted in significant air leakage—equivalent to having a 5-in^2 hole in the outside wall. All summer long, hot outdoor air flows into the home, as shown in the figure to the right, making the A/C run longer and use more energy. This outdoor air reduces comfort for occupants through increased heat and often carries humidity into the home.

A portion of the cool air leaving the A/C is recirculated back into the unit because the outlet and inlet are so close together. Thus, that cool air does not help cool off the home and is a secondary waste of energy. Also, the researchers verified the importance of appliance maintenance and cleaning.

> "Air sealing around the window and the air conditioner is critical for best performance"
> —Chuck Booten, Ph.D., Senior Engineer, NREL

Finally, NREL's team identified simple measures to improve both efficiency and comfort. Accessories provided by manufacturers can be replaced with inexpensive hardware store materials to improve a window A/C installation, increase efficiency, improve comfort, and lower utility bills with a payback of less than one year.

Typical air leakage pathways increase electricity use and decrease comfort. *Illustration by Marjorie Schott, NREL*

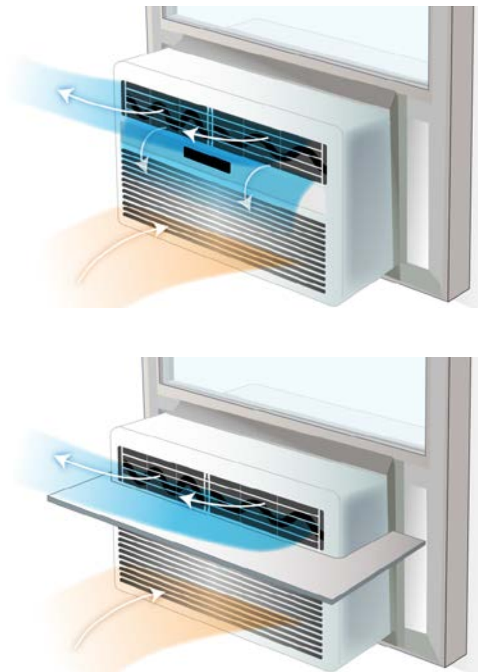
Five Easy Steps to Limit Window A/C Infiltration

1. Remove accordion panels. Typically, a sliding keeper can be removed. Pull the frame out, then remove another keeper from the side of the A/C. *(Do not remove top and bottom braces; they hold the unit in the window. Use manufacturer-supplied hardware to secure the window in place after replacing the unit.)*
2. Cut and install rigid foam panels to fill the spaces beside the A/C. Measure the thickness of the window sash to determine foam thickness; ¾–1½ in. thick will fit most window frame channels. Some foams have a skin to help protect the foam from weather. Exterior grade tape can be used to cover outside surface of foam for increased durability. If this is done, work from bottom to top and overlap tape so water will drain appropriately. (Cost of foam: \$3–\$10 for multiple windows.)
3. Foam strips provided by the manufacturer for sealing between sashes are prone to air leaks. Instead, use backer rod (closed cell cylindrical foam) between sashes. Measure gap thicknesses to select appropriate size. (Cost of backer rod: ~\$4, enough for multiple windows.)
4. No matter what foam is used, it is important to also plug the top of the side channels.
5. Use tape to secure the foam panels and prevent air leaks around joints. Tape the foam panels to the window, window frame, and A/C; tape the top and bottom of the A/C. Different colors of tape are available. If window frames are painted, consider using tape with a less aggressive bond to prevent peeling. (Cost of one roll of duct tape: ~\$6, enough for multiple windows.)

Go Further: Address Cool Air Recirculation

To further enhance performance, install a diverter between the cool air supply and room air return of the air conditioner. This reduces short-circuiting of air from the supply to the return and maximizes the amount of cool air that goes into the room, saving energy and money.

Diverters can be made from ¼-in. medium density fiberboard or similar material. (Cost for one sheet of fiberboard: ~\$5.)



Installing a diverter (bottom) helps to maximize cool air flow from the A/C unit. *Illustration by Marjorie Schott, NREL*

The Bottom Line

- Air leakage wastes energy and costs money, but homeowners can reduce this leakage easily.
- Recirculation of air near the unit lowers efficiency and can be easily reduced.
- Periodic cleaning of intake and exhaust grills on both the indoor and outdoor portion of the unit can help maintain efficient performance.
- Remove unit from window or seal it up completely on the inside after cooling season is over; otherwise, air will leak through the unit itself.

U.S. DEPARTMENT OF ENERGY

Energy Efficiency & Renewable Energy

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The U.S. Department of Energy's Building America program is engineering the American home for energy performance, durability, quality, affordability, and comfort.

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The impact of energy poverty on physical violence

Abebe Hailemariam, Tutsirai Sakutukwa, Siew Ling Yew *

Department of Economics, Monash University, VIC, Australia

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ABSTRACT

Despite the fact that energy poverty and violence are emerging as a priority in many countries' policy agendas, little is known regarding the interplay between energy poverty and violence. This paper is the first to investigate the impact of energy poverty on physical violence. Using longitudinal data from the HILDA survey and employing a variety of methods, including an instrumental variable approach, we find strong evidence that energy poverty increases the likelihood of experiencing physical violence. We find that psychological distress, substance use and social capital are important mechanisms through which the effect of energy poverty is transmitted to physical violence. Our results are robust to alternative specifications and various measures of energy poverty.

1. Introduction

Energy is essential in our lives and economic activities. Thus, access to and the use of energy are emerging as a priority in policy agendas worldwide, and have continued to be a vital determinant of household's well-being and living standards. Although there are many definitions of energy poverty there is a consensus in the literature that energy poverty refers to a situation where the need for energy consumption is not sufficiently satisfied (e.g., Lewis, 1982; Gonzalez-Eguino, 2015; Papada and Kaliampakos, 2016; Llorca et al., 2020). For example, according to Papada and Kaliampakos (2016), the definition of energy poverty can be summarized as "the difficulty or the inability of a household to afford an adequate coverage of its energy needs (heating comfort and other essential energy services)"; and agreeing with Reddy (2000), Gonzalez-Eguino (2015) adopt Reddy's definition of energy poverty which is defined as "the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development". Hence, following the above notions, energy poverty remains a major problem for many parts of the world (OECD, 2007). For example, there were around 1.3 billion people with no access to electricity, and the majority live in developing countries (Gonzalez-Eguino, 2015). It is also well documented that many individuals in developed countries encounter the problem of energy affordability (e.g., McInnes, 2017). Rising energy costs, inadequate income and energy inefficiency of housing (e.g., Boardman, 2010; Hills, 2011; Heindl and Schuessler, 2015; OECD/IEA and International Energy Agency, 2011; Papada and Kaliampakos, 2016; Okushima, 2017), among others, are important factors that increase energy expenditure and, thus, intensify energy poverty among vulnerable households in both developing and developed countries.

When looking at the effects of energy poverty, empirical research in this literature has examined various effects of energy poverty. For example, many existing studies have analysed how energy and social well-being are connected or the impacts of energy poverty on social well-being, including health (e.g., Bridge et al., 2016; Krauss, 2016; Thomson et al., 2017; Phoumin and Kimura, 2019; Rodríguez-Álvarez et al., 2019; Awaworyi Churchill et al., 2020; Llorca et al., 2020; Awaworyi Churchill and Smyth, 2021). According to Bridge et al. (2016) and Krauss (2016), poverty and welfare of households are related to energy and gas tariffs. Compared with households without energy poverty, energy poor households tend to suffer from health problems, spend more on medical care, drop out from schools, and have lower earning opportunities (Phoumin and Kimura, 2019). Despite the growing interest in understanding the impacts of energy poverty, no existing studies have, thus far, explored the impact of energy poverty on physical violence, another pressing welfare issue besides energy poverty.

The purpose of this study is to empirically examine the impact of energy poverty on physical violence in Australia and to explore important mechanisms of influence. We use longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey for the period from 2002 to 2018. To measure physical violence, we use information reported by the participants on whether they were victims of physical violence in the past year (e.g., Johnston et al., 2018; Smith and Weatherburn, 2013). As stated by Johnston et al. (2018), the HILDA

* Corresponding author.
E-mail addresses: abebe.hailemariam@monash.edu (A. Hailemariam), tutsirai.sakutukwa@monash.edu (T. Sakutukwa), siew.ling.yew@monash.edu (S.L. Yew).

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0140-9883/

based definition of physical violence is expected to cover the general forms of violence that encompasses physical and sexual assault, robbery with violence, and all other types of common violence emanating from all sources, including people known and strangers to the victims. We use the ratio of energy (and related) expenses to household income (e.g., Awaworyi Churchill and Smyth, 2019; Awaworyi Churchill et al., 2020; Robinson et al., 2018) as our primary measure of energy poverty, and incorporate alternative measures of energy poverty for robustness exercises. Employing a variety of methods, including an instrumental variable approach, our results suggest that energy poverty increases the likelihood of experiencing physical violence.

Specifically, when we use our primary measure of energy poverty, we find that energy poverty increases the likelihood of experiencing physical violence by 1.9 to 3.2 percentage points across various specifications that include specific control variables and the full set of control variables. Relative to the mean of physical violence at 0.015, these increases are substantial.[1] We also find that the estimated coefficients on various measures of energy poverty are positive and statistically significant at conventional significance levels. Our findings are in line with empirical evidence that violent crime is associated with resource deprivation (e.g., McIlwaine and Moser, 2003; Cunradi et al., 2000; De Olarte and Llosa, 1999). In addition, we find that psychological distress, substance use (given by consumption of cigarettes and tobacco) and social capital are important mechanisms through which the effect of energy poverty is transmitted to physical violence. These findings are consistent with the well-established evidence in the related literature. Conceptually, poverty-related stress that contributes to the development of stress-related disorders such as conduct problems and distress emotions (e.g., Wadsworth and Achenbach, 2005) can lead to physical violence (Gibbs et al., 2018); and decreased social capital that leads to higher levels of social mistrust can also produce economic disadvantages such as physical violence (Kennedy et al., 1998; Lederman et al., 2002). To further understand how energy poverty may influence physical violence, Section 2 provides an extended discussion about the relationship between energy poverty and physical violence, and several potential channels of influence.

We focus on Australia due to the following reasons. First, energy affordability is a key concern for many Australians. The cost of electricity faced by Australian households ranks among the highest globally (Awaworyi Churchill et al., 2020). According to Australian Competition and Consumer Commission (ACCC), in real terms, there is a 35% increase in households' bills and a 56% increase in the price of electricity for the period from 2007 to 08 to 2017–18. More importantly, ACCC reports that, compared to higher income households, the ratio of electricity expenses to disposable income is much higher for low income households. Second, violence is common in Australia. According to a personal safety survey in 2016 by Australian Bureau of Statistics (ABS), 2 in 5 people have experienced one or more incidents of violence since the age of 15, and 1 in 6 women experienced partner violence. ABS also reported that during the 2018–19 period around 5% of Australians aged 15 or older experienced at least one personal crime in the last 12 months, where 2.4% experienced physical assault. In a separate research for Western Australia in the period from 1990 to 2009, Orr et al. (2019) document that hospitalizations for mothers assaulted 12 months before their child's birth month and 36 months after the birth month have increased from 2.7 to 7.7 per 1000 births and from 8.9 to 19.4 per 1000 births, respectively. This indicates that physical violence is a growing problem in Australia. Third, existing studies that examine the impacts of energy poverty mainly focus on countries other than Australia (e.g., Thomson et al., 2017; Phoumin and Kimura, 2019; Rodríguez-Álvarez et al., 2019; Llorca et al., 2020). Hence, Australia makes for an important and interesting case study based on these facts.

Our study fills an important gap in the following two strands of literature that relate violent crime to resource deprivation or climate change. First, there is a vast literature linking resource deprivation with violent crime (e.g., McIlwaine and Moser, 2003; Cunradi et al., 2000; De Olarte and Llosa, 1999). For example, Cunradi et al. (2000) suggest that households living in poor neighbourhood have a higher chance of experiencing violence in the United States. Some other studies find that poverty and inequality are important determinants of violent crime (e.g., Land et al., 1990; Arthur, 1991; Kelly, 2000; Fajnzylber et al., 2002a, 2002b; Gibbs et al., 2018). Second, it has been documented that violent crime is correlated with climate. A recent climate economics literature has found evidence on the effects of extreme temperatures on aggressive behavior or violence (e.g., Anderson, 1989; Ranson, 2014; Baylis, 2020; Bruederle et al., 2017). This is possible when environmental conditions affect people's decision making that may lead them to lose control or behave aggressively (e.g., Card and Dahl, 2011; Baumeister and Heatherton, 1996). Since energy poverty is a distinct form of resource deprivation (Moore, 2012) and climate change tends to aggravate energy poverty (Jessel et al., 2019), both resource deprivation and climate change are closely related to energy poverty. Our study builds on these strands of literature by specifically focusing on the effect of energy poverty on physical violence. Crutchfield and Wadsworth (2003) support the argument of identifying different types of resource deprivation before linking them to violence (e.g., Stark, 1987; Sampson and Groves, 1989; Krivo and Peterson, 1996). Dissecting different types of resource deprivation will aid in granular analysis of the actual effect of each type of resource deprivation on violence and the magnitude of violence.

Our study also contributes to the literature that links negative emotion or social capital with violence. Some recent studies (e.g., Card and Dahl, 2011; Hammack et al., 2004; Wadsworth et al., 2008; Gibbs et al., 2018) find empirical evidence that negative emotional cues such as stress of poverty and occupational-related stress are associated with physical violence. These findings are consistent with the frustration-aggression hypothesis (Dollard et al., 1939; Berkowitz, 1962), i.e., the notion that negative emotion can lead to aggression. For example, Gibbs et al. (2018) find that resource deprivation such as food insecurity drives substance abuse and suboptimal mental health outcomes, which then lead to intimate partner violence in South Africa. Regarding social capital, research has demonstrated a close link between social capital such as social network support and social trust and criminal activities (e.g., De Olarte and Llosa, 1999; Kennedy et al., 1998; Lederman et al., 2002). For example, De Olarte and Llosa (1999) find evidence that physical violence is associated with social support networks in Lima, Peru. Hence, our results, which suggest that psychological distress, substance use and social capital triggered by energy poverty are associated with physical violence, contribute to and extend the literature that links negative emotional cues and social capital with violence by highlighting the role of energy poverty.

The remainder of the paper is organized as follows. The next section discusses how energy poverty may affect physical violence. Section 3 describes the data and provides descriptions of the key variables. Section 4 describes the methodology. Section 5 presents the empirical results and discussions. Section 6 concludes.

2. The relationship between energy poverty and physical violence: channels of influence

In this section, we explore several potential channels given by psychological distress, substance use, social capital and dissatisfaction with partner through which energy poverty may influence physical violence.

Inspired by the literature that examines poverty-related stress and behavior, households living in energy poverty are at higher risk for

[1] Studies that examine the impacts of other factors such as divorce laws or combat services on physical violence also find similar effect size (e.g., Cesur and Sabia, 2016; García-Ramos, 2021). For example, Cesur and Sabia (2016) find that combat services increase the probability of experiencing physical violence by 3.2 to 4.8 percentage points in the U.S.

developing a range of stress-related disorders such as psychological distress than those who do not suffer from energy poverty (e.g., Wadsworth and Compas, 2002; Wadsworth and Achenbach, 2005). Since households living in energy poverty lack the ability to change their situation and cope with stress, they likely experience uncontrollable and overwhelming stress, which may give rise to psychological distress. Evidence shows that there are significant levels of physically violent victimization among people affected by psychological distress or other mental health problems (e.g., Bhavsar and Bhugra, 2018; Maniglio, 2009). For example, based on a review study by Maniglio (2009), rates of victimization among persons with mental health problems are 2.3–140.4 times higher than rates of victimization in the general population. Using data from police reports on the Danish population from 2001 to 2013, Dean et al. (2018) also find that onset of mental health problems is associated with increased risk of exposure to violent crime. Persons with mental health problems are high-risk group because of their poor judgment, social skills, planning and problem solving, among others (Fujii et al., 2004; Gearon and Bellack, 1999).

In addition, criminal victimization is most frequently associated with substance use disorders (Gearon and Bellack, 1999; Maniglio, 2009; Dean et al., 2018). Hence, substance use such as cigarette smoking and alcohol use is another potential channel of influence. Intuitively, the stress of energy poverty could also contribute to substance abuse, which may influence physical violence. Studies that examine the relationship between intimate partner violence victimization and smoking or alcohol use have generally found positive relationships (Foran and O'Leary, 2008; Vest et al., 2002; Feingold et al., 2008). Substance abusers not only are more likely to perpetrate physical violence but also are more likely to experience physical violence. For example, studies by White and Chen (2002) and Anderson (2002) have found a positive association between women's substance abuse and their experiences of intimate partner violence. Cesur and Sabia (2016) find that psychological distress as well as the use of substances are potential channels through which war service increases domestic violence.

The third potential channel is related to social capital. Social capital could broadly be understood as an array of shared values that enable society members to cooperate towards achieving a common purpose or a goal. The literature has several granular definitions of social capital ranging from Fukuyama (1995) who defined social capital as 'the ability of people to work together for common purposes in groups and organizations' to OECD that defined social capital as a set of shared values and social norms that adds to the well-being of the society (OECD, 2013). According to Scrivens and Smith (2013), there are four ways in which social capital could be contextualized: i) personal relationships; ii) social network support; iii) civic engagement; and iv) trust and cooperative norms. Social capital plays an important role on the number and significance of criminal activities including physical violence. According to Lederman et al. (2002), social capital enables peaceful resolution of conflicts and promotes social cohesion which can help communities to overcome problems arising from market failures. Robison et al. (2002) argue that the influence of social capital on societal outcomes via sympathetic relationships depends on networks. These relationships produce economic benefits, for example, socio-emotional goods, however, if neglected, the outcome will produce economic disadvantages such as physical and emotional violence. Indeed, the empirical findings show that decreased social capital given by higher levels of social mistrust was associated with higher levels of violent crime (Kennedy et al., 1998; Lederman et al., 2002).

The fourth potential channel of influence is dissatisfaction or satisfaction with partner. Family studies have highlighted that economic hardship can lead to conflict and relationship dissatisfaction (e.g., Conger et al., 2010), which have been considered as risk factors to intimate partner violence. Evidence shows that intimate partners are at higher risk for physical violence if there are more frequent violent arguments or lower levels of agreement in their relationships (e.g., Aldarondo and Sugarman, 1996; DeMaris et al., 2003). Hence, dissatisfaction or satisfaction with partner may be a potential channel through which energy poverty can affect physical violence.

3. Data and variables

To examine the effect of energy poverty on physical violence, we utilize household and individual levels longitudinal data from the HILDA survey. As a nationally representative longitudinal survey, HILDA provides rich data on the socio-economic aspects of the lives of Australian residents, including income, expenditure, education, work, social support, life events and experiences of physical violence. The survey provides an extensive coverage in socio-economic variables across the Australian states and territories since 2001. This study utilizes the rich dataset from Release 18 of HILDA. As the first four waves of HILDA do not have information concerning household energy expenditure, we use data from waves 5 to 18 over the periods from 2005 to 2018. The HILDA survey maintains highest standards with low attrition rates comparable to other international popular surveys, including German Socio-Economic Panel and the British Household Panel Survey (Watson and Wooden, 2011). HILDA adjusts any selective attrition using cross-sectional and longitudinal weights at individual and household levels (Watson and Wooden, 2012).

3.1. Outcome variable

In line with the literature (see e.g., Johnston et al., 2018; Smith and Weatherburn, 2013), our outcome variable is a binary indicator for experiencing physical violence in the last 12 months of the given wave. HILDA asks respondents regarding the key events that have occurred in their life in the past year including physical violence such as assault. Responses are coded as 1 if they answer "Yes" and 0 if their response is "No". As pointed out by Johnston et al. (2018), the general wordings used in the HILDA survey concerning victimization are expected to incorporate the common forms of violence from all sources, such as physical and sexual assault by spouses, intimate partners, friends, relatives and strangers, among others. Although the HILDA survey does not ask the relationship between offenders and victims, national statistics in 2019 report that around 30% of violent crime are related to family and domestic violence (Australian Bureau of Statistics, 2019).

3.2. Energy poverty (EPOV)

In the literature, several measures of energy poverty have been used to help researchers and policymakers understand energy poverty. These measures include (1) an expenditure-based measure with an objective indicator such as the ratio of energy-related expenditure to household income (e.g., Awaworyi Churchill and Smyth, 2019; Awaworyi Churchill et al., 2020; Robinson et al., 2018) or the ratio of energy related expenses to disposable household income that exceeds 10% (e.g., Awaworyi Churchill and Smyth, 2020; Boardman, 2010; Hills, 2011, 2012; Thomson et al., 2017, 2) a subjective indicator such as self-assessed ability to heat their homes (e.g., Awaworyi Churchill and Smyth, 2020; Price et al., 2012; Thomson and Snell, 2013); and (3) measures that combine multiple indicators (e.g., Lawson et al., 2015). Each of these indicators has its own strength and shortcomings in measuring energy poverty. An expenditure-based measure is easy to measure and interpret but it does not capture an intentional reduction in energy consumption especially by low income households due to the problem of affordability (Papada and Kaliampakos, 2016); a subjective indicator may capture aspects of energy poverty that an expenditure-based measure fails to capture but such indicator may suffer from inconsistency among respondents (Thomson et al., 2017); and measures that combined multiple indicators present broader pictures of the issue but they are not easy to measure, interpret and obtain meaningful insights (Nussbaumer et al., 2012). Since there is no absolute reference for what satisfies adequate and affordable energy needs, there is no single universally accepted measure for energy poverty. Hence, different indicators may complement each other to capture different dimensions of the concept of energy poverty.

A popular measure of energy poverty widely adopted in the literature is the ratio of energy (and related) expenses to household income (see, e.g., Awaworyi Churchill et al., 2020; Awaworyi Churchill and Smyth, 2019; Robinson et al., 2018). A higher ratio indicates more serious energy deprivation since poorer households tend to spend a larger percentage of their income on energy compared to richer households (Healy and Clinch, 2004; Gleeson and Randolph, 2002). Beginning with the fifth round of the HILDA survey, persons responding to HILDA questionnaire have been asked about their household energy spending including electricity, gas, and other sources of energy. Our main measure of energy poverty is the ratio of energy (and related) expenses to household income (EPOV1).

We also use alternative measures of energy poverty for robustness exercises. Research shows that households can be considered as fuel poor if the ratio of energy expenditure to disposable income is beyond a certain threshold level. Specifically, Boardman (1991) suggests that this threshold level is estimated at 10%. This means households are under energy poverty if the fraction of their disposable income spent on energy related bills exceeds 10%. Based on this threshold, this measure of energy poverty (EPOV2) is defined as a binary indicator that takes value of 1 if the energy expenditure share is above 10%, and zero otherwise.

One issue with the threshold method of determining the level of energy poverty is that it may potentially understate or overstate the threshold for certain reasons such as access to energy rationing and energy efficient technologies. For example, as pointed out by Hills (2012), households with access to energy efficient technologies require relatively low spending on energy services. As a result, these households may be classified as fuel poor if their reported income in the survey is very low. Although the objective nature of this measure is appealing, some studies suggest the use of subjective measure of energy poverty such as the feeling to be unable to heat their homes as a measure of energy deprivation (Thomson et al., 2017). Therefore, as a further robustness check we use this subjective measure of energy poverty (EPOV3) which captures the respondents' self-assessed ability to heat their homes based on their responses in the HILDA survey. The responses are coded as a binary indicator taking value of 1 if households respond 'Yes' to the question on the ability to heat their homes, and zero if the response is "No". EPOV3 as a measure of energy poverty has been used in previous studies in other contexts (see e.g., Price et al., 2012; Thomson and Snell, 2013). Although data for EPOV3 is available for all waves except for wave 10, we use data from waves 5 to 18 to maintain consistency in our sample size with the other measures of energy poverty. Lastly, following Awaworyi Churchill et al. (2020), we use data on state-level gas price indices from the Australian Bureau of Statistics to instrument energy poverty as energy prices are strong predictor of energy poverty.[2]

3.3. Control variables

Following the related literature on physical violence, we control a range of covariates that can affect the relationship between physical violence and energy poverty. We control for indicators of life events derived from the responses to HILDA's questions on life events in the past year, such as "the death of spouse or child", "the death of close relative", and "the death of close friend". Consistent with the literature that emphasizes the socio-economic factors, we include education levels, marital status, age, employment status, household disposable income (normalized by its standard deviation), home ownership status and the number of dependents, among others.

3.4. Mediating variables

Following on from the discussion in Section 2, we provide descriptions for these four potential mediating variables- psychological distress, substance use (focusing on consumption of cigarettes and tobacco), social capital and life satisfaction with partner- through which the effect of energy poverty may be transmitted to physical violence.

3.4.1. Psychological distress

Consistent with the literature (e.g., Perales et al., 2014; Awaworyi Churchill et al., 2020b), we use psychological distress (Kessler1) and psychological distress risk categories (Kessler2) to measure the level of psychological distress. In HILDA, the measure of psychological distress (Kessler1) is constructed based on respondents' responses to a 10-item questionnaire. The value of the K10 measure ranges from a minimum of 10 (the lowest level of psychological distress) to a maximum of 50 (the highest level of psychological distress). Kessler psychological distress risk categories (Kessler2), another measure of psychological distress, is constructed from four psychological risk categories based on the responses to the K10 scale. Scores from "10 to 15" represent the "low risk" category; scores from "16 to 21" represent the "moderate risk" category; scores from "22 to 29" represent the "high risk" category; and scores from "30–50" represent the "very high risk" category. These risk categories are reported in an ordinal scale ranging from 1 to 4 in ascending order of psychological distress. Data on Kessler1 and Kessler2 are available in waves 7, 9, 11, 13, 15 and 17 of the HILDA survey.

3.4.2. Consumption of cigarettes and tobacco

Consumption of cigarettes and tobacco products is measured as weekly household expenditures on cigarettes and tobacco based on the responses to the HILDA question: "In a typical week, does this household spend money on … c) cigarettes and other tobacco products?". HILDA reports information on this variable from wave 5 onwards. This measure has been used in the literature that examines issues related to tobacco consumption (see e.g., Bentley et al., 2021).

3.4.3. Social capital

We use social support as a proxy for social capital. Social support is constructed from the responses to a 10-item questionnaire in HILDA about how much support respondents were able to get from other people (see e.g., Milner et al., 2016). Respondents rate the sentiments they perceive about the level of support they are likely to receive from other people including their friends and families in a scale of 1 to 7 where 1 indicates 'strongly disagree' and 7 indicates 'strongly agree'. Following the literature (e.g., Awaworyi Churchill and Farrell, 2020; Milner et al., 2016), we use the average of responses from the 10 items in the scale as a measure of social capital. This variable is available in all waves of HILDA.

3.4.4. Life satisfaction with partner

In all waves of HILDA, respondents were asked to respond how satisfied or dissatisfied they are in their relationship with their partners. The responses are coded on a scale of 0 to 10 where higher numbers indicate more satisfaction with partner. Thus, 0 represents completely dissatisfied and 10 represents completely satisfied. This variable has been used in the literature to examine issues related to satisfaction or dissatisfaction with partner (e.g., Lee and McKinnish, 2018; Lee and McKinnish, 2019).

Table A1 in the Appendix presents an overview of the summary statistics and the descriptions of the key variables. Specifically, Table A1 shows that there are significant variations in the key variables as can

[2] While Awaworyi Churchill et al. (2020) use electricity and gas prices as their instrument variable, we use only gas prices because only gas prices satisfy the criteria for a good instrument for our case.

be observed from the standard deviations of the data relative to the mean values.

4. Methodology

To investigate whether energy poverty increases the probability of experiencing physical violence, we estimate a linear probability model of the form:

$$VIO_{iht} = \beta_1 EPOV_{ht} + \sum_j \beta_j X_{j,it} + \mu_t + \varepsilon_{iht} \tag{1}$$

where VIO_{iht} is a binary dependent variable of physical violence indicator which is equal to 1 if an individual i in household h experiences physical violence at time t, and 0 otherwise. $EPOV_{ht}$ is a measure of energy poverty for household h at time t, X denotes a vector of covariates that are described in Section 3.3. μ_t denotes time fixed effect and ε is the error term. Our parameter of interest is β_1 which captures the response of *VIO* to changes in *EPOV*.

An important issue in estimating Eq. (1) is a potential bias arising from endogeneity of *EPOV* due to reverse causality, omission of relevant variables, or measurement errors. To address this potential issue of endogeneity, we employ an instrumental variable approach where energy poverty is instrumented with fuel prices. The use of fuel prices to instrument energy poverty is adopted in the recent literature (see e.g., Awaworyi Churchill et al., 2020). Our first stage regression is specified as:

$$EPOV_{ht} = \Theta_1 EPRICE_{st} + \sum_j \theta_j X_{j,it} + \gamma_t + v_{iht} \tag{2}$$

where $EPRICE_{st}$ denotes energy prices (fuel prices) in state s at time t, γ_t is the wave fixed effect, v is the error term, and other variables are as defined in Eq. (1). Θ_1 captures the effect of energy prices on energy poverty.

Concerning the quality of our instrumental variable, the first criteria for a good instrument is the existence of a canonical correlation between the instrument and the endogenous variable, which is energy poverty in our case. It is a stylized fact that the demand for energy (measured as energy spending) is correlated with energy prices (see e.g., Awaworyi Churchill et al., 2020; Narayan and Smyth, 2005). Thus, the relevance of energy prices as an instrument is plausible given that energy prices contain predictive information on energy poverty. With regard to the validity of the instrument, the key exclusion assumption is that energy prices will affect physical violence only via energy poverty. This assumption is reasonable because higher energy prices imply higher energy spending as a fraction of household income, which may then lead to financial stress and frustration, and, thus, physical violence. Therefore, we argue that the exclusion restriction is plausible as without energy poverty, one cannot establish a direct link from energy prices to physical violence. Hence, exogeneous variations in energy prices can be used to empirically isolate the causal effect of energy poverty on physical violence.

5. Results and discussions

5.1. Baseline results

Table 1 presents the estimates from the linear probability model. Column 1 presents the estimates where we regress the physical violence indicator only on energy poverty measured by the ratio of energy (and related) expenses to household income (EPOV1). In Column 2 we control for socio-economic status, and in Column 3 we include life events such as deaths of family members, close friends or relatives in addition to the socio-economic control variables. Column 4 presents the unrestricted model that includes the full set of control variables including educational status of respondents. Table 1 shows that the estimated coefficient on EPOV1 is positive and statistically significant at conventional significance levels in all regressions, suggesting that energy poverty is positively associated with the likelihood of experiencing physical violence. The interpretation of the coefficient of 0.032 in Column 1 is that energy poverty has led to an increase in the probability of experiencing physical violence of 3.2 percentage points, holding other things constant. Notice that this positive relationship between energy poverty and physical violence remains strongly consistent across alternative specifications given in Columns 2–4. In summary, we find that energy poverty increases the likelihood of experiencing physical violence by 1.9 to 3.2 percentage points across these specifications, and these increases are substantial relative to the mean of physical violence at 0.015. Hence, our baseline results are in line with the literature that has demonstrated a positive link between resource deprivation and violence (e.g., McIlwaine and Moser, 2003; Cunradi et al., 2000; De Olarte and Llosa, 1999).

Coming to the control variables, our results show that access to better education significantly reduces the likelihood of experiencing physical violence. Household disposable income and home ownership have

Table 1
Estimates of linear probability model- Full results.

	Unconditional	Socio-economic	Life events	Education level
Variables	(1)	(2)	(3)	(4)
EPOV1	0.0317***	0.0256***	0.0191**	0.0190**
	(0.0093)	(0.0097)	(0.0091)	(0.0091)
Income		−0.0014***	−0.0012***	−0.0009***
		(0.0003)	(0.0003)	(0.0003)
Female		−0.0005	−0.0007	−0.0003
		(0.0006)	(0.0006)	(0.0006)
Age		0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
Age squared		−0.0004***	−0.0005***	−0.0005***
		(0.0001)	(0.0001)	(0.0001)
Married		−0.0069***	−0.0059***	−0.0058***
		(0.0007)	(0.0007)	(0.0007)
Divorced		0.0043***	0.0051***	0.0051***
		(0.0015)	(0.0015)	(0.0015)
Single		0.0084***	0.0088***	0.0090***
		(0.0012)	(0.0012)	(0.0012)
Separated		0.0207***	0.0208***	0.0208***
		(0.0029)	(0.0029)	(0.0029)
Dependents		0.0011***	0.0011***	0.0011***
		(0.0003)	(0.0003)	(0.0003)
Unemployed		0.0075***	0.0071***	0.0070***
		(0.0025)	(0.0025)	(0.0025)
Employed		−0.0091***	−0.0085***	−0.0081***
		(0.0009)	(0.0009)	(0.0009)
Home		−0.0105***	−0.0101***	−0.0101***
		(0.0008)	(0.0008)	(0.0008)
Death of spouse or child			0.0327***	0.0327***
			(0.0058)	(0.0058)
Death of close relative			0.0092***	0.0090***
			(0.0011)	(0.0011)
Death of close friend			0.0177***	0.0175***
			(0.0012)	(0.0012)
Postgrad				−0.0025**
				(0.0011)
Bachelor				−0.0052***
				(0.0008)
Graduate diploma				−0.0027***
				(0.0010)
Diploma				−0.0007
				(0.0010)
Certificate				0.0013
				(0.0009)
Year 12				−0.0041***
				(0.0010)
Observations	179,415	179,405	178,527	178,441

The dependent variable is a dummy indicator for victim of physical violence. All regressions include wave fixed effects. Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

negative and statistically significant effects on the probability of experiencing physical violence. Life events such as the death of a close family member have a positive and statistically significant association with the likelihood of experiencing physical violence. With regard to socio-economic variables, being employed and being married are found to be negatively associated with the likelihood of experiencing physical violence. On the other hand, the probability of experiencing physical violence increases with being unemployed, being single, being separated, and divorced.[3]

We also re-estimate Eq. (1) using a probit model. Table 2 shows the estimated marginal effects of energy poverty on physical violence following the probit estimations. The results are consistent with our estimates from the linear probability model presented in Table 1. The estimated coefficient on EPOV1 remains robust, confirming that energy poverty leads to a higher probability of experiencing physical violence.

5.2. Instrumental variable (IV) estimates

As mentioned in Section 3.2, we use data on state-level gas price indices from the Australian Bureau of Statistics to instrument energy poverty as energy prices are strong predictor of energy poverty (Awaworyi Churchill et al., 2020). Thus, this section considers our main two stage least square (2SLS) estimates. Table 3 presents the estimates from the 2SLS along with the associated first-stage diagnostic test results where energy poverty is instrumented with gas prices. The instrumental variable (IV) estimates reveal that energy poverty causes an increase in the probability of experiencing physical violence. The results from the 2SLS estimation are quantitatively larger compared to the baseline results, suggesting a downward bias in the baseline results that may be driven by endogeneity. Specifically, it is likely that energy poverty may have a feedback effect and that the data could be measured with errors. For example, earlier studies suggest that respondents underreport their annual spending on energy bills of up to 20% in their responses to the HILDA survey (Wilkins and Sun, 2010). This kind of classical measurement errors could attenuate the basic estimates of the impact of energy poverty on physical violence. Similarly, omitted variable bias could lead to an upward or downward bias on the coefficient estimate of energy poverty. As pointed out by Forbes (2000), one cannot precisely identify the direction of the bias as there could be several unobserved factors that may lead to either overestimation or underestimation of the parameter of interest. However, in our case, it is evident that the direction of the bias is downward.

With regard to the instrument quality, the Kleibergen-Paap F-statistic is way above 10 in all regressions, indicating the rejection of the null of weak instrument. Moreover, the first stage F-statistics far exceeded the rule of thumb of 10. The coefficient on fuel prices from the first stage regression shows that there is a significant positive correlation between the instrument and the endogenous variable in all regressions. These results confirm the relevance of the instrument. Since our model is exactly identified with one endogenous variable and one instrument, the Sargan test of overidentification cannot be computed. However, the fact that our estimates are consistent across alternative specifications suggest that the assumption of the exclusion restriction is unlikely to be violated.

5.3. Robustness check

To check the sensitivity of our main results, we estimate our model using alternative measures of energy poverty, namely EPOV2 and EPOV3, as described in Section 3. Panel A of Table 4 shows the results from the linear probability model, while Panel B presents that estimates from the probit model. The coefficient estimates are positive and statistically significant in all regressions. This suggests that our main finding that energy poverty is associated with higher probability of experiencing physical violence is robust.

We perform additional robustness checks by including the lagged dependent variable in our specification. The results reported in Table A2 of the Appendix show that our main conclusion is robust. The coefficient of energy poverty remains positive and statistically significant. The coefficient of the lagged dependent variable is

Table 2
Marginal effects from probit estimates.

	Unconditional	Socio-economic	Life events	Education level
	(1)	(2)	(3)	(4)
EPOV1	0.024***	0.013***	0.009***	0.009***
	(0.005)	(0.004)	(0.004)	(0.004)
Socio-economic	No	Yes	Yes	Yes
Life events	No	No	Yes	Yes
Educational level	No	No	No	Yes
Full controls	No	No	No	Yes
Observations	179,415	179,405	178,527	178,441

The dependent variable is a dummy indicator for victim of physical violence. All regressions include wave fixed effects. Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3
IV estimates of the effect of energy poverty on physical violence.

	Unconditional	Socio-economic	Education level	Life events
	(1)	(2)	(3)	(4)
Two-stage least square				
EPOV1	0.870**	0.786**	0.815**	0.754**
	(0.397)	(0.384)	(0.381)	(0.373)
Socio-economic	No	Yes	Yes	Yes
Education level	No	No	Yes	Yes
Life events	No	No	No	Yes
Full controls	No	No	No	Yes
Observations	179,415	179,405	179,319	178,441
Kleibergen-Paap F statistic	73.754	84.544	86.581	90.047
First stage				
Gas prices	0.011***	0.011***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
F statistic	73.75	84.54	86.58	90.05

The dependent variable is a dummy indicator for victim of physical violence. All regressions include wave fixed effects. Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
Sensitivity of estimates to alternative measures of energy poverty.

	Panel A: Linear probability model		Panel B: Probit model	
	(1)	(2)	(3)	(4)
EPOV2	0.005**		0.002***	
	(0.002)		(0.001)	
EPOV3		0.048***		0.012***
		(0.004)		(0.001)
Controls	Yes	Yes	Yes	Yes
Observations	178,441	173,946	178,441	173,946

The dependent variable is a dummy indicator for victim of physical violence. All regressions include wave fixed effects. Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$.

[3] Since energy poverty may be correlated with state-level macroeconomic conditions, we have used monthly labour force data from the Australian Bureau of Statistics, including the employment rate, unemployment rate and participation rate, to re-estimate our model. The results show that the coefficient of energy poverty is still significant and robust, while the coefficients of these macro variables are statistically indistinguishable from zero. Thus, we do not report these results to conserve space. Results are available upon request.

Table 5
Heterogeneous effects by age group.

	Age group				
	15–24	25–34	35–44	45–54	≥55
EPOV1	0.077	0.008	0.120**	0.055***	0.003
	(0.048)	(0.035)	(0.054)	(0.021)	(0.007)
Observations	29,977	26,618	27,428	28,266	54,064
Controls	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. All regressions include wave fixed effects.
*** $p < 0.01$, ** $p < 0.05$.

also positive and statistically significant suggesting the persistent nature of physical violence. We further investigate the sensitivity of our results by including the lagged value of energy poverty. As shown in Table A3 in the Appendix, our main results on the effect of energy poverty on physical violence remain robust, while the coefficient on the lagged value of energy poverty is statistically indistinguishable from zero.

5.4. Heterogeneous effects

In this section, we examine the impact of energy poverty on physical violence based on age groups, gender and income levels to further understand the link between energy poverty and physical violence.

Regarding age, we split our sample into five categories capturing age groups of 15 to 24, 25 to 34, 35 to 44, 45 to 54, and 55 years and above. As depicted in Table 5, the relationship between energy poverty and physical violence is statistically insignificant for relatively young people who are below the age of 35 years. However, the effect of energy poverty on the likelihood of experiencing physical violence is statistically significant to those in the age group 35 to 54 years. The effect is much stronger in the 45 to 54 years cohort. We find no evidence of the link between energy poverty and the probability of experiencing physical violence in the age group of 55 years and above.

Additionally, the impact of energy poverty on the probability of experiencing physical violence might differ by gender and income levels. As presented in Table 6, even though energy poverty is a statistically significant predictor of the probability of experiencing physical violence for both males and females, males are more likely to experience physical violence than females. The last two columns of Table 6 show that income levels tend to influence the relationship between energy poverty and physical violence. For households with income below the median, energy poverty increases the likelihood of experiencing physical violence. For households with income above the median, the relationship between energy poverty and the probability of experiencing physical violence is negative but is statistically insignificant. By comparing our results with the related empirical evidence, our findings lend support to the findings of some recent studies, including Cunradi et al. (2002) and Smith and Weatherburn (2013). Since low-income households typically live in energy poverty, our empirical evidence supports Cunradi et al.'s finding that intimate partner violence is more likely to take place in low-income households. Using longitudinal data from HILDA, Smith and Weatherburn (2013) also find that there is a

Table 6
Heterogeneous effects by gender and income.

	Male	Female	Below median income	Above median income
EPOV1	0.029**	0.021*	0.019**	−0.003
	(0.013)	(0.012)	(0.010)	(0.022)
Observations	83,797	94,644	78,089	100,352
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses. All regressions include wave fixed effects.
** $p < 0.05$, * $p < 0.1$.

Table 7
Estimates of the effect of energy poverty on the proposed mediating variables.

	(1)	(2)	(3)	(4)	(5)
	Kessler1	Kessler2	Cigarette	Social capital	Satisfaction with partner
EPOV1	5.398***	0.711***	0.157***	−0.568***	−0.277
	(0.759)	(0.096)	(0.031)	(0.072)	(0.192)
Observations	78,174	78,174	124,018	178,183	128,950
Controls	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. All regressions include wave fixed effects.
*** $p < 0.01$.

higher probability of experiencing physical violence by those who reported financial stress, including the inability to pay electricity and gas bills, which tends to be experienced by households with lower income levels.

5.5. Mechanisms

As implied by the discussions given in Section 2, this section examines if the four potential mediating variables given by: (i) psychological distress (Kessler1 and Kessler2), (ii) substance use (consumption of cigarettes and tobacco), (iii) social capital, and (iv) life satisfaction with partner, are primary mechanisms linking energy poverty with the likelihood of experiencing physical violence.

To be qualified as mechanisms through which energy poverty influences physical violence, the potential mediating variables need to be correlated with energy poverty and the indicator of physical violence. Furthermore, the coefficient on energy poverty is expected to become smaller in magnitude or statistically insignificant when the potential mediating variables are included in the regression of physical violence on energy poverty as additional covariates.

Table 7 shows the effect of energy poverty on these four potential mediating variables: psychological distress (Kessler1 and Kessler2), consumption of cigarettes and tobacco, social capital, and life satisfaction with partner. Column (1) reports the effect of energy poverty on Kessler1; Column (2) presents the effect on Kessler2; Column (3) reports the effect on consumption of cigarettes and tobacco; Column (4) and Column (5) report the effects on social capital and life satisfaction with partner, respectively. The results support the existence of a statistically significant correlation between energy poverty and each of the proposed mechanisms except for life satisfaction with partner. Specifically, energy poverty is positively associated with both measures of psychological distress as well as with consumption of cigarettes and tobacco but it is negatively associated with social capital. Although the relationship between energy poverty and life satisfaction with partner is statistically insignificant, they are negatively correlated. Hence, all these results are consistent with the discussions given in Section 2.

Table 8 presents the results that include the measures of the potential mediating variables as additional covariates in the regression of physical violence on energy poverty. In Column 1, we include Kessler1 as an additional covariate, and Column (2) reports the results where we exclude the distress variable, i.e., Kessler1, with the same sample size so that we can compare the coefficient on energy poverty. We repeat such pairs of regressions in the subsequent columns for the remaining mechanism variables. Our results reveal that both measures of psychological distress and substance use (consumption of cigarettes and tobacco) lead to a higher likelihood of experiencing physical violence. As shown in Table 8, the inclusion of these additional covariates leads to a decrease in the magnitude of the coefficient on energy poverty. For example, in Column (2) the coefficient on EPOV1 is 0.027. When Kessler1 is included in Column (1), the coefficient on EPOV1 becomes statistically indistinguishable from zero. Similarly, the coefficient

Table 8
Transmission mechanism.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EPOV1	0.017	0.027**	0.019	0.027**	0.024**	0.026**	0.021**	0.024***	0.024**	0.025***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.009)	(0.009)	(0.012)	(0.012)
Kessler1	0.002***									
	(0.000)									
Kessler2			0.012***							
			(0.001)							
Cigarette					0.009***					
					(0.001)					
Social capital							−0.007***			
							(0.000)			
Satisfaction with partner									−0.003**	
									(0.0002)	
Observations	78,004	78,004	78,004	78,004	123,746	123,746	177,800	177,800	128,702	128,702
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is a dummy indicator for victim of physical violence. All regressions include wave fixed effects.
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$.

Table 9
Estimates of the structural equation model.

	Mediating variable				
	(1)	(2)	(3)	(4)	(5)
	Kessler1	Kessler2	Cigarette	Social capital	Satisfaction with partner
Direct effect	0.017	0.018*	0.024***	0.020***	0.025***
	(0.011)	(0.011)	(0.011)	(0.008)	(0.009)
Indirect effect	0.010***	0.008***	0.002***	0.004***	0.001
	(0.001)	(0.001)	(0.000)	(0.023)	(0.001)
Total effect	0.027**	0.026**	0.026***	0.024***	0.025***
	(0.030)	(0.011)	(0.009)	(0.008)	(0.009)

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

on EPOV1 is 0.026 in Column (6) and the coefficient on EPOV1 is reduced to 0.024 in Column (5) when we add consumption of cigarettes and tobacco as an additional explanatory variable to the regression. Similar results are observed for social capital (Column 7 and Column 8).

In Table 9, we employ a structural equation model to pin down the magnitude of the direct effect of energy poverty and its indirect effect through each of the potential mediating variables. The economic interpretation of the results is as follows. For example, the results in Column (3) of Table 9 show that the effect of energy poverty on the probability of experiencing physical violence is significantly mediated by consumption of cigarettes and tobacco. As shown by Column (3) of Table 9, energy poverty has a total effect of increasing the probability of experiencing physical violence by 2.6 percentage points, of which 2.4 percentage points are the direct effect and 0.2 percentage points are the indirect effect through higher level of substance use (cigarettes and tobacco). A similar interpretation applies to other potential mediating variables except for life satisfaction with partner. Notice that life satisfaction with partner has no role in mediating the link between energy poverty and the likelihood of experiencing physical violence. Hence, we find no evidence that life satisfaction with partner can mediate the relationship between energy poverty and physical violence, and instead we find that psychological distress, substance use and social capital are important channels through which energy poverty influences the probability of experiencing physical violence. Our results are consistent with some recent studies which also find psychological distress, substance use and social capital as important variables that can affect violence (Cesur and Sabia, 2016; Gibbs et al., 2018; Kennedy et al., 1998; Lederman et al., 2002).

6. Conclusions

Energy poverty and physical violence generate substantial socio-economic costs to society at individual, community, and national levels. At national levels, energy poverty thwarts economic development and sustainability (OECD, 2007); and at individual and community levels, energy poverty reduces the quality of life of energy poor households (e.g., Thomson et al., 2017; Phoumin and Kimura, 2019). Physical violence is another major socio-economic problem due to the fact that there has been an outstanding increase in violent crime (e.g., Fajnzylber et al., 2002b). Physical violence not only reduces the well-being of victims and people close to them but also threatens social stability (e.g., Dolan et al., 2005; Cohen, 2005; Mervin and Frijters, 2014).

Although the issues related to energy poverty and violence have received separate attention in the literature, the interplay between energy poverty and violence has not yet been examined. In this paper we examine the effect of energy poverty on the probability of experiencing physical violence using Release 18 of the HILDA survey. Interestingly, our results reveal that energy poverty increases the likelihood of experiencing physical violence. We identified potential channels that link energy poverty with physical violence. Specifically, we find that psychological distress, substance use and social capital are important channels through which the effect of energy poverty is transmitted to the likelihood of experiencing physical violence.

Our results have important policy implications for policymakers and advocates. Specifically, policy approaches that promote access to affordable energy to low income households could be effective in combating the adverse effects of energy poverty on physical violence. Moreover, our analysis of the mechanisms suggests that mental health service, counselling on substance abuse and policies that reinforce and promote social capital could help in dampening the effect of energy poverty on physical violence.

Declaration of Competing Interest

None

Appendix

Table A1
Description of variables and summary statistics.

Variable	Descriptions	Mean	SD
VIO	Life events in past year: Victim of physical violence	0.015	0.123
EPOV1	Energy expenditure share of household income	0.025	0.034
EPOV2	Dummy variable equals 1 if EPOV1 exceeds 10%	0.019	0.137
EPOV3	Dummy variable equals 1 if unable to heat home	0.030	0.172
Death of spouse or child	Life events in past year: Death of spouse or child	0.009	0.093
Death of close relative	Life events in past year: Death of close relative/family member	0.118	0.322
Death of close friend	Life events in past year: Death of a close friend	0.113	0.316
Postgrad	Highest level of education is masters or doctorate	0.042	0.200
Bachelor	Highest level of education is Bachelor or honours	0.132	0.338
Graduate diploma	Highest level of education is graduate diploma or certificate	0.051	0.220
Diploma	Highest level of education is diploma	0.088	0.283
Certificate	Highest level of education is certificate III or IV	0.207	0.405
Year12	Highest level of education is Year 12	0.153	0.360
Female	Gender indicator if the respondent is female	0.513	0.500
Age	Age of respondent	36.283	22.667
Age squared	Age squared divided by 100	18.303	18.528
Married	Respondent is legally married	0.479	0.500
Divorced	Respondent is divorced	0.060	0.237
Single	Respondent is never married and not de facto	0.241	0.428
Separated	Respondent is legally separated	0.027	0.163
Dependents	Number of dependents	0.477	0.955
Unemployed	Labor force status is unemployed	0.039	0.193
Employed	Labor force status is employed	0.633	0.482
Income	Annual household disposable income ('000)	82.609	59.657
Home	Home ownership status	0.640	0.480
Kessler1	Kessler Psychological Distress Scale (K10) score	15.955	6.532
Kessler2	Kessler Psychological Distress Scale (K10) risk categories	1.592	0.889
Cigarette	Weekly household expenditures on cigarettes and tobacco ($)	14.933	39.093
Social capital	Social support	5.417	1.020
Satisfaction with partner	Life satisfaction with partner	8.266	2.035
Gas prices	State-level gas prices ($)	96.696	30.348

Table A2
Sensitivity of estimates to the inclusion of lagged dependent variable.

	Unconditional	Life events	Education level	Socio-economic	Unrestricted model
	(1)	(2)	(3)	(4)	(5)
EPOV1	0.031***	0.019**	0.026***	0.031***	0.021**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Lag violence	0.224***	0.223***	0.224***	0.216***	0.214***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Life events	No	Yes	No	No	Yes
Education level	No	No	Yes	No	Yes
Socio-economic	No	No	No	Yes	Yes
Full controls	No	No	No	No	Yes
Observations	155,647	154,929	155,580	155,643	154,858

Standard errors in parentheses. All regressions include wave fixed effects. *** $p < 0.01$, ** $p < 0.05$.

Table A3
Sensitivity of estimates to the inclusion of lagged energy poverty.

	Unconditional	Life events	Education level	Socio-economic	Unrestricted model
	(1)	(2)	(3)	(4)	(5)
EPOV1	0.034***	0.024**	0.028***	0.034***	0.026***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Lag EPOV1	0.001	−0.003	−0.005	0.001	−0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Life events	No	Yes	No	No	Yes
Education level	No	No	Yes	No	Yes
Socio-economic	No	No	No	Yes	Yes
Full controls	No	No	No	No	Yes
Life events	No	Yes	No	No	Yes
Observations	146,588	145,916	146,518	146,583	145,841

Standard errors in parentheses. All regressions include wave fixed effects. *** $p < 0.01$, ** $p < 0.05$.

References

Aldarondo, E., Sugarman, D.B., 1996. Risk marker analysis of the cessation and persistence of wife assault. J. Consult. Clin. Psychol. 64 (5), 1010–1019.

Anderson, C., 1989. Temperature and aggression: ubiquitous effects of heat on occurrence of human violence. Psychol. Bull. 106 (1), 74–96.

Anderson, K.L., 2002. Perpetrator or victim? Relationships between intimate partner violence and well-being. J. Marriage Fam. 64, 851–863.

Arthur, J.A., 1991. Socioeconomic predictors of crime in rural Georgia. Crim. Justice Rev. 16, 29–41 Australian Bureau of Statistics. https://www.abs.gov.au/statistics/people/crime-and-justice.

Australian Bureau of Statistics, 2019. https://www.abs.gov.au/statistics/people/crime-and-justice/recorded-crime-victims/latest-release.

Awaworyi Churchill, S., Farrell, L., 2020. Social capital and gambling: evidence from Australia. J. Gambl. Stud. 36 (4), 1161–1181.

Awaworyi Churchill, S., Smyth, R., 2019. Transport poverty and subjective wellbeing. Transp. Res. A Policy Pract. 124, 40–54.

Awaworyi Churchill, S., Smyth, R., 2020. Ethnic diversity, energy poverty and the mediating role of trust: evidence from household panel data for Australia. Energy Econ. 86, 104663.

Awaworyi Churchill, S., Smyth, R., 2021. Energy poverty and health: panel data evidence from Australia. Energy Econ. 97, 105219.

Awaworyi Churchill, S., Smyth, R., Farrell, L., 2020. Fuel poverty and subjective wellbeing. Energy Econ. 86, 104650.

Awaworyi Churchill, S., Munyanyi, M.E., Prakash, K., Smyth, R., 2020b. Locus of control and the gender gap in mental health. J. Econ. Behav. Organ. 178, 740–758.

Baumeister, R., Heatherton, T., 1996. Self-regulation failure: an overview. Psychol. Inq. 7 (1), 1–15.

Baylis, P., 2020. Temperature and temperament: evidence from Twitter. J. Public Econ. 184, 104161.

Bentley, R., Baker, E., Martino, E., Li, Y., Mason, K., 2021. Alcohol and tobacco consumption: what is the role of economic security? Addiction. https://doi.org/10.1111/add.15400.

Berkowitz, L., 1962. Aggression: A Social Psychological Analysis. McGraw-Hill.

Bhavsar, V., Bhugra, D., 2018. Violence towards people with mental illness: assessment, risk factors, and management. Psychiatry Clin. Neurosci. 72 (11), 811–820.

Boardman, B., 1991. Fuel Poverty: From Cold Homes to Affordable Warmth. Pinter Pub Limited.

Boardman, B., 2010. Fixing Fuel Poverty: Challenges and Solutions. Earthscan, Abingdon.

Bridge, B.A., Adhikari, D., Fontenla, M., 2016. Household-level effects of electricity on income. Energy Econ. 58, 222–228.

Bruederle, A., Peters, J., Roberts, G., 2017. Weather and Crime in South Africa. Technical Report, Ruhr Economic Papers.

Card, D., Dahl, G., 2011. Family violence and football: the effect of unexpected emotional cues on violent behavior. Q. J. Econ. 126 (4), 1879–1907.

Cesur, R., Sabia, J.J., 2016. When war comes home: the effect of combat service on domestic violence. Rev. Econ. Stat. 98 (2), 209–225.

Cohen, M.A., 2005. The Costs of Crime and Justice. Routledge, London and New York.

Conger, R.D., Conger, K.J., Martin, M.J., 2010. Socioeconomic status, family processes, and individual development. J. Marriage Fam. 72, 685–704.

Crutchfield, R.D., Wadsworth, T., 2003. Poverty and violence. International Handbook of Violence Research. Springer, Dordrecht, pp. 67–82.

Cunradi, C.B., Caetano, R., Clark, C., Schafer, J., 2000. Neighborhood poverty as a predictor of intimate partner violence among White, Black, and Hispanic couples in the United States: a multilevel analysis. Ann. Epidemiol. 10 (5), 297–308.

Cunradi, C.B., Caetano, R., Schafer, J., 2002. Socioeconomic predictors of intimate partner violence among White, Black, and Hispanic couples in the United States. J. Fam. Violence 17 (4), 377–389.

De Olarte, E.G., Llosa, P.G., 1999. Does Poverty Cause Domestic Violence? Some Answers from Lima. PUCP, CISEPA.

Dean, K., Laursen, T.M., Pedersen, C.B., Webb, R.T., Mortensen, P.B., Agerbo, E., 2018. Risk of being subjected to crime, including violent crime, after onset of mental illness: a Danish National Registry Study Using Police Data. JAMA Psychiat. 75 (7), 689–696. https://doi.org/10.1001/jamapsychiatry.2018.0534.

DeMaris, A., Benson, M.L., Fox, G.L., Hill, T., Van Wyk, J., 2003. Distal and proximal factors in domestic violence: a test of an integrated model. J. Marriage Fam. 65 (3), 652–667.

Dolan, P., Loomes, G., Peasgood, T., Tsuchiya, A., 2005. Estimating the intangible victim costs of violent crime. Br. J. Criminol. 45, 958–976.

Dollard, J., Doob, L., Miller, N., Mowrer, O., Sears, R., 1939. Frustration and Aggression. Yale University Freer, New Haven.

Fajnzylber, P., Lederman, D., Loayza, N., 2002a. Inequality and violent crime. J. Law Econ. 45 (1), 1–40.

Fajnzylber, P., Lederman, D., Loayza, N., 2002b. What causes violent crime? Eur. Econ. Rev. 46 (2), 1323–1357.

Feingold, A., Kerr, D.C.R., Capaldi, D.M., 2008. Associations of substance use problems with intimate partner violence for at-risk men in long-term relationships. J. Fam. Psychol. 22 (3), 429–438.

Foran, H.M., O'Leary, K.D., 2008. Alcohol and intimate partner violence: a meta-analytic review. Clin. Psychol. Rev. 28 (7), 1222–1234. https://doi.org/10.1016/j.cpr.2008.05.001.

Forbes, K.J., 2000. A reassessment of the relationship between inequality and growth. Am. Econ. Rev. 90 (4), 869–887.

Fujii, D.E., Wylie, A.M., Nathan, J.H., 2004. Neurocognition and long-term prediction of quality of life in outpatients with severe and persistent mental illness. Schizophr. Res. 69 (1), 67–73. https://doi.org/10.1016/S0920-9964(03)00122-1.

Fukuyama, F., 1995. Trust: The Social Virtues and the Creation of Prosperity. Hamish Hamilton, London.

Gearon, J.S., Bellack, A.S., 1999. Women with schizophrenia and cooccurring substance use disorders: an increased risk for violent victimization and HIV. Community Ment. Health J. 35 (5), 401–419. https://doi.org/10.1023/a:1018778310859.

Gibbs, A., Jewkes, R., Willan, S., Washington, L., 2018. Associations between poverty, mental health and substance use, gender power, and intimate partner violence amongst young (18-30) women and men in urban informal settlements in South Africa: a cross-sectional study and structural equation model. PLoS One 13 (10), e0204956.

Gleeson, B., Randolph, B., 2002. Social disadvantage and planning in the Sydney context. Urban Policy Res. 20 (1), 101–107.

Gonzalez-Eguino, M., 2015. Energy poverty: an overview. Renew. Sust. Energ. Rev. 47, 377–385.

Hammack, P.L., Robinson, W.L., Crawford, I., Li, S.T., 2004. Poverty and depressed mood among urban African-American adolescents: a family stress perspective. J. Child Fam. Stud. 13, 309–323.

Healy, J.D., Clinch, J.P., 2004. Quantifying the severity of fuel poverty, its relationship with poor housing and reasons for non-investment in energy-saving measures in Ireland. Energy Policy 32 (2), 207–220.

Heindl, P., Schuessler, R., 2015. Dynamic properties of energy affordability measures. Energy Policy 86, 123–132. https://doi.org/10.1016/j.enpol.2015.06.044.

Hills, J., 2011. Fuel Poverty: The Problem and its Measurement. LSE, London.

Hills, J., 2012. Getting the Measure of Fuel Poverty: Final Report of the Fuel Poverty Review.

Jessel, S., Sawyer, S., Hernández, D., 2019. Energy, poverty, and health in climate change: a comprehensive review of an emerging literature. Front. Public Health 7, 357.

Johnston, D.W., Shields, M.A., Suziedelyte, A., 2018. Victimisation, well-being and compensation: using panel data to estimate the costs of violent crime. Econ. J. 128 (611), 1545–1569.

Kelly, M., 2000. Inequality and crime. Rev. Econ. Stat. 82 (4), 530–539.

Kennedy, B.P., Kawachi, I., Prothrow-Stith, D., Lochner, K., Gupta, V., 1998. Social capital, income inequality, and firearm violent crime. Soc. Sci. Med. 47 (1), 7–17.

Krauss, A., 2016. How natural gas tariff increases can influence poverty: results, measurement constraints and bias. Energy Econ. 60, 244–254.

Krivo, L.J., Peterson, R.D., 1996. Extremely disadvantaged neighborhoods and urban crime. Soc Forces 75 (2), 619–648.

Land, K.C., McCall, P.L., Cohen, L.E., 1990. Structural covariates of homicide rates: are there any invariances across time and social space? Am. J. Sociol. 95, 922–963.

Lawson, R., Williams, J., Wooliscroft, B., 2015. Contrasting approaches to fuel poverty in New Zealand. Energy Policy 81, 38–42.

Lederman, D., Loayza, N., Menéndez, A.M., 2002. Violent crime: does social capital matter? Econ. Dev. Cult. Chang. 50 (3), 509–539.

Lee, W., McKinnish, T., 2018. The marital satisfaction of differently aged couples. J. Popul. Econ. 31, 337–362.

Lee, W., McKinnish, T., 2019. Locus of control and marital satisfaction: couple perspectives using Australian data. J. Econ. Psychol. 74, 102205.

Lewis, P., 1982. Fuel Poverty Can Be Stopped. National Right to Fuel Campaign, Bradford.

Llorca, M., Rodriguez-Alvarez, A., Jamasb, T., 2020. Objective vs. subjective fuel poverty and self-assessed health. Energy Econ. 87, 104736.

Maniglio, R., 2009. Severe mental illness and criminal victimization: a systematic review. Acta Psychiatr. Scand. 119 (3), 180–191. https://doi.org/10.1111/j.1600-0447.2008.01300.x.

McIlwaine, C., Moser, C., 2003. Poverty, violence and livelihood security in urban Colombia and Guatemala. Prog. Dev. Stud. 3 (2), 113–130.

McInnes, G., 2017. Understanding the Distributional and Household Effects of the Low-Carbon Transition in G20 Countries. OECD.

Mervin, M.C., Frijters, P., 2014. Is shared misery double misery? Soc. Sci. Med. 107, 68–77.

Milner, A., Krnjacki, L., Butterworth, P., LaMontagne, A.D., 2016. The role of social support in protecting mental health when employed and unemployed: a longitudinal fixed-effects analysis using 12 annual waves of the HILDA cohort. Soc. Sci. Med. 153, 20–26.

Moore, R., 2012. Definitions of fuel poverty: implications for policy. Energy Policy 49, 19–26.

Narayan, P.K., Smyth, R., 2005. The residential demand for electricity in Australia: an application of the bounds testing approach to cointegration. Energy Policy 33 (4), 467–474.

Nussbaumer, P., Bazilian, M., Modi, V., 2012. Measuring energy poverty: focusing on what matters. Renew. Sust. Energ. Rev. 16 (1), 231–243.

OECD, 2007. OECD Contribution to the United Nations Commission on Sustainable Development 15. Energy for sustainable development.

OECD, 2013. Trust in government. Government at a Glance. OECD Publishing, Paris.

OECD/IEA, International Energy Agency, 2011. Evaluating the co-benefits of low-income energy-efficiency programmes. Workshop Report. In: Heffner, Grayson, Campbell, Nina (Eds.), Results of the Dublin Workshop, 27–28 January, Paris.

Okushima, S., 2017. Gauging energy poverty: a multidimensional approach. Energy 137, 1159–1166. https://doi.org/10.1016/j.energy.2017.05.137.

Orr, C., Preen, D., Fisher, C., Sims, S., O'Donnell, M., 2019. Trends in hospital admissions for intimate partner violence in Australian mothers with children born from 1990 to 2009. J. Interpers Violence https://doi.org/10.1177/0886260519832905.

Papada, K., Kaliampakos, D., 2016. Measuring energy poverty in Greece. Energy Policy 94, 157–165.

Perales, F., Pozo-Cruz, J.D., Pozo-Cruz, B.D., 2014. Impact of physical activity on psychological distress: a prospective analysis of an Australian national sample. Am. J. Public Health 104 (12), e91–e97. https://doi.org/10.2105/AJPH.2014.302169.

Phoumin, H., Kimura, F., 2019. Cambodia's energy poverty and its effects on social wellbeing: empirical evidence and policy implications. Energy Policy 132, 283–289.

Price, C.W., Brazier, K., Wang, W., 2012. Objective and subjective measures of fuel poverty. Energy Policy 49, 33–39.

Ranson, M., 2014. Crime, weather, and climate change. J. Environ. Econ. Manag. 67 (3), 274–302.

Reddy, A., 2000. Energy and social issues. editors. In: World Energy Council, UNEP (Eds.), Energy and the Challenge of Sustainability. New York, NY.

Robinson, C., Bouzarovski, S., Lindley, S., 2018. Getting the measure of fuel poverty: the geography of fuel poverty indicators in England. Energy Res. Soc. Sci. 36, 79–93.

Robison, L.J., Siles, M.E., Schmid, A.A., 2002. Social Capital and Poverty Reduction: Toward a Mature Paradigm (No. 1091-2016-87428).

Rodríguez-Álvarez, A., Orea, L., Jamasb, T., 2019. Fuel poverty and well-being: a consumer theory and stochastic frontier approach. Energy Policy 131, 22–32.

Sampson, R.J., Groves, W.B., 1989. Community structure and crime: testing social–disorganization theory. Am. J. Sociol. 94 (4), 774–802.

Scrivens, K., Smith, C., 2013. Four Interpretations of Social Capital: An Agenda for Measurement.

Smith, N., Weatherburn, D., 2013. Personal stress, financial stress, social support and women's experiences of physical violence: a longitudinal analysis. BOCSAR NSW Crime Justice Bull. 20.

Stark, R., 1987. Deviant places: a theory of the ecology of crime. Criminology 25 (4), 893–909.

Thomson, H., Snell, C., 2013. Quantifying the prevalence of fuel poverty across the European Union. Energy Policy 52, 563–572.

Thomson, H., Snell, C., Bouzarovski, S., 2017. Health, well-being and energy poverty in Europe: a comparative study of 32 European countries. Int. J. Environ. Res. Public Health 14 (6), 584.

Vest, J., Catlin, T., Chen, J., Brownson, R., 2002. Multistate analysis of factors associated with intimate partner violence. Am. J. Prev. Med. 22 (3), 156–164.

Wadsworth, M.E., Achenbach, T.M., 2005. Explaining the link between low socioeconomic status and psychopathology: testing two mechanisms of the social causation hypothesis. J. Consult. Clin. Psychol. 73 (6), 1146–1153.

Wadsworth, M.E., Compas, B.E., 2002. Coping with family conflict and economic strain: the adolescent perspective. J. Res. Adolesc. 12 (2), 243–274.

Wadsworth, M.E., Raviv, T., Reinhard, C., Wolff, B., Santiago, C.D., Einhorn, L., 2008. An indirect effects model of the association between poverty and child functioning: the role of children's poverty-related stress. J. Loss Trauma 13, 156–185.

Watson, N., Wooden, M.P., 2011. Re-Engaging with Survey Non-Respondents: The BHPS, SOEP and HILDA Survey Experience.

Watson, N., Wooden, M.P., 2012. The HfigILDA survey: a case study in the design and development of a successful household panel survey. Longitud. Life Course Stud. 3 (3), 369–381.

White, H.R., Chen, P.-H., 2002. Problem drinking and intimate partner violence. J. Stud. Alcohol 63, 205–214.

Wilkins, R., Sun, C., 2010. Assessing the Quality of the Expenditure Data Collected in the Self-Completion Questionnaire.

LARA MPSC

Customer Outage History

When a utility is experiencing outages beyond a threshold level, they report their status and estimated number of customers affected to the MPSC. The MPSC uses this information to monitor restoration activities and coordinate with utilities and local emergency responders when help is needed.

For the latest information during storm events, many Michigan utilities have outage maps on their respective webpages to assist customers in identifying affected areas and estimated restoration times. These maps are updated frequently and are the best source of information regarding an outage. In addition, customers may receive restoration updates via text messages or emails to their phones. Click here for access to your utility's outage map.

Poweroutage.us is a resource to view outages around the country in real time, including Michigan's map.

Storm outage data through September 2025 is shown below for the utilities regulated by the MPSC. For Consumers Energy and DTE Electric, outage events greater than 20,000 customers are listed. For all other utilities, outage events greater than 5% of the company's customers are listed. This data will be updated as final numbers are received from the utility reports submitted in U-21122 and U-12270. Initial reported outages are denoted by an asterisk (*).

2025 Utility Outages

Start Date of Event	Utility	Total Outages

2/6/2025	CE	31,597
3/15/2025	CE	98,226
3/29/2025	Alpena	16,774
3/29/2025*	Cloverland	10,137
3/29/2025	CE	380,064
3/29/2025*	Great Lakes Energy	43,900
3/29/2025	I&M	26,173
3/29/2025*	Presque Isle	31,655
3/29/2025	UMERC	23,746
3/29/2025*	Midwest	9,300
3/29/2025	DTE	84,711
4/29/2025	CE	52,788
5/15/2025	CE	321,747
5/15/2025*	I&M	33,000
5/15/2025	UMERC	2,680
6/18/2025*	DTE	38,837
6/18/2025	CE	25,723
6/19/2025	CE	46,104

6/21/2025	UMERC	2,011
6/25/2025	DTE	88,038
7/24/2025*	CE	58,638

* Initial Report - Will be updated with final numbers

The next U-21122 filings are due November 15, 2025

Historical Outage Information

- Prior Years: 2024, 2023, 2022, 2021, 2020, 2019

Outage Credits

Customers may be eligible for a credit on their electric bill if they experience lengthy or frequent service outages. Residential customers may qualify for the greater of a $40.00 credit or their monthly customer charge. For commercial and other classes of service, the credit is determined based on a customer's minimum bill. Customers will now receive the outage credit automatically on their bill, eliminating the prior need to apply for the credit.

Condition Type	Customers Outage Length	Credit Amount
Normal	16 hrs	$40 Plus $40 for each additional day
Gray Sky	48 hrs	
Catastrophic	96 hrs	

Credits for Repetitive Outages	Credit amount

6 or more interruptions in 12 months	$40

Current MPSC Efforts

The MPSC is working to address reliability issues and improve the quality of service for customers.

Updated Rules

The MPSC's MI Power Grid – Grid Security and Reliability Standards workgroup provided input to the revisions incorporated into the MPSC's Service Quality and Reliability Standards for Electric Distribution Systems and Technical Standards for Electric Service Rules. For more information on the revised rules click here.

2023 Power Outage Town Hall

March 2023 Power Outage Town Hall Meeting Recap

Third-Party Review and Audit of Consumers Energy's and DTE Electric's Distribution Systems

In an order issued on October 5, 2022 in Case No. U-21305, the Commission described the 2-part audit:

Part 1 will consist of a physical audit of the existing installed infrastructure to determine whether the existing installed infrastructure matches the company's records. This part will involve physical measurements of installed distribution infrastructure to ensure compliance with the utility's engineering standards. Measurements will include a statistically significant sample of infrastructure at a variety of locations and considering a variety of types of distribution infrastructure to get a statistically relevant understanding of the state of the utility's overall distribution system. This part will include a comparison of the condition of the company's distribution system to that of other utilities in similar climates.

Part 2 will consist of an audit of each utility's programs and processes to determine whether the existing programs and processes for emergency preparedness, storm restoration, distribution system maintenance, and investment are sufficient and equitable, and whether they properly plan for climate change and changing load profiles. This part will include a review of each company's engineering standards and inspection and maintenance programs to ensure they meet the needs of the distribution system, now and into the future. It will include an audit of the accounting process for the distribution system to ensure costs are being accurately managed and recorded. It will also include a review of how the utility manages the operations of the distribution system, including how maintenance prioritization is determined, how personnel are managed during outage recovery, and company management and internal policies and procedures regarding outages, distribution management, safety, and planning.

In response to an order issued on March 3, 2022, the Staff worked with utilities to create a reporting template enabling the utilities to file updated information pertinent to reliability, outages and storm response.

Reportable data will include existing and proposed reliability metrics, as well as data on outage numbers and restoration times for each month and each storm, and monthly tree trimming data that includes the miles of power lines cleared and the amount spent on tree trimming. For data reported on storms, the Commission also seeks information on storm type, customers interrupted, storm duration and restoration in days, the amount of dollars spent for each storm event, dollars paid in customer outage credits, and mutual aid requests and expenses for each storm event. The Commission specifically seeks data by ZIP code and Census tract, finding it especially useful to have that level of granularity.

The first utility data submissions will be provided to the Commission by May 15, 2023 and will include data for January, February, and March 2023. The Commission's Distribution System Reliability webpages will be updated with the new data when available.

Statewide Energy Assessment Report

The Statewide Energy Assessment Report (SEA Report) is a statewide review of the supply, engineering, and deliverability of natural gas, electricity, and propane systems, as well as contingency planning related to those systems.

SEA Report SEA Fact Sheet 2021 SEA Progress Report

Distribution Investment and Maintenance Plans

These reports include an overview of the utility's distribution system, plans for future improvement, vegetation management plans, and reliability performance metrics.

Consumers Energy

DTE Electric

Indiana Michigan- Revised Page 52

Michigan Infrastructure Council

Participation in the Michigan Infrastructure Council's 30 Year Infrastructure Planning Project

Customer Outage History

nature communications

Article

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Spatiotemporal distribution of power outages with climate events and social vulnerability in the USA

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Check for updates

Vivian Do[1], Heather McBrien[1], Nina M. Flores[1], Alexander J. Northrop[2], Jeffrey Schlegelmilch[3], Mathew V. Kiang[4] & Joan A. Casey[1,5]

Power outages threaten public health. While outages will likely increase with climate change, an aging electrical grid, and increased energy demand, little is known about their frequency and distribution within states. Here, we characterize 2018–2020 outages, finding an average of 520 million customer-hours total without power annually across 2447 US counties (73.7% of the US population). 17,484 8+ hour outages (a medically-relevant duration with potential health consequences) and 231,174 1+ hour outages took place, with greatest prevalence in Northeastern, Southern, and Appalachian counties. Arkansas, Louisiana, and Michigan counties experience a dual burden of frequent 8+ hour outages and high social vulnerability and prevalence of electricity-dependent durable medical equipment use. 62.1% of 8+ hour outages co-occur with extreme weather/climate events, particularly heavy precipitation, anomalous heat, and tropical cyclones. Results could support future large-scale epidemiology studies, inform equitable disaster preparedness and response, and prioritize geographic areas for resource allocation and interventions.

As climate change intensifies, the power grid ages, and energy demand from population growth increases, power outages will likely increase[1]. In 2020, US electricity customers faced slightly over 8 h of electricity interruptions on average – the highest on record—primarily driven by major events such as hurricanes, wildfires, and snowstorms[2]. When outages occur, human health suffers[3]. The United States Federal Emergency Management Agency (FEMA) identifies the power grid among Community Lifelines, which are fundamental services that society needs in order to operate[3]. Documented health effects include carbon monoxide poisoning from improper generator use, anxiety, stress, and exacerbation of existing cardiovascular and respiratory conditions[4]. Because outages can prevent the use of temperature-controlling devices, risk of hypothermia and heatstroke can increase when outages occur during extreme cold spells and heatwaves[5]. Moreover, outages can lead to acute food insecurity when refrigerators lack power[6], fear related to personal safety[7], and economic losses in commercial and industrial sectors[8].

Power outages represent acute health hazards for certain vulnerable groups. Those using electricity-dependent durable medical equipment (DME), such as oxygen concentrators, infusion pumps, and mobility devices rely on electricity to maintain their health[9,10]. Others vulnerable to power outages include under-resourced communities and historically marginalized groups. Pathways include disrupted hourly employment, older and less-insulated housing stock resulting in dangerous indoor temperatures, lack of access to cooling facilities, and a higher burden of underlying chronic diseases sensitive to extreme temperatures[11,12]. Other historically marginalized groups may face more adverse health outcomes following outages, or worse

[1]Department of Environmental Health Sciences, Columbia University Mailman School of Public Health, New York, NY, USA. [2]Vagelos College of Physicians and Surgeons, Columbia University, New York, NY, USA. [3]National Center for Disaster Preparedness at the Columbia Climate School, Columbia University, New York, NY, USA. [4]Department of Epidemiology and Population Health, Stanford University School of Medicine, Stanford, CA, USA. [5]Department of Environmental and Occupational Health Sciences, University of Washington School of Public Health, Seattle, WA, USA. e-mail: jacasey@uw.edu

outage exposures[4,13]. Communities with a higher proportion of Hispanic/Latino residents may experience longer outages following hurricane and winter storm-related events[14–16].

Although technical problems such as equipment failure and supply shortages can cause outages, severe weather events, which can physically damage the grid, are major drivers[4,17]. Power distribution infrastructure such as transmission lines are also vulnerable to extreme environmental events such as high temperatures, wildfires, and floods[18]. From 2000–2021, storms and severe weather caused 83% of large-scale outages affecting at least 50,000 customers in the US[1]. There is limited work on the link between environmental events and smaller-scale (but more frequent) outages.

No standard method exists to measure power outages of health relevance, making it challenging to compare outage events[19]. Most population health power outage studies have focused on a single, large event, such as Hurricane Sandy in 2012 or Hurricane Irma in 2017[4]. These studies generally did not measure customers without power and instead used the timing and location of the disaster as a proxy for outage exposure[4]. Presently, no national power outage datasets exist at the temporal or spatial resolutions necessary for health studies. Here, we address this gap by creating relative and absolute measures to characterize power outages across the US from 2018–2020 by hour at the county-level. The relative metric accounts for population size, while the absolute metric identifies counties with the largest count of customers without power. Both metrics provide important information about which counties to prioritize for intervention and resource allocation, especially in the context of social and medical vulnerabilities. In secondary analyses, we determine the overlap between weather events occurring on the same day as 8+ hour (a medically-relevant duration with potential health consequences) county-level outages and clustering of counties experiencing high outage burden and high social vulnerability.

Between 2018–2020, we identified 231,174 1+ hour outages and nearly 17,500 8+ hour (medically relevant) outages at the county-level. 62.1% of the 8+ hour outages co-occur with an extreme weather or climate event and 8+ hour outages are 3.4x more common on days with a single event and 10x more common on days with multiple events. Outages are more common in the Northeast, South, and Appalachia. Clusters of counties in Arkansas, Louisiana and Michigan experience a dual burden of high outage exposure and high social and medical vulnerability.

Results

The study included 2447 counties (77.9% of US counties) of which 2038 (83.3%) had 2+ years of reliable data from 2018–2020 after data quality and reliability checks (Fig. 1). These counties experienced a median of 60 (IQR = 97) 1+ hour outages and 2 (IQR = 5) 8+ hour outages each year. Between 2018–2020, over 70% of included counties experienced at least one 8+ hour outage and a total of 231,174 1+ hour outages and 17,484 8+ hour outages occurred (Table 1). Medically relevant 8+ outages happened more often during the summer than the winter and peaked during late spring and mid-summer (Fig. 2). 8+ hour outages typically had an onset around 6 PM with a range of 3 PM-8 PM (Fig. 2), coinciding with peak electricity use, and this pattern was especially prominent in the South (Supplementary Fig. 2). In the ten states with the most 8+ hour outages, outages were more common in April and October (Supplementary Fig. 3). Our analysis did not cover all counties; states with the highest percent of counties missing all years of data were Montana (98.2%), Alaska (93.1%), and Utah (72.4%) (Supplementary Table 1).

Characterizing outage events and customers without power

In our 2447 study counties, the highest average counts of 8+ hour outages occurred in the South, Maine, Michigan, and Appalachia (Fig. 3a). Figure 3 also illustrates the pattern of data availability and reliability, with a higher prevalence of counties with 3 years of complete and reliable data on the East Coast (darker shading) and a low prevalence of availability and reliability in the middle of the U.S (lighter or no shading). The states with the highest annual average counts of 8+ hour outage events were Louisiana ($n = 553$), Texas ($n = 527$), Michigan ($n = 447$), Mississippi ($n = 381$), and North Carolina ($n = 372$). When we created deciles of county-level annual average 8+ hour outage counts, the states with the highest number of counties in the top outage decile were Michigan ($n = 32$) and Louisiana ($n = 29$) (Supplementary Table 2).

The spatial distribution of 1+ hour outages generally mirrored that of 8+ hour outages but extended to additional counties; outages were

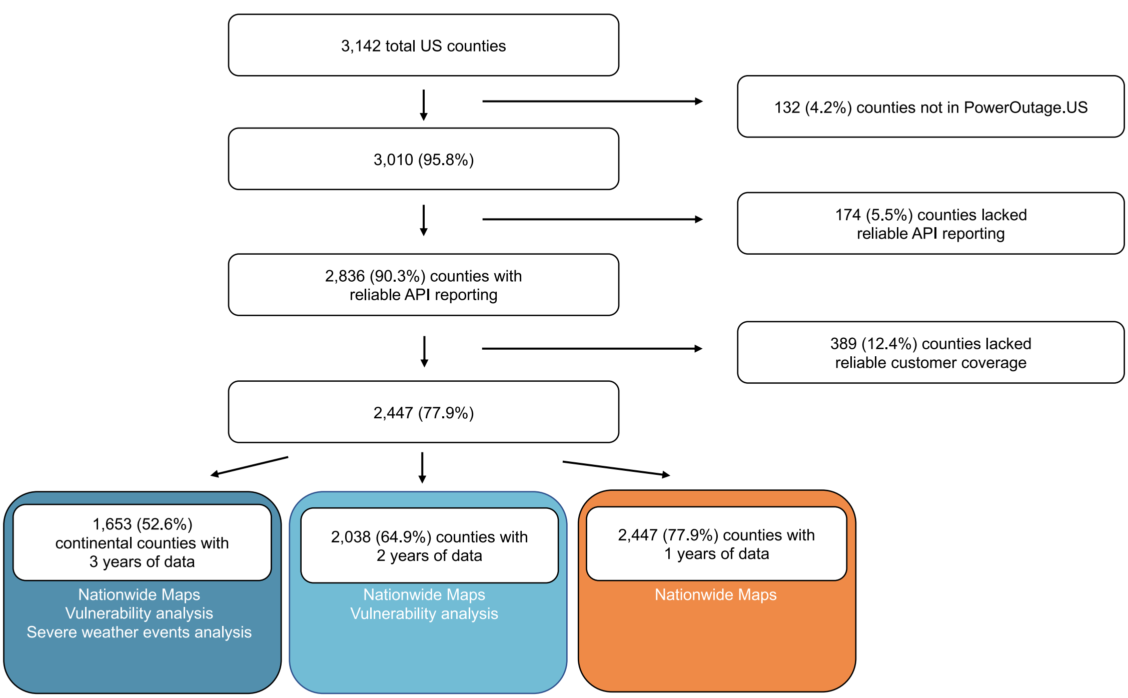

Fig. 1 | Flowchart of US counties included in the study of power outages, 2018–2020. We state the subsets of counties used for specific analyses in colored boxes. Power outage data was purchased from PowerOutage.us.

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Table 1 | Summary statistics of 8+ hour outages and 1+ hour outages among counties with 2+ years of reliable data

	Annual average 8+ hour outage	Annual average 1+ hour outage
Counties included in analysis, *N*	2038	2038
Counties with ≥1 outage, *N* (%)	1436 (70.5)	1530 (75.1)
Total outage count	17,484	231,174
Median (IQR) county-level outage count	2 (5)	60 (97)
Min county-level outage count	0	0
Max county-level outage count	35	414

Summary statistics refer to the average yearly totals per county, which is the total of outage types per county that are averaged across the study period (2018–2020). Power outage data was purchased from PowerOutage.us.

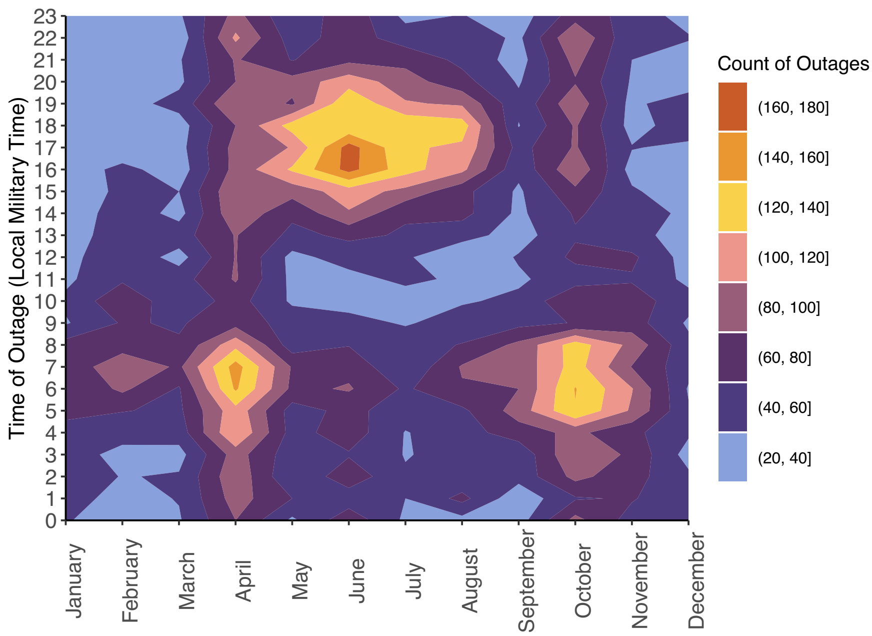

Fig. 2 | Contour plot of the counts of 8+ hour outages nationwide according to start time of outage per month. The x-axis indicates start month, the y-axis indicates the start hour of an 8+ hour outage in local military time, and the colors indicate the total count of outages for that month and start hour. Power outage data was purchased from PowerOutage.us.

concentrated in the South, the Northeast, Appalachia, and parts of California. The lowest counts of 1+ hour outages appeared in the Midwest (Fig. 3b). The top 5 states for highest annual average counts of 1+ hour outages were Texas ($N = 11{,}504$), Georgia ($N = 10{,}609$), Louisiana ($N = 7826$), Mississippi ($N = 7188$), and Alabama ($N = 6240$). Like 8+ hour outages, Texas, Louisiana, and Mississippi had the largest number of counties in the top outage decile of 1+ hour outage counts with 37, 28, and 22 counties involved, respectively (Supplementary Table 2).

The absolute annual average total customer hours without power partially reflected population size, with a high number of customers without power along the Gulf Coast, the Northeast Coast, and parts of the Pacific Northwest (Fig. 4a). Outages resulted in an annual average of 5.2 million customer-hours without power across 2447 study counties. Some counties in Southern states such as Louisiana, as well as throughout Appalachia, and the Northeast consistently experienced both high counts of outage events and high total customer-hours out. Overall, the state of Louisiana led with an annual average of >52 million customer-hours out, followed by North Carolina (38.3 million customer-hours out), California (30.3 million customer-hours out), Texas (30 million customer-hours out), and New York (28.8 million customer-hours out). Counties with the highest annual average total hours of customers without power were Calcasieu, LA (10.0 million), Los Angeles, CA (7.8 million), Fairfield, CT (7.6 million), Davidson, TN (7.4 million), and Jefferson, LA (6.2 million) (Supplementary Table 3). When accounting for county-level customers, counties where the average customer experienced a high annual average of hours without power (107+ hours) concentrated around the Gulf Coast and the Northeast, particularly Maine (Fig. 4b). Orleans (NY) led, where the average customer experienced 251.4 h, or over 10 full days, without power each year.

Severe weather and climate events and 8+ hour outages

We explored the role of severe weather and climate events in county-level 8+ hour power outages by determining days where isolated and multiple events co-occurred with outages in the continental counties with 3 years of reliable data ($n = 1653$). Approximately 13% of county-days ($n = 22{,}793$) had an 8+ hour outage, 62.1% ($n = 14{,}156$) of these county-days co-occurred with one or more weather or climate events (Table 2). Because multiple weather and climate events can occur in the same county on the same day, we divided analysis into county-days with isolated events and county-days with multiple events. 8+ hour outages were 3.4x more common on county-days with an isolated event and 10x more common on days with multiple events, compared to county-days without any severe weather or climate event. Every severe weather or climate event we evaluated, except anomalous cold alone, were related to increased occurrence of 8+ hour outages. Tropical cyclone county-days, while not particularly common (0.2% of outage county-days), were much more likely (13.7x) to co-occur with an 8+ hour outage than county-days without any event. When tropical cyclones happened with other severe weather or climate events the

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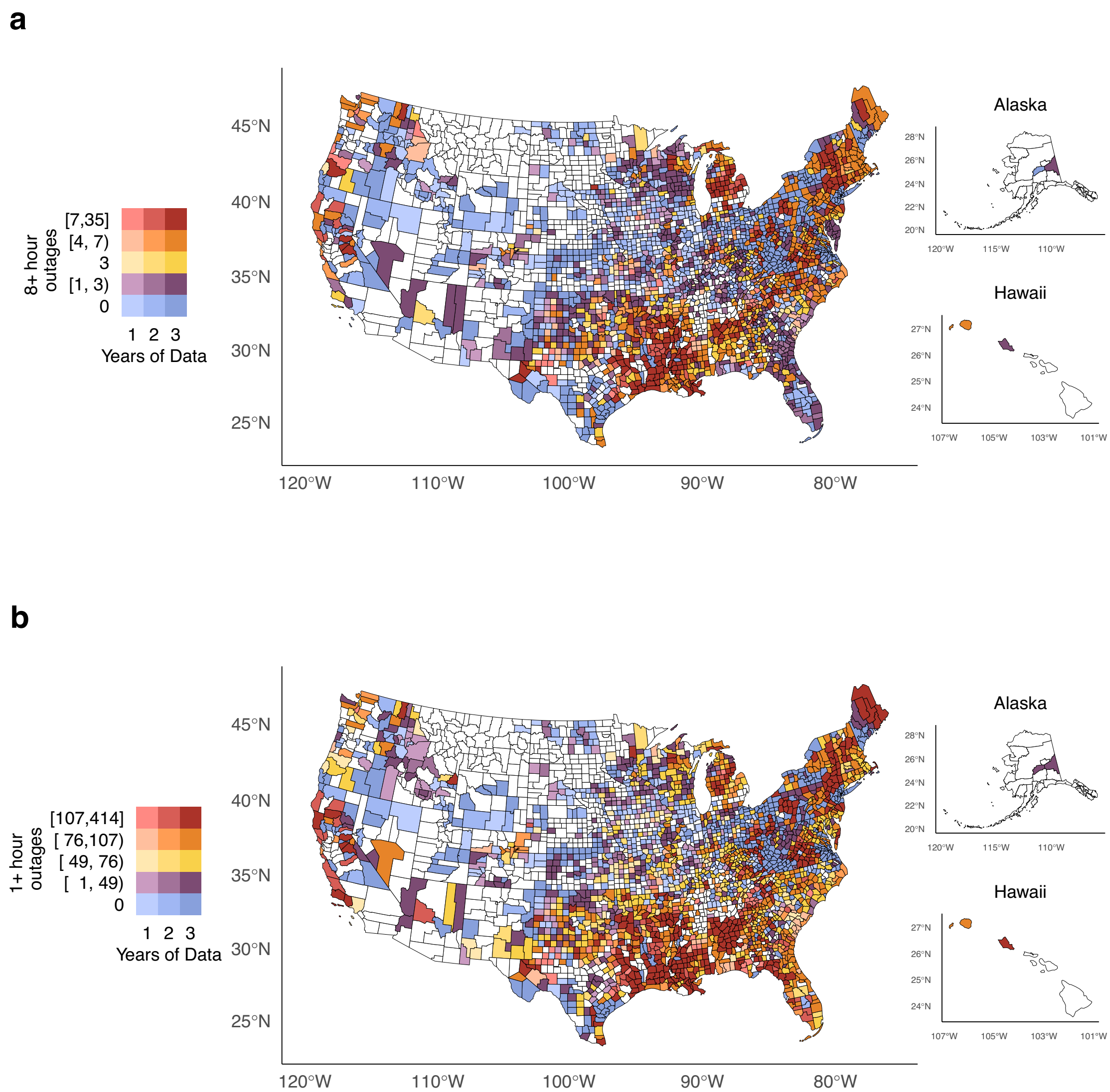

Fig. 3 | County-level yearly average outage events lasting 8+ h and 1+ hour in 2447 counties with 1 + years of reliable data. Counties shaded in white lacked any reliable data. **a** Geographic distribution for county-level yearly average of 8+ hour outage events. **b** Geographic distribution for county-level yearly average of 1+ hour outage events. Power outage data was purchased from PowerOutage.us and county basemaps were obtained from the usmap R package version 0.6.1.

likelihood of an 8+ hour outage was even greater. For example, county-days with heavy precipitation and a tropical cyclone (representing 3.0% of total outage county-days) were 37.6x more likely to have an 8+ h outage than county-days without an event. County-days with simultaneous heavy precipitation, anomalous heat, and a tropical cyclone were 51.6x more likely to have an 8+ h outage.

While tropical cyclones seemed to confer the greatest increase in 8+ hour outages, other events were more common. On county-days when 8+ hour outage occurred in conjunction with a single weather or climate event, 75.2% ($n = 8507$) happened with heavy precipitation. When heavy precipitation county-days occurred, 8+ hour outages happened 4.7x more frequently than county-days without an event. Over a third ($n = 2846$) of days when a county faced 8+ hour outages co-occurred with multiple weather or climate events. The most common multiple events co-occurring with 8+ hour outages were heavy precipitation and anomalous heat (32.2%), heavy precipitation and tropical cyclones (23.9%) and heavy precipitation and lightning (22.6%). Other multiple event types occurred on the remaining 606 county-days with an 8+ hour outage and a multiple event (Supplementary Table 4).

Seasonal and geographic patterns of county-level 8+ hour outage-days and severe weather and climate type emerged. For isolated events nationwide, heavy precipitation and snowfall predominated in the winter months, anomalous heat in the summer months, and tropical cyclones and wildfires played a role between July and November (Fig. 5a). Most days with 8+ hour outages in the Northeast, Midwest, and South happened simultaneously with heavy precipitation. Snowfall contributed more 8+ hour outages in the winter in the West, and wildfires made up nearly 75% of co-occurring events in the West in September and October (Supplementary Fig. 4a). Regarding outage county-days co-occurring with multiple events, during summer months the heavy precipitation-anomalously hot temperatures combination happened most often. During the fall, heavy-precipitation and tropical cyclone predominated, while snowfall and anomalous cold was the most common during winter and into spring when heavy precipitation and lightning took over as the most frequency combination (Fig. 5b).

High 8+ hour outage exposure and vulnerability factors

Our vulnerability analyses relied on the 2038 counties with 2+ years of reliable data. We categorized counties with SVI indices in the 4th

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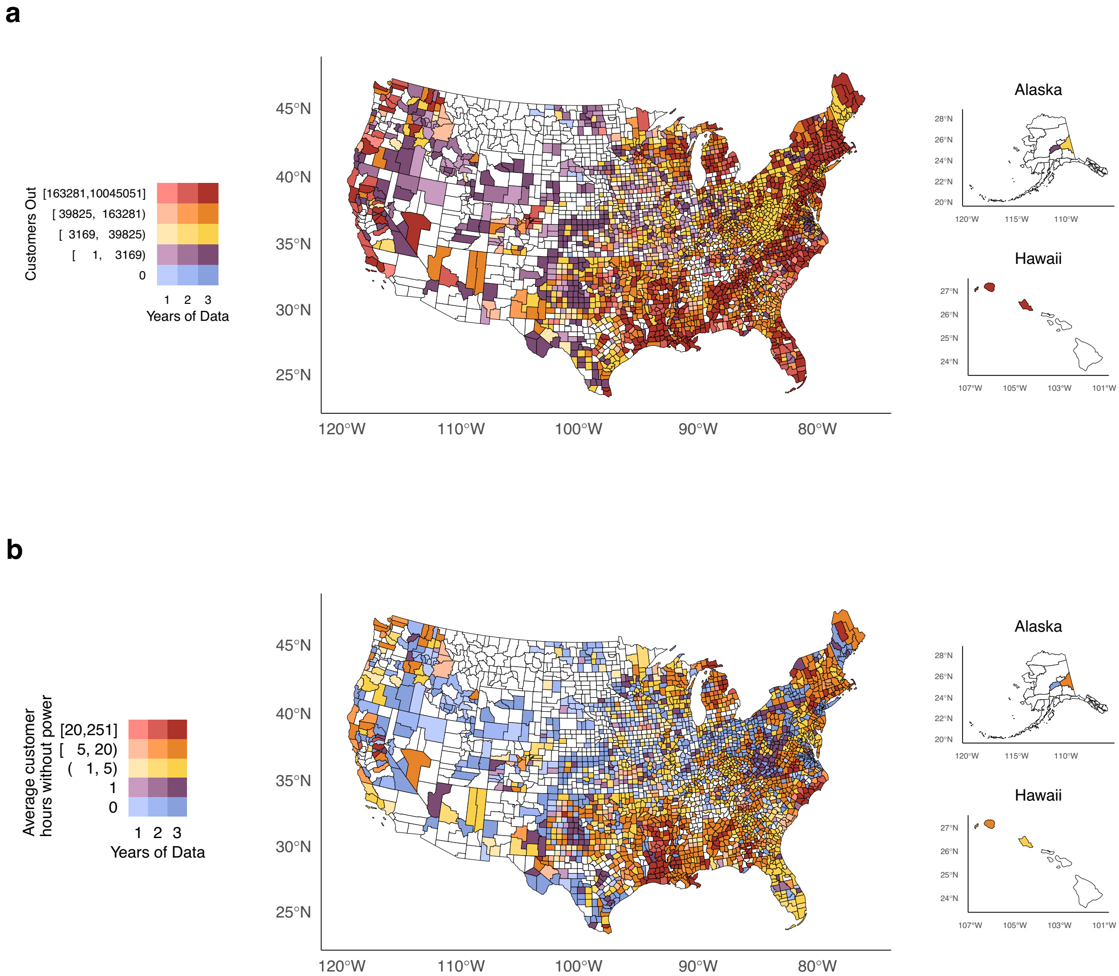

Fig. 4 | County yearly averages of customers without power. Counties shaded in white lacked any reliable data. **a** Average total customer hours without power. **b** Average total customer hours without power per customer. Panel **b** can be interpreted as the county-level annual average hours without power that an average customer in that county experienced. Power outage data was purchased from PowerOutage.us and county basemaps were obtained from the usmap R package version 0.6.1.

quartile (range: 0.77–1) as high vulnerability. We observed high SVI in parts of the West Coast, the Southeast, and throughout the South (Supplementary Fig. 5a). Counties in the highest SVI quartile experienced an annual median of 3 (IQR = 5) 8+ hour outages and 80 (IQR = 83) 1+ hour outages compared to an annual median of 1 (IQR = 4) 8+ hour outages and 40 (IQR = 73) 1+ hour outages for counties in the lowest SVI quartile (Table 3, Wilcoxon Rank Sum p-value < 0.01). Outages for counties with the top SVI quartile occurred most often in April, June, and October (Fig. 6a). This trend persisted across census regions, driven by the South (Supplementary Fig. 6).

DME analyses also included the 2038 counties with 2+years of reliable data. The 4th quartile for our DME metric ranged from 74–478 Medicare DME users per 1000 Medicare beneficiaries and most counties in this category were in the Mountain West, parts of the South, and Appalachia (Supplementary Fig. 5b). Counties in the highest DME use prevalence quartile experienced a yearly median of 1 (IQR = 3) 8+ hour outages and 42 (IQR = 82) 1+ hour outages, significantly lower counts compared to the other three quartiles (Fig. 6b, Wilcoxon Rank Sum test p-value < 0.01).

We used bivariate LISA analysis with a false discovery rate method to identify clusters of counties with a dual burden of high 8+ hour power outage counts and high SVI (4th quartile) or high DME use prevalence (4th quartile). We identified 63 counties in 7 states with both high 8+ hour outages and high SVI. These high-high county clusters were largely concentrated in Louisiana (n = 26), Mississippi (n = 12), Arkansas (n = 9), and Michigan (n = 8) (Fig. 7a). Among high outage-high SVI counties compared to all others, the components of SVI contributing to a high SVI score were higher percentages of "racial and ethnic minority" individuals (40.4% vs. 24.0%), individuals living below 150% poverty (34.0% vs. 24.3%), and those living in mobile homes (20.1% vs. 12.4%). T-tests also showed that these differences were statistically significant (p-value < 0.05) (Supplementary Table 4). For Medicare DME use prevalence, there were 38 counties in 8 states with high annual average counts of 8+ hour outages and high DME use prevalence. States with the most high-high clusters were Arkansas (n = 12), Michigan (n = 10), and Louisiana (n = 9) (Fig. 7b).

Discussion

This study used hourly county-level data between 2018–2020 from 2447 US counties, covering 73.7% of the US population, to provide a sub-state national analysis of power outages affecting Americans. Over 70% of study counties experienced at least one 8+ hour outage during the study period. Medically relevant 8+ hour outages were prevalent in the South, Northeast, and Appalachia and some areas on the West Coast, while 1+ hour outages patterned similarly with a higher

Table 2 | County-day co-occurrence of severe weather or climate events and 8+ hour outages

Severe weather or climate event	County-days, *N* (%)	8+ h outage county-days, *N* (%)	Co-occurrence Ratio[a]
Total	1,799,319 (100.0)	22,793 (100.0)	—
None	1,265,213 (70.2)	8637 (37.9)	–
Isolated event[b]	492,489 (27.4)	11,310 (49.7)	3.4
Heavy precipitation	267,823 (14.9)	8507 (37.3)	4.7
Snowfall	25,523 (1.4)	1172 (5.1)	6.7
Anomalous heat	131,727 (7.3)	1090 (4.8)	1.2
Anomalous cold	57,924 (3.2)	344 (1.5)	0.9
Wildfire	5381 (0.3)	84 (0.4)	2.3
Lightning	3578 (0.2)	63 (0.3)	2.6
Tropical cyclone	533 (0.03)	50 (0.2)	13.7
Multiple event[c]	41,617 (2.3)	2846 (12.5)	10.0
Heavy precipitation-anomalous heat	17,415 (1.0)	917 (4.0)	7.7
Heavy precipitation-cyclone	2650 (0.2)	679 (3.0)	37.5
Heavy precipitation-lightning	8142 (0.5)	644 (2.8)	11.6
Snowfall-anomalous cold	7151 (0.1)	250 (1.1)	5.1
Heavy precipitation-anomalous cold	1779 (0.1)	134 (0.6)	11.0
Heavy precipitation-cyclone-anomalous heat	244 (0.0)	86 (0.4)	51.6
Heavy precipitation-anomalous heat-lightning	1197 (0.1)	78 (0.3)	9.5
Other	3039 (0.2)	58 (0.3)	2.8

Analysis included the 1653 continental counties with 3 years of reliable data. We defined co-occurrence if the weather/climate event occurred in the same county on the same day the 8+ hour outage began. We separated snowfall out from heavy precipitation.

[a]The co-occurrence ratio was the proportion of county-days with severe weather or climate event type *i* that co-occurred with an 8+ hour outage divided by the proportion of county-days without any weather or climate event that co-occurred with an 8+ hour outage. A co-occurrence ratio > 1 means that 8+ hour outages were more likely to occur on county-days with severe weather or climate event *i* compared to days with no event and a ratio <1 means that 8+ hour outages were less likely to occur on county-days with severe weather or climate event *i* compared to days with no event.

[b]An isolated event was a county-day where only a single severe weather or climate event occurred. We defined a county exposed to lightning if a lightning flash happened, tropical cyclone if the county was within 100 km of a cyclone path, wildfire if the county intersects a ≥ km^2 wildfire, heat if temperatures exceed 24 °C and that is above the 85th percentile, cold if temperatures are below 0 °C and below the 15th percentile, snowfall if snow accumulation > 1 inch, and heavy precipitation if precipitation > 85th percentile.

[c]Multiple events indicate county-days where multiple severe weather or climate events occurred. We include the top 7 most common multiple event types (among power outage days) plus all other multiple events grouped and provide the full breakdown in Supplemental Table 3. Power outage data was purchased from PowerOutage.us.

concentration in the South. Most outages co-occurred with severe weather or climate events, particularly heavy precipitation, anomalous heat, and tropical cyclones. We observed clusters of counties facing both frequent 8+ hour outages and high social and medical vulnerability measured by SVI and Medicare DME use prevalence. Louisiana and Arkansas had many counties with high 8+ hour outage-high SVI and high 8+ hour outage-high DME use prevalence.

Few studies have evaluated power outage exposure nationally. Prior studies have used US Department of Energy data and characterized "electric emergency incidents and disturbances" at the state-level. This included outages affecting 50,000+ customers or an unplanned loss of 300 MW. Most such outage events affected coastal states[4, 17]. The EIA reports yearly summaries of annual outage interruptions at the state level and found that 2020 had the longest average durations of outage events[2]. Our county-level study evaluating national power outage exposure at a sub-state geographic scale contributes to the growing literature on outages as an environmental health exposure.

We used commercial data from PowerOutage.us to generate relative metrics that accounted for differences in county customer counts and an absolute metric that based on total annual customer hours without power. Both metrics have utility but provide different information. Relative metrics describe disparities and are commonly used to evaluate health inequities, while absolute metrics measure the total burden of exposure in a population[20]. A strength of our study is that we provide both types of metrics for use in a range of contexts, from health studies to policy to emergency preparedness and management.

We observed that most county-days with an 8+ hour outage coincided with one or more severe weather or climate events. Prior national state-level studies reported that storms and severe weather led to over 50% of outages[1,17]. When evaluating blackouts, outages affecting 50,000+ customers or a loss of 300 MW, Hines et al. found that wind/rain-driven blackouts increased between 1984–2006 across all US regions[21]. As severe weather and climate events increase with climate change, this trend is likely to continue[22]. Our study identified specific event types most likely to co-occur with 8+ hour outages regionally and seasonally, with heavy precipitation (year-round) and snowfall (winter) predominating in the Northeast, Midwest, and South and snowfall (winter) and wildfire (fall) leading in the West. Utilities, customers, and policymakers could use this information for planning and resource allocation. We also found that nearly 40% of county-days with 8+ hour outages occurred without one of the included severe weather or climate event that our study considered. These cases were likely due to technical problems such as equipment failure or transmission delays[17]. Although weather and climate events seem to drive recent large-scale outages, issues with the aging electrical grid and increases in demand remain, both of which may be contributors to smaller-scale outages at the county level.

A robust literature has established that environmental exposures such as air pollution and drinking water violations disproportionately affect certain groups such as low-income, communities of color, and under-resourced groups[23,24]. However, the environmental justice literature has not equally engaged with power outages, power restoration, or their possible inequitable distribution. Prior energy justice studies have noted that natural disasters can accentuate disparities in power outages and restoration. For example, power restoration time reflects which communities are prioritized and by extension which communities are neglected. In Puerto Rico after Hurricane Maria, Sotolongo et al. observed that rural and Black communities experienced the longest restoration times[25], and Tormos-Aponte et al. found that social vulnerability and political marginalization were linked to longer wait times for the arrival of restoration crews[26]. During the

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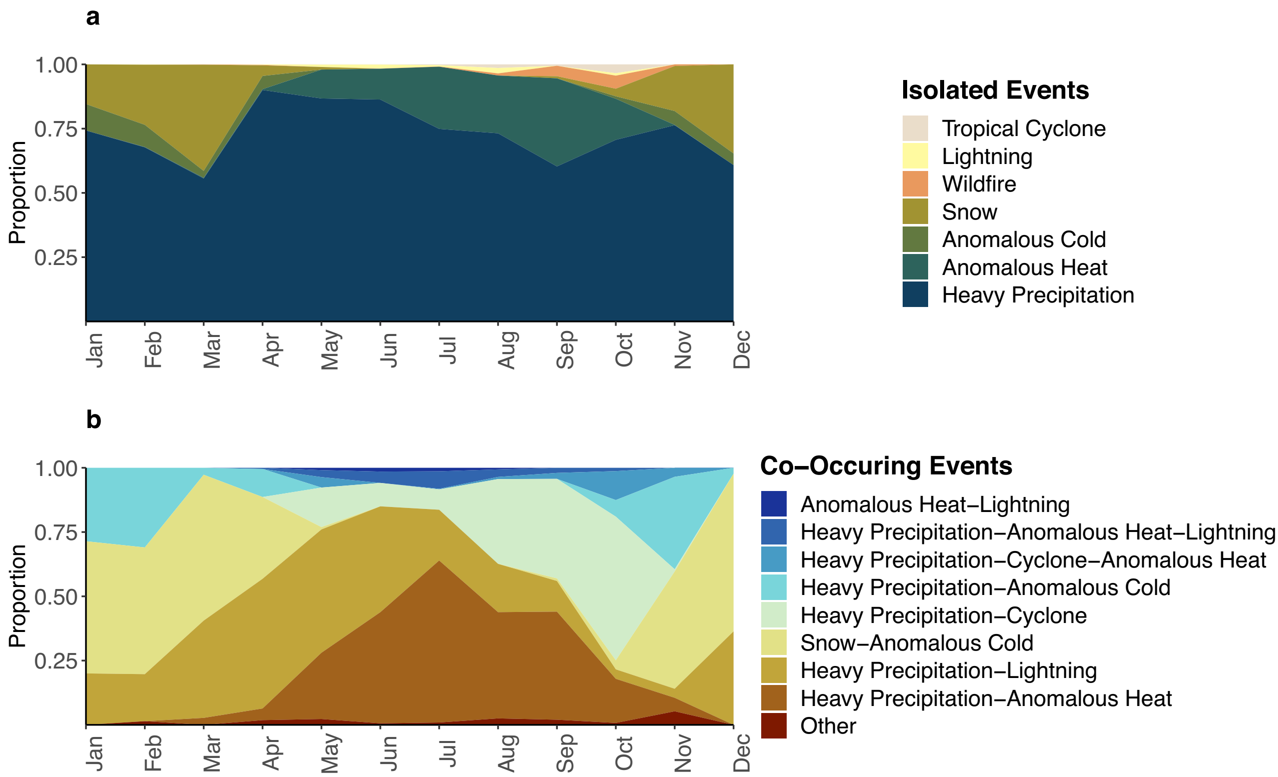

Fig. 5 | Monthly distribution of severe weather or climate events on days they co-occurred with 8 + hour outages among counties with 3 years of data. **a** Isolated severe weather and climate events ($n = 11{,}310$ county-days). **b** Multiple severe weather and climate event combinations ($n = 2{,}846$ county-days). An isolated event was a county-day where only a single severe weather or climate event occurred and multiple events were county-days where more than one event occurred. We defined a county exposed to lightning if a lightning flash happened, tropical cyclone if the county was within 100 km of a cyclone path, wildfire if the county intersects a ≥ km^2 wildfire, anomalous heat if temperatures exceed 24 °C and that is above the 85th percentile, anomalous cold if temperatures are below 0 °C and below the 15th percentile, snowfall if snow accumulation > 1 inch, and heavy precipitation if precipitation > 85th percentile. Power outage data was purchased from PowerOutage.us.

Table 3 | Distribution of 1 + hour and 8 + hour outages by quartile of SVI and prevalence of Medicare DME users per 1000

Metric	Quartile	Quartile values	Total count, N		Median (IQR) count, N		Max count, N	
			1+ hour	8+ hour	1+ hour	8+ hour	1+ hour	8+ hour
SVI	Q1	[0–0.28]	22,468	1185	40 (73)	1 (4)	195	25
	Q2	(0.28–0.53]	28,228	1405	57 (92)	2 (4)	217	22
	Q3	(0.53–0.77]	34,911	1678	68 (99)	2 (5)	330	26
	Q4	(0.77–1]	40,600	1888	80 (83)	3 (5)[a]	414	35
DME use, per 1000 Medicare enrollees	Q1	[0–45]	32,211	1616	62 (95)	2 (5)	234	26
	Q2	(45–58]	33,565	1704	63 (98)	2 (5)	394	35
	Q3	(58–74)	35,276	1765	68 (98)	2 (5)	414	25
	Q4	(74–478]	25,155	1071	42 (82)	1 (3)[a]	217	22

Analysis includes 2038 counties with 2+ years of reliable data.
[a]The Wilcoxon rank sum test *p*-value < 0.01 when comparing the median of 8+ hour power outages in (1) counties belonging to the highest SVI (social vulnerability index) quartile versus all other counties and (2) counties belonging to the highest DME (durable medical equipment) use quartile versus all other counties. Power outage data was purchased from PowerOutage.us.

Texas winter storm in 2021, Flores et al. observed that counties with a higher proportion of Hispanic/Latino residents faced more severe outages and that Black individuals reported more day-long outages via questionnaires[15]. In Florida after Hurricane Irma, higher percentages of Hispanic/Latino populations were associated with longer outages[14]. Our nationwide study found significantly higher median annual counts of 1+ and 8+ hour outages in high versus low SVI counties.

Studies have previously incorporated SVI into research about COVID-19, heat exposure, and hurricanes[27–29]. Flanagan et al. demonstrated SVI's utility in informing policy and intervention for those most affected by disaster events like Hurricane Katrina[28]. Our study identified counties that experienced high 8+ hour outage exposure and high SVI, largely concentrated in Louisiana, Mississippi, Arkansas, and Michigan. These counties versus all others had significantly higher proportions of residents living in poverty, of "racial/ethnic minority status," and living in mobile homes, making them potentially more vulnerable to disasters and likely in need of more resources to deal with such events. For example, the co-occurrence of natural disasters and outages has the potential to exacerbate adverse health outcomes among vulnerable communities. This can occur in the case of co-occurring anomalous temperatures and outages where disadvantaged groups may have worse baseline health, lower access to generators, higher occupational exposures, and more urban heat island effect exposure[4,30]. Further, New Yorkers living in public housing after

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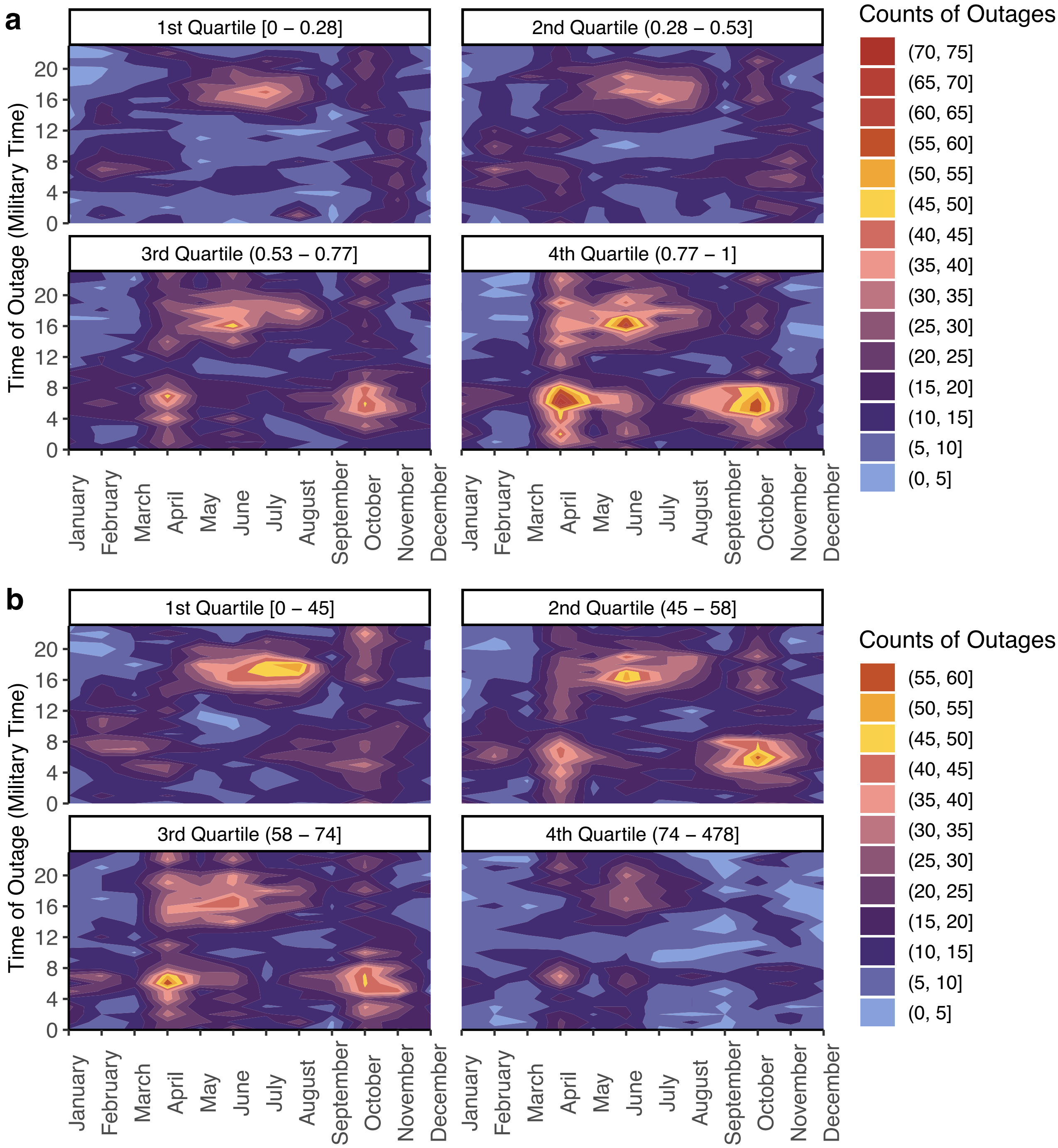

Fig. 6 | Contour plot of the count of 8+ hour outages according to start time of outage per month by county SVI and DME use quartile. Analysis includes 2038 counties with 2+ years of reliable data. **a** SVI quartile category. **b** Medicare DME use per 1000 Medicare enrollees quartile category. DME, durable medical equipment; SVI, social vulnerability index. Power outage data was purchased from PowerOutage.us.

Hurricane Sandy reported inability to purchase basic necessities because of widespread power outages in stores[7]. Outages shaped some participants' decision to remain in place despite evacuation warnings because people worried about personal safety and property theft[7]. Communities with high vulnerability face a particular set of concerns during outage events, which have implications for their health, so it is important to allocate resources to these communities to support them during outage events.

We found lower median annual 8+ hour outage exposure (1 versus 2) in the highest quartile of Medicare DME use compared to other quartiles. Despite this trend, it is crucial to consider that DME users are particularly susceptible to the health consequences of outages. Prior research showed that during outages, emergency rooms saw a higher proportion of DME users seeking care and hospitals needed to make external referrals for treatment[31,32]. Medicare DME users may be especially vulnerable because they are either older adults or individuals with disabilities. Longer outages especially endanger DME users due to possible limited battery life of equipment. For example, typical battery life ranges from 3–4 h for oxygen concentrators on the lowest settings[10]. Emergency planning guidance tends to place the onus on DME users to adequately prepare[33]. A study in Michigan found that only a quarter of older adults using essential electricity-dependent

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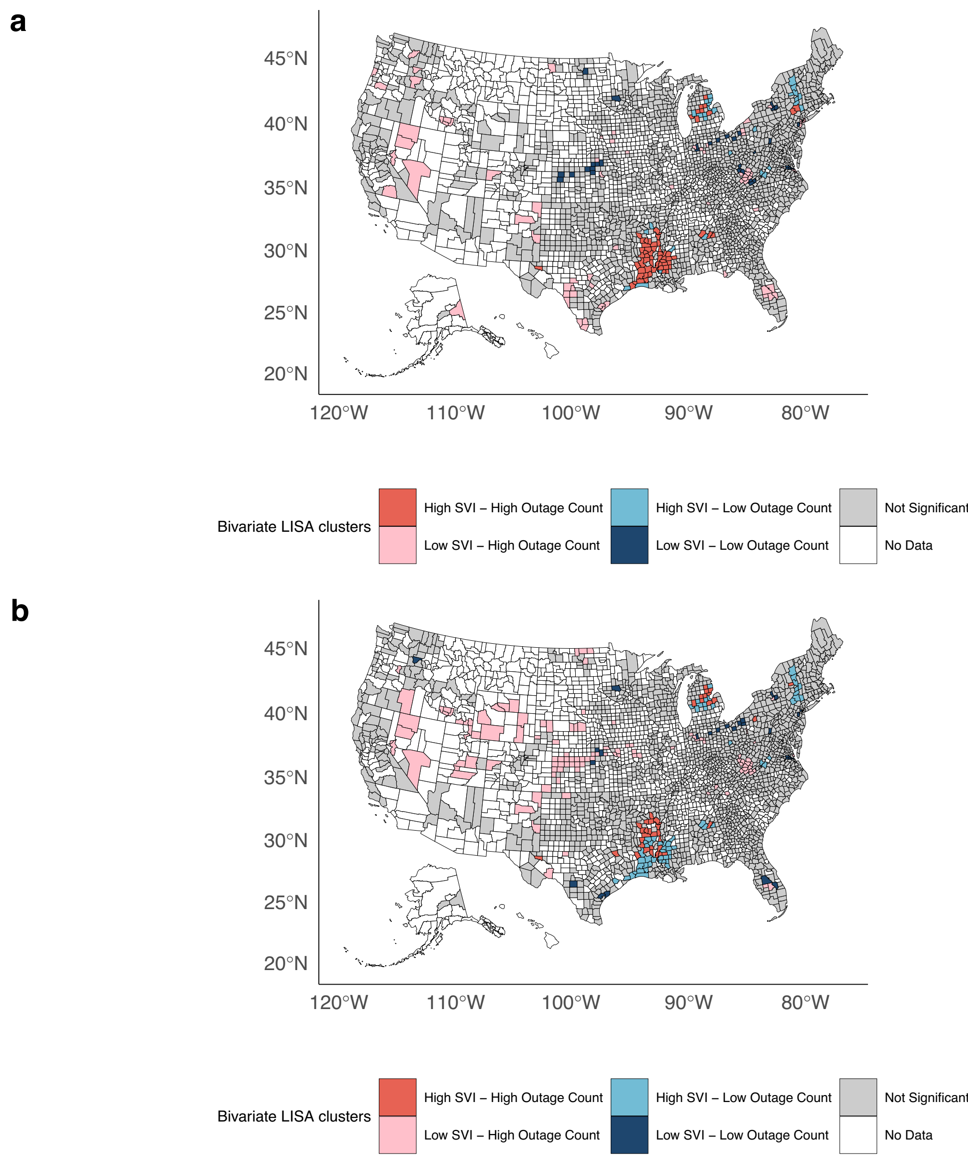

Fig. 7 | Bivariate Local Spatial Clustering Analysis (LISA) of 8+ hour outages and SVI and DME use quartiles. The analysis includes 2038 counties. **a** SVI and 8+ hour outage LISA. Counties in red indicate high SVI and high 8+ hour outage counts. **b** Medicare DME users and 8+ hour outage LISA. Counties in red indicate high prevalence of Medicare DME users and high 8+ hour outage counts. DME, durable medical equipment; SVI, social vulnerability index. Power outage data was purchased from PowerOutage.us and county basemaps were obtained from the usmap R package version 0.6.1.

medical equipment had an alternative power source[34]. In New York City, those with electricity-dependent household members had lower perceived preparedness (32%) than those without a DME user at home (47%)[35]. Data from California suggests that DME use prevalence and equipment rental days have increased over time, particularly among lower SES individuals (e.g., users of Medicaid)[36]. While we did not identify disproportionate exposure to 8+ hour outages among Medicare DME users, given the growing Medicare DME population, their high vulnerability to power outages, and our findings of geographic clustering of high 8+ hour outage exposure and high concentrations of DME users, emergency preparedness officials should prioritize this demographic in planning[37].

Our study identified clusters of counties that experienced high 8+ hour outage exposure and were either socially or medically vulnerable. Knowledge about vulnerability can inform equitable disaster preparedness and response, and several organizations have begun efforts to collect it. Though not designed explicitly for power outages, the California Office of Environmental Health and Hazard Assessment created the California Communities Environmental Health Screening Tool (CalEnvironScreen) to identify specific communities most affected by social stressors and various sources and forms of pollution[38]. The tool's purpose is to inform and guide regulations with environmental justice in mind. We used other vulnerability metrics, the CDC's SVI and the Department of Health and Human Services' emPOWER dataset, which are part of larger efforts to identify vulnerable communities with the goal of disaster preparation[37,39]. Prior studies leveraged medical records from hospital databases to map the location of DME users in Massachusetts and Centers for Medicaid and Medicare Service's list of individuals using oxygen concentrators or ventilators in New Orleans[40], proposing that there are publicly available data and sources for informing disaster preparedness as well[22,36]. While social vulnerability is increasingly integrated into disaster management for equitable emergency response, it lacks a major role in grid investment strategies. Initial work has integrated social vulnerability into micro-

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grid strategies, considering critical infrastructure locations under different outage scenarios[41]. Our results point to US counties where medically and socially vulnerability overlaps with high outage burden, information that could guide investments to reduce societal burdens from outages among the most vulnerable.

Our study had limitations, several related to the PowerOutage.us data. Not all US utilities appeared in the dataset, with small rural utilities most often absent. Due to a combination of the proportion of customer coverage and temporal missingness, we lacked reliable data on 563 counties, many of which were in the Midwest and Mountain West. However, our report still represents the most comprehensive, county-level summary of power outages to date, covering 2447 (78.9%) US counties. Our data spanned only 3 years, so we could not evaluate long-term trends. We assessed power outages at the county-level, which did not account for sub-county heterogeneity in exposure. For example, a county-level outage could occur due to either several minor sub-county outages or a single large outage at one sub-county location. Further, our county-aggregated data did not ensure the same customers were without power during 1+ and 8+ hour outages. For example, in one outage definition, we required 0.1% of total county customers to be without power for 8+ hours, but the composition of the 0.1% without power could change during the outage. Spatiotemporal granularity is necessary for accurate outage exposure measurement, so future studies, particularly those interested in linking outages to individual health outcomes, should consider exposure at a sub-county geographic resolution such as the household or building level, perhaps using improved power utility data, internet-connected devices, or satellite imagery[42–46]. Finally, we identified county-days where severe weather and climate events co-occurred with outages, but due to data limitations, we could not causally link severe weather and climate events to outages. Future studies that have access to cause-specific outage data would add to this growing literature.

There were also limitations with selected vulnerability metrics. As with the power outage data, county-level measures of vulnerability may have masked sub-county level trends. While we found a correlation between county-level outages and high SVI, it is possible this relationship would differ with finer-scale data. SVI is a summed rank of many vulnerability factors, which comprehensively describes county composition but may also include factors less relevant to power outage vulnerability. The metric is constructed to identify counties vulnerable to disasters but not designed specifically for power outages. Future studies may be interested in evaluating individual sociodemographic characteristics or other metrics at finer spatial resolutions. Regarding DME use prevalence, the emPOWER dataset undercounts total DME users as it only covers Medicare recipients. However, DME use increases with age and disability, and older adults and individuals with disabilities are eligible for Medicare, so we likely capture the majority of DME use[36].

Despite health consequences of outages, few studies have characterized their duration, geographic distribution, linkage to weather/climate events, or exposure disparities. Policymakers and public health and emergency preparedness officials need this data to equitably allocate resources to communities most burdened by and vulnerable to outage events. Our county-level power outage exposure data could also support future large-scale epidemiology studies[4], as we continue to learn more about the health effects of these primarily climate-driven events. The absolute and relative power outage metrics generated herein can inform future policy about electricity and healthcare infrastructure planning in the face of climate change.

Methods

Ethics statement

The Columbia University Institutional Review Board approved this research (Protocol #AAAT5765).

Power outages and utility customers data. From PowerOutage.us, we purchased 10 min resolution power outage information, which included the number of customers without power and the time of reporting from 2017–2020 for counties in all US states. Due to the low spatial coverage for 2017, we a priori excluded this year from analyses, so the study spanned 2018–2020. Customers refers to residential consumers such as families and non-residential consumers such as businesses. PowerOutage.us gathered outage data at subcounty levels (e.g., cities census-designated places) at regular 10 min intervals using utility providers' application programming interfaces (API).

We summarized the coverage of our power outage data by utility type using information from the US Energy Information Administration (EIA). The EIA tracks information about power usages for each US state and should theoretically record all operating utility providers. They have annual data on utility providers by state and service providers by county. Our power outage data captured cooperatives (59.4%), which typically serve rural communities, and most investor-owned utilities (84.4%), which tend to serve large populations.

To generate our outage dataset, we aggregated PowerOutage.us data to the county and hourly level. Of the 3,142 US counties, PowerOutage.us reported some data from 3010 (95.8%). We completed data quality and reliability checks and removed unreliable counties from certain analyses (Fig. 1). Broadly, we considered county APIs to be reliably reporting on outages if the APIs report ≥50% of the time, and we consider an API to reliably capture customers within a county if reported customers covered ≥50% of total county customers (Supplementary Methods 1.1 and 1.2). After applying these criteria, 2447 counties remained, covering 73.7% of the US population. Most analyses focused on the 2,038 counties with 2+ years of reliable data.

Power outage metrics: power outage event and outage experience definitions. We set out to define a binary power outage variable for each county-hour (1 = power out, 0 = power on). To do so, we had to define a threshold of customers without power over which we considered the county to be experiencing an outage. This relative power outage event definition accounted for county total customers and enabled us to compare outage counts across counties with varying population sizes.

We defined a power outage event as occurring whenever the percent of customers without power met or exceeded 0.1% of the county customers. Counts of customers without power came from PowerOutage.us data, and we estimated the total number of county customers based on households from the 2015–2019 American Community Survey and business establishments from the 2021 Census Bureau (Supplementary Methods 1.1). If county A had 100,000 customers, it met our power outage definition when 100 customers or more lost power; county B, with 1 million customers, would require at least 1000 customers to lose power to meet the definition. We used a 0.1% threshold corresponding to the 90th percentile of customers out per hour at the county-level during the study period. Prior studies have used the 90th percentile to determine outage events[35,42].

We computed the duration of outage events as the total time a county's percent of customers without power continuously reached or exceeded the 0.1% threshold (Supplementary Figure 1). We considered outages of 8+ hour and 1+ hour duration. Outages of 1+ hour duration would disrupt commerce and other activities, and 8+ hour outages would likely impact health by surpassing critical thresholds, including the maximum battery life for certain DME[10]. To summarize 8+ hour and 1+ hour outages, we took the average of the total number of events annually by county over the study period. This metric is similar to the System Average Interruption Frequency Index (SAIFI)[47].

We also calculated an absolute outage metric: annual average county-level customers without power. This metric identifies counties where the greatest absolute count of customers experienced loss of power. Because county-level customer density differs dramatically, we also computed a second absolute metric: annual average county-level number of minutes without power per customer. This metric is similar to the System Average Interruption Duration Index (SAIDI)[47]. It can be interpreted as minutes without power experienced by the average customer in a county.

Characterizing power outage exposure – especially when investigating disparities – necessitates both relative and absolute metrics. Our relative metric for outage events accounts for county customer density so that we may compare across counties. Our absolute metrics for outage experiences identify counties with the highest count of affected customers and the geographic distribution of total time without power.

Severe weather and climate event data and definitions. We identified the following severe weather and climate events at the daily-county-level: anomalous heat/cold, heavy precipitation, snowfall, lightning, tropical cyclones, and wildfires from a variety of data sources (Supplementary Methods 2). Data sources included the Parameter-elevation Regressions on Independent Slopes Model (temperature, precipitation), the National Gridded Snowfall Analysis (snowfall), the International Space Station Lightning Imaging Sensor (lightning), the International Best Track Archive for Climate Stewardship project (tropical cyclones), and the National Interagency Fire Center (wildfires). We defined a county as exposed to an anomalous heat event if the temperature exceeded 24 °C and was above the 85th percentile of weekly temperatures from 1981–2010, an anomalous cold event if temperatures dipped below 0 °C and was below the 15th percentile of weekly temperatures from 1981–2010, heavy precipitation if daily precipitation exceeded the 85th county percentile, snowfall if 2.54 cm (1″) or above of snow accumulation occurred, a lightning event if a lightning flash occurred within a county, a tropical cyclone if the county boundary was within 100 km of a tropical cyclone track center, and a wildfire if the county intersected with a $\geq 1\,km^2$ wildfire. We identified days with a single, isolated event and days with multiple events separately as more severe and co-occurring weather and climate events likely cause more damage to the electrical grid than single events. We did not include wind since wind and precipitation were previously observed to be highly correlated[48].

Vulnerability data and definitions. Those relying on electricity-dependent DME require constant access to electricity to maintain and manage their health. This vulnerability means power outages can rapidly worsen health conditions and increase mortality risk. To characterize this group, we generated county-level prevalence of DME use among Medicare enrollees using the December 2020 emPOWER dataset from the US Department of Health & Human Services. We calculated quartiles of DME use prevalence per 1000 Medicare beneficiaries in each county for analysis.

Another group vulnerable to the consequences of outages are disadvantaged communities requiring extra support before, during, and after disasters. To identify such counties, we used the US Centers for Disease Control and Agency for Toxic Substances and Disease Registry's Social Vulnerability Index (SVI). SVI has the stated purpose to identify specific areas that may need additional disaster-related support. Such information about a county's overall social vulnerability can shape decisions about future preparedness strategies or resource allocation, particularly in the event of longer outages that may affect health. SVI is based on 16 census variables from the 2016–2020 American Community Survey (below 150% poverty, unemployed, housing cost burden, no high school diploma, no health insurance, aged 65 and older, aged 17 and younger, civilian with a disability, single-parent households, English language proficiency, racial and ethnic minority status, multi-unit structures, mobile homes, crowding, no vehicle, and group quarters), which are used to create 4 vulnerability themes (socioeconomic status, household composition & disability, minority status & language, housing type & transportation). SVI ranges from 0 to 1 where county indices closer to 0 indicate lower vulnerability and indices closer to 1 indicate higher vulnerability. We generated quartiles of SVI for analysis.

Statistical analysis. Initial analyses were descriptive leveraging all reliable counties in our dataset ($N = 2447$), reporting the frequency of outages by county and total and average customer-hours without power. To better understand the relationship between severe weather and climate events and outages, we identified county-days where severe weather and climate events co-occurred with 8+ hour outage events. We summarized this information by month. Because this was a daily analysis and weather data was available for the continental US, we used only continental counties with 3 full years of data ($n = 1653$). Additionally, we calculated a co-occurrence ratio of severe weather and climate events with 8+ hour outages. The co-occurrence ratio was computed as the proportion of county-days with severe weather or climate event type i that co-occurred with an 8+ hour outage divided by the proportion of county-days without any weather or climate event that co-occurred with an 8+ hour outage. A co-occurrence ratio >1 means that 8+ hour outages were more likely to occur on county-days with severe weather or climate event i compared to days with no event and a ratio <1 means that 8+ hour outages were less likely to occur on county-days with severe weather or climate event i compared to days with no event.

We then conducted Wilcoxon Rank Sum tests to evaluate the relationship between county-level annual averages of 8+ hour outage counts for counties with 2+ years of reliable data ($n = 2038$) and DME use prevalence and SVI (vulnerability metrics). To identify spatial clusters of counties with both high outage exposure and high vulnerability, we ran separate bivariate local indicators of association (LISA) analyses, two-sided tests[49]. The bivariate analyses capture the relationship between the value of our vulnerability metric at one county location and the spatial lag of 8+ hour outages in surrounding counties. We used the rgeoda package version 0.0.9 to run 99,999 permutations, set the cluster significance at $\alpha = 0.05$, and applied the false discovery rate method to correct for multiple comparison testing[50]. Because the bivariate LISA conducts multiple hypothesis testing for each county, the probability of spurious statistical significance increases. Applying the false discovery rate is recommended and limits spurious positive findings[51,52]. We investigated whether the underlying components of SVI differed between high-outage-high SVI county clusters and all others and used two-sided t-tests to evaluate whether they differed statistically. All analyses were conducted in R version 4.1.0 (2021-05-18). Code used to run the bivariate LISA can be found on GitHub at https://github.com/viviando/National-Power-Outages[53]. We used the usmap R package version 0.6.1 to generate our nationwide maps for this study[54]. The package uses the U.S Census Bureau cartographic boundary files and the Albers equal-area conic projection.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The power outage data that support the findings of this study are available for purchase from PowerOutage.us at https://PowerOutage.us/products. Processed data containing annual average counts of outage events and customers without power are available at https://github.com/viviando/National-Power-Outages. The Centers for Disease Control and Prevention Social Vulnerability Index data is available publicly at https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html and the Health and Human Services Medicare durable medical equipment data is available for download at https://empowerprogram.hhs.gov/empowermap. A full description of data used to generate severe weather and climate events is available in Supplementary Information Methods 2.

Code availability

The code for analysis can be found at the GitHub repository[55]: https://doi.org/10.5281/zenodo.7668274.

References

1. Climate Central. *Surging Power Outages and Climate Change.*; 2022.
2. Lindstrom A, Hoff S. U.S. electricity customers experienced eight hours of power interruptions in 2020. U.S. Energy Information Administration. Published November 10, 2021. Accessed January 11, 2022. https://www.eia.gov/todayinenergy/detail.php?id=50316.
3. FEMA. Community Lifelines. Published July 27, 2020. Accessed January 11, 2022. https://www.fema.gov/emergency-managers/practitioners/lifelines.
4. Casey, J. A., Fukurai, M., Hernández, D., Balsari, S. & Kiang, M. V. Power Outages and Community Health: a Narrative Review. *Curr. Envir Health Rpt* **7**, 371–383 (2020).
5. Cheshire, W. P. Thermoregulatory disorders and illness related to heat and cold stress. *Autonomic Neurosci.* **196**, 91–104 (2016).
6. Hecht, A. A., Biehl, E., Buzogany, S. & Neff, R. A. Using a trauma-informed policy approach to create a resilient urban food system. *Pub. Health Nutr.* **21**, 1961–1970 (2018).
7. Hernández, D. et al. Public Housing on the Periphery: Vulnerable Residents and Depleted Resilience Reserves post-Hurricane Sandy. *J. Urban Health.* **95**, 703–715 (2018).
8. LaCommare, K.H., Eto, J.H. *Understanding the Cost of Power Interruptions to U.S. Electricity Consumers*. Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States); 2004. https://doi.org/10.2172/834270.
9. Alberts, E. et al. Durable Medical Equipment in Disasters. *February 2021*.:9.
10. Molinari, N. A. M., Chen, B., Krishna, N. & Morris, T. Who's at Risk When the Power Goes Out? The At-home Electricity-Dependent Population in the United States, 2012. *J. Public Health Manag. Pract.* **23**, 152–159 (2017).
11. Hernández, D. Understanding 'energy insecurity' and why it matters to health. *Soc. Sci. Med.* **167**, 1–10 (2016).
12. Lewis, J., Hernández, D. & Geronimus, A. T. Energy efficiency as energy justice: addressing racial inequities through investments in people and places. *Energy Efficiency*. **13**, 419–432 (2020).
13. Berberian, A. G., Gonzalez, D. J. X. & Cushing, L. J. Racial Disparities in Climate Change-Related Health Effects in the United States. *Curr. Environ. Health Rep.* **9**, 451–464 (2022).
14. Mitsova, D., Esnard, A. M., Sapat, A. & Lai, B. S. Socioeconomic vulnerability and electric power restoration timelines in Florida: the case of Hurricane Irma. *Nat. Hazards.* **94**, 689–709 (2018).
15. Flores, N. M. et al. The 2021 Texas Power Crisis: distribution, duration, and disparities. *J. Expo. Sci. Environ. Epidemiol. Pub. online August.* **13**, 1–11 (2022).
16. Coleman, N. et al. Energy Inequality in Climate Hazards: Empirical Evidence of Social and Spatial Disparities in Managed and Hazard-Induced Power Outages. Published online https://doi.org/10.48550/arXiv.2210.13781 (2022).
17. Mukherjee, S., Nateghi, R. & Hastak, M. A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. *Reliab. Eng. Syst. Saf.* **175**, 283–305 (2018).
18. Dumas, M., Kc, B., Cunliff, CI. *Extreme Weather and Climate Vulnerabilities of the Electric Grid: A Summary of Environmental Sensitivity Quantification Methods*.:ORNL/TM-2019/1252, 1558514. https://doi.org/10.2172/1558514 (2019).
19. U.S. Department of Energy. OE-417 Electric Emergency Incident and Disturbance Report. Published March 31, 2021. Accessed January 11, 2022. https://www.oe.netl.doe.gov/docs/OE417_Form_Instructions_05312021.pdf.
20. King, N. B., Harper, S. & Young, M. E. Use of relative and absolute effect measures in reporting health inequalities: structured review. *BMJ* **345**, e5774 (2012).
21. Hines, P., Apt, J. & Talukdar, S. Large blackouts in North America: Historical trends and policy implications. *Energy Policy*. **37**, 5249–5259 (2009).
22. Webb, E., Balaji, L., Nathanson, L.A., Balsari, S., Dresser, C. Who's at Risk in a Changing Climate? Mapping Electricity-Dependent Patient Populations in a Coastal City. R I Med. J. 104,14–19 (2013)
23. Hajat, A., Hsia, C. & O'Neill, M. S. Socioeconomic Disparities and Air Pollution Exposure: a Global Review. *Curr. Envir Health Rpt.* **2**, 440–450 (2015).
24. McDonald, Y. J. & Jones, N. E. Drinking Water Violations and Environmental Justice in the United States, 2011–2015. *Am. J. Publ. Health.* **108**, 1401–1407 (2018).
25. Sotolongo, M., Kuhl, L. & Baker, S. H. Using environmental justice to inform disaster recovery: Vulnerability and electricity restoration in Puerto Rico. *Environ. Sci. Policy*. **122**, 59–71 (2021).
26. Tormos-Aponte F, García-López G, Painter MA. Energy inequality and clientelism in the wake of disasters: From colorblind to affirmative power restoration. *Energy Policy*. 158 (C). Accessed September 30, 2022. https://ideas.repec.org/a/eee/enepol/v158y2021ics0301421521004201.html (2021).
27. Karaye, I. M. & Horney, J. A. The Impact of Social Vulnerability on COVID-19 in the U.S.: An Analysis of Spatially Varying Relationships. *Am. J. Prev. Med.* **59**, 317–325 (2020).
28. Lehnert, E. A., Wilt, G., Flanagan, B. & Hallisey, E. Spatial exploration of the CDC's Social Vulnerability Index and heat-related health outcomes in Georgia. *Int. J. Disaster Risk Reduct.* **46**, 101517 (2020).
29. Flanagan, B.E., Gregory, E.W., Hallisey, E.J., Heitgerd, J.L., Lewis, B. A Social Vulnerability Index for Disaster Management. *J. Homeland Security Emergency Management*. 8. https://doi.org/10.2202/1547-7355.1792 (2011).
30. Gronlund, C. J. Racial and Socioeconomic Disparities in Heat-Related Health Effects and Their Mechanisms: a Review. *Curr. Epidemiol. Rep.* **1**, 165–173 (2014).
31. Anderson, G. B. & Bell, M. L. Lights Out: Impact of the August 2003 Power Outage on Mortality in New York, NY. *Epidemiology* **23**, 189–193 (2012).
32. Abir, M., Jan, S., Jubelt, L., Merchant, R. M. & Lurie, N. The Impact of a Large-Scale Power Outage on Hemodialysis Center Operations. *Prehosp. Disaster Med.* **28**, 543–546 (2013).
33. Pacific ADA Center. Emergency Power Planning for People Who Use Electricity and Battery Dependent Assistive Technology and Medical Devices. Published 2018. Accessed January 11, 2022. https://www.adapacific.org/assets/documents/emergency-power-planning-factsheet_revised-5.2018.pdf.
34. Bell, SA. After the storm: The health impacts of weather and climate-related disasters on older adults in the U.S. Published February 2020. Accessed January 11, 2022. https://ihpi.umich.edu/news/ihpi-briefs/disasters.
35. Dominianni, C. et al. Power Outage Preparedness and Concern among Vulnerable New York City Residents. *J. Urban Health.* **95**, 716–726 (2018).
36. Casey, J. A. et al. Trends from 2008 to 2018 in Electricity-dependent Durable Medical Equipment Rentals and Sociodemographic Disparities. *Epidemiology* **32**, 327–335 (2021).
37. U.S. Department of Health & Human Services. HHS emPOWER Program Platform. Accessed January 11, 2022. https://empowerprogram.hhs.gov/about-empowermap.html.
38. August L. CalEnviroScreen 3.0. OEHHA. Published June 25, 2018. Accessed January 11, 2022. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30.

39. Agency for Toxic Substances & Disease Registry. CDC/ATSDR's Social Vulnerability Index (SVI). Published April 28, 2021. Accessed January 11, 2022. https://www.atsdr.cdc.gov/placeandhealth/svi/index.html.
40. DeSalvo, K. et al. Using Medicare Data to Identify Individuals Who Are Electricity Dependent to Improve Disaster Preparedness and Response. *Am. J. Public Health*. **104**, 1160–1164 (2014).
41. Jeffers, R.F. et al. *Analysis of Microgrid Locations Benefitting Community Resilience for Puerto Rico*. Sandia National Lab. (SNL-NM), Albuquerque, NM (United States); 2018. https://doi.org/10.2172/1530167.
42. Zhang, W. et al. Power Outage. *Chest* **158**, 2346–2357 (2020).
43. Meier, A., Ueno, T. & Pritoni, M. Using data from connected thermostats to track large power outages in the United States. *Appl. Energy*. **256**, 113940 (2019).
44. Min, B., O'Keeffe, Z., Zhang, F. *Whose Power Gets Cut? Using High-Frequency Satellite Images to Measure Power Supply Irregularity*. World Bank, Washington, DC; 2017. https://doi.org/10.1596/1813-9450-8131.
45. Levin, N. et al. Remote sensing of night lights: A review and an outlook for the future. *Remote Sens. Environ*. **237**, 111443 (2020).
46. Shah, Z. et al. The electricity scene from above: Exploring power grid inconsistencies using satellite data in Accra, Ghana. *Appl. Energy*. **319**, 119237 (2022).
47. U.S. Energy Information Administration, Form EIA-861, Annual Electric Power Industry Report. Reliability Metrics of U.S. Distribution System. Accessed November 21, 2022. https://www.eia.gov/electricity/annual/html/epa_11_01.html.
48. Pathan, M.S., Wu, J., Lee, Y.H., Yan, J., Dev, S. Analyzing the Impact of Meteorological Parameters on Rainfall Prediction. Published online October 21, 2021. Accessed December 1, 2022. http://arxiv.org/abs/2110.11059.
49. Anselin, L. Local Indicators of Spatial Association-LISA. *Geographical Anal*. **27**, 93–115 (2010).
50. Li, X., Anselin, L. rgeoda: R Library for Spatial Data Analysis. Published online 2022. https://github.com/geodacenter/rgeoda/, https://geodacenter.github.io/rgeoda/.
51. Benjamini, Y. & Hochberg, Y. Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *J. R. Stat. Soc.: Ser. B*. **57**, 289–300 (1995).
52. Glickman, M. E., Rao, S. R. & Schultz, M. R. False discovery rate control is a recommended alternative to Bonferroni-type adjustments in health studies. *J. Clin. Epidemiol*. **67**, 850–857 (2014).
53. Pereira, R. Map of bivariate spatial correlation in R (bivariate LISA). GitHub Gist. Published July 29, 2017. Accessed January 11, 2022. https://gist.github.com/rafapereirabr/5348193abf779625f5e8c5090776a228.
54. Di Lorenzo, P. usmap. Published online November 13, 2022. Accessed March 28, 2023. https://github.com/cran/usmap.
55. Do, V. et al. Power outages often co-occur with climate events and in socially vulnerable counties in the USA. *National-Power-Outages* https://doi.org/10.5281/zenodo.7668274.

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Author contributions

V.D. made contributions to the conception/design of the work, the analysis and interpretation of data, and draft of the work. She approves the submitted version and agrees both to be personally accountable and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately resolved. H.B. made contributions to the interpretation of data and draft of the work. She approves the submitted version and agrees both to be personally accountable and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately resolved. N.M.F. made contributions to the interpretation of data and draft of the work. She approves the submitted version and agrees both to be personally accountable and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately resolved. A.J.N. made contributions to the interpretation of data and draft of the work. He approves the submitted version and agrees both to be personally accountable and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately resolved. M.V.K. made contributions to the interpretation of data and draft of the work. He approves the submitted version and agrees both to be personally accountable and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately resolved. J.S. made contributions to the interpretation of data and draft of the work. He approves the submitted version and agrees both to be personally accountable and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately resolved. J.A.C. made contributions to the conception/design of the work, the analysis and interpretation of data, and draft of the work. She approves the submitted version and agrees both to be personally accountable and to ensure that questions related to the accuracy or integrity of any part of the work are appropriately resolved.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Joan A. Casey.

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MSA MEDICAL SERVICES ADMINISTRATION

Bulletin

Michigan Department of Health and Human Services

Bulletin Number: MSA 17-06

Distribution: Pharmacy Providers

Issued: March 1, 2017

Subject: Early Refills for Prescription Drugs

Effective: April 1, 2017

Programs Affected: Medicaid, Healthy Michigan Plan, Children's Special Health Care Services (CSHCS), Maternity Outpatient Medical Services (MOMS)

The purpose of this bulletin is to announce the Michigan Department of Health and Human Services (MDHHS) policy on early refills for prescription drugs in certain situations.

Early refill overrides may be granted once per drug per 12 months for any of the following circumstances:

- To replace medication that has been lost, stolen or destroyed
- For the purposes of vacation or travel

The early refill will not exceed a 34-day supply. The pharmacy may contact the MDHHS Pharmacy Benefits Manager Technical Call Center at 877-624-5204 to request an override for an early refill.

MDHHS or its designee may limit the number of instances early refill overrides are approved in cases of suspected fraud or abuse, and may request additional documentation before an override is authorized.

Refer to the D.0 Claims Processing Manual at Michigan.fhsc.com for instructions on submitting an early refill request.

Manual Maintenance

Retain this bulletin until the information is incorporated into the Michigan Medicaid Provider Manual.

Questions

Any questions regarding this bulletin should be directed to Provider Inquiry, Department of Health and Human Services, P.O. Box 30731, Lansing, Michigan 48909-8231, or e-mail at ProviderSupport@michigan.gov. When you submit an e-mail be sure to include your name, affiliation, and phone number so you may be contacted if necessary. Providers may phone toll-free 1-800-292-2550.

Approved

Chris Priest, Director
Medical Services Administration

Longer Term Assistance Programs

If you need longer term help paying your bills, the programs below may be the answer.

The CARE Program

See If You're Eligible (/Residential/Account-And-Billing/Billing-And-Payment/Payment-Assistance/Care-Program)

An affordable payment plan for managing your bill.

If you need help with your energy bill, the Consumers Affordable Resource for Energy (CARE) Program may right for you.
As a CARE member, you will get these benefits:

- A part of your monthly bill will be paid by the program.
- Any past due balance you might have will be forgiven over time as a reward for on time payments.

Click the green button to learn about eligibility and the enrollment process.

The Budget Plan

About The Budget Plan (/Residential/Account-And-Billing/Billing-And-Payment/Budget-Plan)

Get a consistent payment year-round.

If your past due balance is less than $75, consider our Budget Plan. The Budget Plan helps you avoid high bills during times of higher energy use.

The Budget Plan may be a good option for you if:

- You want a bill that you can predict each month.
- You have a past due balance of no more than $75.
- You haven't defaulted on your payment more than two times in the last year

To enroll, call 800-477-5050 (tel:8004775050).

Shut-Off Protection Plan (SPP)

A year-round protection plan against shut-off for all seniors (65 and older) and qualifying customers.

How it works:

- An initial down payment is required.
- This plan spreads out your yearly energy costs into equal monthly payments. This is based on your expected monthly energy use, plus monthly portions of your past due balance.

To enroll, call 800-477-5050 (tel:8004775050)**.**

Winter Protection Plan (WPP)

A protection plan for wintertime against shut-off and high payments for seniors (65 or older) and qualifying customers.

How it works:

- An initial down payment is required.
- From November through March, you pay 7% of your estimated annual bill along with a portion of any past due amount.
- In April, we will finalize your bill for the previous months. The amount due is equal to 9% of your estimated yearly energy use, plus 1/6 of the account balance.

Enrollment starts November 1 and runs through March 31.
To enroll, call 800-477-5050 (tel:8004775050)**.**

Explore Energy Efficiency Solutions

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ABOUT US

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[Surplus Sales (/Work-With-Us/Investment-Recovery)]

[Lab Services (/Work-With-Us/Lab-Services)]

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M-F: 7 a.m. - 6 p.m.

BUSINESS

M-F: 8 a.m. - 4:30 p.m.

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*Appliance Service Plan Is Not Regulated By The Michigan Public Service Commission. Appliance Service Plan Does Not Affect Your Regulated Utility Service.

MDHHS

State Emergency Relief (SER) Program

The State Emergency Relief (SER) Program provides immediate help to individuals and families facing conditions of extreme hardship or for emergencies that threaten health and safety. Through a combination of direct financial assistance and contracts with a network of non-profit organizations such as the Salvation Army and local Community Action Organizations, SER helps low-income households meet emergency needs such as:

- Heat & Utilities
- Home Repairs
- Relocation Assistance
- Home Ownership Services
- Burial

The SER program is primarily designed to maintain low-income households who are normally able to meet their needs but occasionally need help when unexpected emergency situations arise. The SER program is not an appropriate solution to ongoing or chronic financial difficulties.

Local Department of Human Services specialists only should make eligibility determinations for this program due to many variables. Ask for details when turning in a completed application.

MDHHS

State Emergency Relief (SER) Program

Additional State Emergency Relief (SER) Now Available

Read More

Payment Plans & Assistance

Finding it Hard to Pay Your Bill?

These payment assistance programs offer the help you need.

Log In

SHOP

OUTAGE

PAY BILL

(/)

Search Con

Residential **Business**

Find Helpful Payment Assistance Programs

Many in our community are struggling. We might be able to help. Answer a few simple questions and we'll suggest financial assistance programs that could be a good fit for you.

1 Let's Get Started

I only need help this one time.

Select

I may need help in the future, and am looking at my options for help.

Select

I need help with budgeting and would like to even out my payments or pay off my balance over time.

Select

Discover Energy Saving Programs And Tips

Behind on Your Bill? Explore These Payment Plans

The CARE Program

See If You're Eligible (/Residential/Account-And-Billing/Billing-And-Payment/Payment-Assistance/Care-Program)

An Affordable Payment Plan

If you need help with your energy bill, the Consumers Affordable Resource for Energy (CARE) Program may be right for you.

As a CARE member, you will get these benefits:

- Your monthly payments will be at a fixed, affordable rate.
- Any past due balance you might have will be forgiven over time as a reward for on time payments.

Learn about eligibility and the enrollment process. (https://www.consumersenergy.com/residential/programs-and-services/payment-assistance/care-program)

Please note that this program is only available if you have received a State Emergency Relief (SER) energy payment. See information about the State Emergency Relief Program on our One Time Assistance Programs page. (/residential/account-and-billing/billing-and-payment/payment-assistance/one-time-assistance)

Payment Arrangements

Get Started (/Customer/Account/Flex-Payment)

Pay Off Your Balance on Your Own Schedule

Finding it hard to make your payments on time? With a payment arrangement, you can pay off your balance little by little on a schedule that best fits you.

How it works:
First, you put an initial down payment towards your balance. Then, the rest of your balance is split between even payments over time. Payments can be made weekly, bi-weekly and monthly.

Eligibility, payment amounts and length of the payment arrangement plan depend on these factors:

- Length of service
- How many times shut off notices were received in a 12-month period
- Number of times service was turned off due to missing a payment
- Number of payment arrangement defaults in a 12-month period
- Number of payments returned for non-sufficient funds

The Budget Plan

About The Budget Plan (/Residential/Account-And-Billing/Billing-And-Payment/Budget-Plan)

Get a Consistent Payment Year-Round

If your past due balance is less than $75, consider our Budget Plan. The Budget Plan helps you avoid high bills during times of higher energy use.

The Budget Plan may be a good option for you if:

- You want a bill that you can predict each month
- You have a past due balance of no more than $75
- You haven't defaulted on your payment more than two times in the last year

PROGRAMS FOR ACTIVE DUTY MILITARY

If you are currently serving in the military, we recommend:

- **Shut-off Protection – Active Duty in the Military:** If you (or your spouse) are the main contact for your account and are called to full-time active military service, you may request protection from disconnection. This protection may last for up to 90 days. You may also request an extension by reapplying.
    - If you (or your spouse) are the customer of record and you're called to full-time active military service, you may apply for shut-off protection for up to 90 days. After 90 days, you may request to extend this extension by reapplying.
        - You must verify your active duty status.
        - At the end of active duty, you must let us know of your change in status.
        - You still will need to pay for the energy you used while you were in this program.
        - We will set up a payment plan for all past due amounts to be paid within one year.
        - To join, call us at 800-477-5050 (tel:8004775050).

More resources:
Michigan Veterans Trust Fund (https://www.michigan.gov/mvaa/quality-of-life/emergency-assistance/panel-content): Provides eligible wartime veterans and their families in Michigan with temporary energy assistance for emergencies or hardships.

PROGRAMS FOR SENIORS

As a senior citizen, you qualify for the following assistance:

- Winter Protection Plan: Pay part of your charges through winter months while being protected from a service disconnect during the season.
- Electric Senior Citizen Bill Credits: This income assistance credit is designed to help seniors on fixed incomes.
    - The Electric Senior Citizen provision helps you with your electric bill with an added credit of $4.00 to your bill each month. Qualifying customers must meet age requirements and be the head of the household.
    - If you are eligible to receive the Electric Income Assistance credit, you will no longer receive the Electric Senior Citizen credit.

More resources:

- Area Agency on Aging Association of Michigan (https://www.michigan.gov/mdhhs/adult-child-serv/adults-and-seniors/behavioral-and-physical-health-and-aging-services/aging-services): Local agencies that are located within communities around the state that provide a variety of senior services and activities.
- Elder Law of Michigan (https://www.michigan.gov/reinventretirement/resources/emergency/emergency-financial-resources-and-services-directory): Older adults and people with disabilities can get help paying for the cost of basic needs like food, medicine, healthcare, utilities, housing and taxes.

DO YOU HAVE A LIFE-THREATENING MEDICAL CONDITION OR NEED LIFE SUPPORT?

- Critical Care Program (/outages-and-safety/life-support): If you are on life support or have a life-threatening medical condition, you can be protected from a shut-off. Please complete the Medical Certification Form (/-/media/CE/Documents/form-1339-certificate-of-medical-emergency.pdf) to get started. Please note, if you have life support shut-off protection, you need to re-enroll every year.
    - PLEASE NOTE: Backup generators and transportation services are not part of this program. Being in this program does not mean your electric power will be restored sooner than others.

- Medical Emergency Protection (/outages-and-safety/life-support): If you have a qualifying, documented medical emergency, you can be protected from an energy service shut-off for up to 21 days.
    - Send us written proof from a doctor or a notice from a public health official that service shutoff will make an existing medical condition worse with this form. Once you've filled out the form, call us at 800-477-5050 (tel:8004775050).
    - For the complete details, see Consumer Standards and Billing Practices For Electric and Gas Residential Service (/-/media/CE/Documents/mpsc-billing-rules.pdf).

- **Third Party Notification**: We'll send a copy of any shut-off notice you receive to a third party, with your written authorization. This third party may be a consenting friend, relative or agency.
    - Your third-party contact is not responsible for paying your bill but may act as a liaison between you and Consumers Energy. To set up Third Party Notifications, call us at 800-477-5050 (tel:8004775050).

DO I QUALIFY FOR ASSISTANCE?

We partner with several agencies across the state who provide energy assistance. Check your income below to see if you're eligible for an energy assistance program.

Federal Poverty Guidelines (FPL):

Number of Household Members	**110% FPL HHC**	**150% FPL SER, CARE, WPP, RIA**	**200% FPL WAP, SPP, Helping Neighbors**
	(Annual)	**(Monthly)**	**(Monthly)**
1	$16,566	$1,883	$2,510
2	$22,484	$2,555	$3,407
3	$28,402	$3,228	$4,303
4	$34,320	$3,900	$5,200
5	$40,238	$4,573	$6,097
6	$46,156	$5,245	$6,993
For each additional person add	$5,918	$673	$897

* Some non-profit agencies might provide assistance to households with a higher income level. Please contact the agency for details.

Residential Income Assistance Credit –

If you are below 150% of the federal level, you may qualify for additional assistance credits toward your monthly gas and electric bill.

To determine eligibility, complete the Residential Income Assistance Credit Self Attestation form (/-/media/CE/Documents/Customer Forms/1933.pdf) and return to energyassistance@cmsenergy.com (mailto:energyassistance@cmsenergy.com) or fax to 517-325-8227.

THIRD PARTY NOTIFICATION

- We'll send a copy of any shut-off notice you receive to a third party, with your written authorization. This may include a consenting friend, relative or agency.
- Your third-party contact is not responsible for paying your bill but may act as a liaison between you and Consumers Energy. To set up Third Party Notifications online, go to https://www.consumersenergy.com/privacy/third-party-notification (/privacy/third-party-notification). You can also call us at 800-477-5050 (tel:8004775050).

Michigan Energy Assistance Program

We work with agencies to provide energy assistance programs that include help paying energy bills, household budgeting and energy efficiency.

Call 2-1-1 (tel:211) or contact one of the participating agencies below:

The United Way of South Central Michigan
uwenergyhelp.org
(https://unitedwayofsouthcentralmichigan.org/site/copy/uwenergyhelp/)
517-741-0202 (tel:5177410202)

The Heat and Warmth Fund (THAW)
thawfund.org/assistance/
(https://thawfund.org/assistance/)
800-866-8429 (tel:8008668429)

St. Vincent de Paul Society
helpwithmybill.com
(http://helpwithmybill.com/)
877-788-4623 (tel:8777884623)

True North Community Services
tnempower.org (https://tnempower.org/)
231-355-5880 (tel:2313555880)

Barry County United Way
bcunitedway.org (https://www.bcunitedway.org/)
269-945-4010 (tel:2699454010)

The United Way of Southeastern Michigan
unitedwaysem.org/utility-assistance/ (https://unitedwaysem.org/get-help/community-resources/utility-assistance/)
844-211-4994 (tel:8442114994)

The Salvation Army
salarmy.us/energy (https://sawmni.org/wmni/energy-assistance)
616-929-1645 (tel:6169291645)

Bureau of Community Action and Economic Opportunity
micommunityaction.org (https://micommunityaction.org/agency-locator-map/)
Or contact your local Community Action Agency

Energy Saving Tips

Explore Energy Efficiency Solutions

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[Energy Supply Plan (/About-Us/Clean-Energy-Plan)](/About-Us/Clean-Energy-Plan)

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Economic Development (/Work-With-Us/Economic-Development)

Pole Attachments (/Work-With-Us/Pole-Attachments)

Become A Supplier (/Work-With-Us/Become-A-Supplier)

Become A Trade Ally (/Work-With-Us/Become-A-Trade-Ally)

Surplus Sales (/Work-With-Us/Investment-Recovery)

Lab Services (/Work-With-Us/Lab-Services)

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(Https://Www.instagram.com/Consumersenergy

(Http://Www.force4michigan.com/)

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M-F: 7 a.m. - 6 p.m.

BUSINESS

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*Appliance Service Plan Is Not Regulated By The Michigan Public Service Commission. Appliance Service Plan Does Not Affect Your Regulated Utility Service.

Question:

1. Refer to Direct Testimony of Jessica R. Byrom at pages 40–42, where the witness details the Company's "Analytics and Outreach efforts" and projected "$2.88 million in O&M expenses for the test year ending April 30, 2027."1

a. Witness Byrom states that "Analytics and Outreach efforts allow the Company to more efficiently utilize its resources, target communication to precise customer segments, and select, develop, and implement programs that are most likely to provide customer value."2

i. Please describe in detail how the Company has created each "precise customer segment."

ii. Please provide a list of and describe in detail each "customer segment" the Company has identified.

iii. Please describe in detail each communication method used for each "precise customer segment."

iv. How do concerns about the affordability of the Company's rates or offerings affect the Company's decisions regarding the selection, development, and implementation of programs "programs that are most likely to provide customer value"?

v. Does the Company use any customer input to "select, develop, and implement programs that are most likely to provide customer value"? If yes, please describe in detail how customer input is gathered and what customer input the Company uses for these programs.

b. Witness Byrom states that "the primary driver of [the $763,000 increase in O&M expenses from 2024] is an increase in labor-related costs in the test year."3 Please describe in detail why there has been "an increase in labor-related costs."

c. Witness Byrom refers to Exhibit A-53 at page 42. Exhibit A-53 at page 1 provides the actual and projected O&M expenses for "Customer Interactions."

i. Please list and describe in detail all Company personnel and activities that all considered as "Labor" under "Customer Interactions."

ii. Please list and describe in detail all "Materials" under "Customer Interactions."

iii. Please describe in detail what "Contractor" under "Customer Interactions" includes.

iv. Please describe in detail what "Non-Labor Overhead" under "Customer Interactions" includes.

v. Please describe in detail what "Non-Labor Other" under "Customer Interactions" includes.

vi. Does Exhibit A-53 provide all the projected investments for customer engagement and outreach? If no, please identify where in the record the costs for each investment aimed at customer engagement are.

vii. Are any advertising costs included in the actual or projected O&M expenses under "Customer Interactions"? If yes, please describe in detail the projected expenses for advertising.

Response:

a. i. These payment segments were created by doing an analysis of customer payment behaviors to determine customer suitability for these customer segments. See response to U21870-UCC-CE-0369. The Company also has created customer segments for Residential, Low Income, and Commercial & Industrial customers. Additionally, while not officially classified as segments, our analytics team creates customer email lists to allow us to target customers for programs that meet their needs and that they would likely be interested in based on geographical location, service type, past program participation, etc.

ii. Please see response to question U-21870-UCC-369 for segments and standard definitions. Residential customers are defined as customers that receive residential service and fall under Residential rates. Low Income customers are defined as customers that have received assistance in the past and/or have self-identified through the Low Income enrollment flow as meeting income eligibility. Commercial & Industrial customers are defined as customers that receive commercial and industrial service and fall under Commercial and Industrial rates.

iii. The Company does not communicate to customers based on these segments. The Company primarily uses email and social media advertising to target all customers based on geographical location, fuel type, past program participation, etc.

iv. The Company considered affordability and the impact on rates when designing new programs in accordance with cost effectiveness requirements for each product.

v. Yes, the Company leverages customer research and customer experience surveys on our transactional channels and program enrollment/participation to understand customer pain points and positive sentiment related to programs to help inform program design, changes, and potential new offerings.

b. Please see U21780-UCC-CE-0365_Att 1 for a detailed breakdown of increased labor costs in the test year.

c. i. Please see U21780-UCC-CE-0365_Att 1 for requested list/details.

ii. Please see U21780-UCC-CE-0365_Att 1 for requested list/details.

iii. Please see U21780-UCC-CE-0365_Att 1 for requested list/details.

iv. Please see U21780-UCC-CE-0365_Att 1 for requested list/details.

v. Please see U21780-UCC-CE-0365_Att 1 for requested list/details.

vi. Yes.

vii. None.

Witness: Jessica R. Byrom
Date: September 16, 2025

Question:

12. Refer to the Company's response to UCC's First Discovery Request, U21870-UCC-CE-0237, from pages 2–9 in which Witness Jessica R. Byrom discusses the Company's plans for the LMI Customer Support Enhancement project.

a. On page 2, Witness Byrom states, "[T]he Company is focused on strengthening its data analytics capabilities, improving digital workflows, and expanding outreach mechanisms."10 Will the Company improve "digital workflows" on the customer-facing end, for Company employees, or both?

b. On page 3, Witness Byrom discusses the planned "Notification Preference Center" feature. Will there be a default method of delivery in a customer's Notification Preference Center? If yes, what will be the default method of delivery in a customer's Notification Preference Center?

c. On page 3, Witness Byrom states, "Communications will be timed around highbill seasons . . . and major life events . . . to maximize relevance."11

i. Please list any and all life events the Company considers to be "major life events."

ii. Please describe in detail how the Company has knowledge of and determines when a customer is experiencing a "major life event."

d. On pages 4–5, Witness Byrom discusses planned "Community Partnerships" with "a diverse set of community organizations."12

i. Please list the name of each community organization with which the Company currently plans to collaborate. If the Company has not made plans with specific organizations, please provide a list of similar organizations that the Company has partnered with in the past.

ii. Does the Company have any plans to partner with environmental coalitions or collectives within the community?

e. On page 4, Witness Byrom explains that "Health and Human Service Agencies" involves "[c]oordinating with Medicaid and SNAP outreach efforts to identify and support eligible customers." Please see the Citizens Research Council of Michigan's June 25, 2025 report, "Federal Medicaid Cuts Will Have Big Consequences in Michigan," which estimates that more than 200,000 Michiganders could lose Medicaid coverage.13

i. Has the Company conducted any analysis about how Medicaid cuts could affect the Company's ability to "identify and support eligible customers"? If yes, please describe in detail and provide any documentation resulting from those analyses. If no, does the Company plan to conduct any analysis about how these recent Medicaid cuts could affect the Company's ability to "identify and support eligible customers"?

f. On page 4, Witness Byrom states, "The comprehensive support system consolidates access to a wide range of existing offerings into a single, streamlined enrollment experience for LMI customers."14

i. Please provide a detailed timeline of when the Company will finalize this "comprehensive support system" and deploy it for customer use.

ii. Will the Company's CARE MB program be a part of the "wide range of existing offerings" to be consolidated in the "comprehensive support system"? If yes, please clarify which "key program category" the CARE MB program is a part of.

g. On page 4, Witness Byrom responds, "The [comprehensive support system] is designed to simplify the customer journey, reduce barriers to participation, and deliver personalized support."15 Do the Company's initiatives to "reduce barriers to participation" include language translation services? If yes, please list all the language options and the corresponding information that can be translated into those languages.

Response:

a. The Company is planning to improve digital workflows on both the customer-facing end and for internal operations. These enhancements are designed to streamline service delivery, enable earlier identification of at-risk customers, and support more personalized engagement across channels.

b. As part of the planned Notification Preference Center, the Company anticipates establishing a default communication method—likely email or SMS—while enabling customers to customize how and when they receive messages to better align with their preferences.

c.

i.As part of the LMI Customer Support Enhancement Project, the Company is considering a range of major life events that may impact a customer's ability to manage energy costs. These include job loss or reduction in income, divorce or separation, loss of a spouse or household member, relocation or housing instability, health-related challenges, retirement, birth or adoption of a child, and changes in public benefits such as Medicaid or SNAP.

ii. The Company recognizes that these events can significantly affect household financial stability and energy affordability. While it does not currently track personal life events directly, the Company is exploring how it might access or infer this type of information in the future to better support customers during times of change.

In the interim, the Company plans to use behavioral indicators—such as missed or partial payments, de-enrollment from autopay, payment plan defaults, and other billing-related patterns—to proactively identify customers who may be experiencing financial stress and offer timely, personalized support.

d.

i. U21870-UCC-CE-0237 includes a list of partners with whom the Company has plans to collaborate. Those include:

- **Michigan 2-1-1**: Providing direct links and click-to-call options to connect customers with state and local assistance resources.
- Local Nonprofits and Human Service Agencies: Partnering with organizations that serve low- and moderate-income households to co-host events, distribute materials, and assist with enrollment.

- Faith-Based Organizations and Community Centers: Leveraging trusted community hubs to share information and offer in-person support.
- Food Banks and Housing Assistance Providers: Integrating energy assistance messaging into broader support services.
- Educational Institutions and Workforce Development Programs: Reaching moderate-income customers through job training and adult education networks.
- Health and Human Service Agencies: Coordinating with Medicaid and SNAP outreach efforts to identify and support eligible customers.

Additional identified partners include:

- **MEAP agencies**
- **VITA sites**
- **WellWise Services Area Agency on Aging**

Partners in **bold** represent organizations the Company has partnered with in the past. These partnerships are designed to help connect customers to available resources, increase awareness of energy assistance programs, and support enrollment through trusted, community-based channels.

ii. While not currently formalized, the Company is open to exploring partnerships with environmental coalitions where such collaboration supports clean energy goals and benefits LMI communities.

e.

i. The Company has not yet conducted a formal analysis on the impact of Medicaid cuts but recognizes the potential implications and may consider future analysis to ensure outreach strategies remain effective in identifying and supporting eligible customers.

f. i. The Company launched the initial component of the comprehensive support system known as the Simplified Enrollment Experience or My Personalized Offerings in December 2024. This digital experience allows customers to access and enroll in relevant programs through a streamlined, account-based interface.

Building on this foundation, the Company currently has plans to expand the system throughout 2025 and 2026.

ii. The Company would like to include the CARE MB program within the comprehensive support system to streamline access for eligible customers. However, because the Company does not currently own the enrollment experience for CARE MB, integration requires additional design and coordination efforts. The program is aligned with the Energy Assistance category, and the Company will continue to explore options for inclusion as part of its broader system enhancements planned for 2026.

g. The Company understands the importance of language accessibility in reducing barriers to participation and is actively exploring how translation services can be incorporated into the comprehensive support system. This functionality remains under evaluation as part of future enhancements.

Witness: Jessica R. Byrom
Date: September 15, 2025

STATE OF MICHIGAN
BEFORE THE MICHIGAN PUBLIC SERVICE COMMISSION

In the matter of the Application of **CONSUMERS ENERGY COMPANY** for authority to increase its rates for generation and distribution of electricity and for other relief.	Case No. U-21870 ALJ Jonathan F. Thoits

PROOF OF SERVICE

I, Mark N. Templeton, certify that an electronic copy of the Official Exhibits of Tabitha Williams on Behalf of Urban Core Collective, UCC-101 to UCC-112, was served on the following on November 13, 2025.

Name/Party	E-mail Address
Administrative Law Judge Jonathan F. Thoits	 thoitsj@michigan.gov
Consumers Energy Company Gary A. Gensch Jr. Anne M. Uitvlugt Evan B. Keimach Mark R. Ruszkiewicz Spencer A. Sattler Bret A. Totoraitis Kelly Hall	mpsc.filings@cmsenergy.com gary.genschjr@cmsenergy.com anne.uitvlugt@cmsenergy.com evan.keimach@cmsenergy.com mark.ruszkiewicz@cmsenergy.com spencer.sattler@cmsenergy.com bret.totoraitis@cmsenergy.com kelly.hall@cmsenergy.com
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Citizens Utility Board of Michigan, Michigan Environmental Council, Natural Resources Defense Council, Sierra Club Christopher M. Bzdok Holly L. Hillyer Tracy Jane (TJ) Andrews Natasha Fowles Sean Clark Tanya Stasio Jordan Burt Tyler Comings Caroline Palmer John Liskey Matt Bandyk Julielyn Gibbons Jackson Neme Rick Bunch	 chris@tropospherelegal.com holly@tropospherelegal.com tjandrews@tropospherelegal.com natasha@tropospherelegal.com sean@tropospherelegal.com tanya.stasio@eaclinic.org Jordan.burt@aeclinic.org Tyler.comings@aeclinic.org cpalmer@synapse-energy.com john@liskeypllc.com mbandyk@synapse-energy.com jgibbons@5lakesenergy.com jackson@tropospherelegal.com rbunch@5lakesenergy.com
Anonymous Customer A Valerie J.M. Brader, Esq.	ecf@rivenoaklaw.com valerie@rivenoaklaw.com
Great Lakes Renewable Energy Association (GLREA) Don L. Keskey Brian Coyer Carol Dane	 donkeskey@publiclawresourcecenter.com bwcoyer@publiclawresourcecenter.com cdane@publiclawresourcecenter.com
Walmart, Inc. Melissa M. Horne	 mhorne@hcc-law.com
Association of Businesses Advocating Tariff Equity Michael J. Pattwell Benjamin J. Holwerda Stephan A. Campbell James Dauphinais Lauren Degnan Christina Hildebrandt Jessica York	 mpattwell@clarkhill.com bholwerda@clarkhill.com scampbell@clarkhill.com jdauphinais@consultbai.com ldegnan@clarkhill.com childebrandt@consultbai.com jyork@consultbai.com
Heston Hemlock Semiconductor Operations, LLC and Solar Technology LLC Jennifer U. Heston	 jheston@potomaclaw.com
The Ecology Center, The Environmental Law & Policy Center, Union of Concerned Scientists, and Vote Solar Daniel H.B. Abrams Katie Duckworth Alondra Estrada Katie Toolan	MPSCDocket@elpc.org dabrams@elpc.org kduckworth@elpc.org aestrada@elpc.org ktoolan@elpc.org

The Kroger Company Kurt J. Boehm Jody Kyler Cohn Michael L. Kurtz Justin Bieber	 kboehm@bkllawfirm.com jkylercohn@bkllawfirm.com mkurtz@bkllawfirm.com jbieber@energystrat.com
Michigan Cable Telecommunications Association Sean P. Gallagher Jon Austin	 sgallagher@fraserlawfirm.com jaustin@fraserlawfirm.com
Michigan Electric Transmission Company, LLC Richard J. Aaron Courtney F. Kissel Olivia R.C.A. Flower Hannah Buzolits Josh Kluzak Anthony J. Hunt	 raaron@dykema.com ckissel@dykema.com oflower@dykema.com hbuzolits@dykema.com jkluzak@dykema.com ahunt@dykema.com
Foundry Association of Michigan, Energy Michigan, Michigan Energy Innovation Business Council, Institute for Energy Innovation, and Advanced Energy United Timothy J. Lundgren Laura A. Chappelle Justin K. Ooms Lydia Lubbers	 tjlundgren@varnumlaw.com lachappelle@varnumlaw.com jkooms@varnumlaw.com lmlubbers@varnumlaw.com
Urban Core Collective Amanda Urban Mark Templeton Jacob Schuhardt Alex Miskho Emma Young	aelc_mpsc@lawclinic.uchicago.edu aurbanlaw@gmail.com templeton@uchicago.edu jschuhardt@uchicago.edu amiskho@uchicago.edu eyoung28@uchicago.edu

The statements above are true to the best of my knowledge, information, and belief.

Counsel for Urban Core Collective

Date: November 13, 2025

By: /s/ Mark N. Templeton

Mark N. Templeton *(pro hac vice)*
University of Chicago Law School
Abrams Environmental Law Clinic
6020 S. University Avenue
Chicago, IL 60637
Phone: (773) 702-9611
templeton@uchicago.edu