Power outages increase cardiovascular and respiratory hospitalizations among US older adults

Intro:

As the climate warms, the incidence and duration of power outages across the US is increasing[[1]](#endnote-1). US electrical customers experienced an average of 8 hours without power in 2020—the longest duration on record.[[2]](#endnote-2) 40-60% of these outages were caused by severe weather events.[[3]](#endnote-3) Aging electrical grid components, already at risk of failure, were not built to withstand previously rare extreme weather events now common with climate change.[[4]](#endnote-4),[[5]](#endnote-5) Additionally, climate-change induced heat and cold events will increase electricity use, outstripping supply, and cause outages.[[6]](#endnote-6),[[7]](#endnote-7)

Power outages threaten health.[[8]](#endnote-8),[[9]](#endnote-9) Power outages disable air conditioners and heaters, exposing those affected to extreme temperatures.[[10]](#endnote-10) This heat and cold exposure may cause or exacerbate respiratory and cardiovascular illness.[[11]](#endnote-11),[[12]](#endnote-12),[[13]](#endnote-13) Prior epidemiological studies have found elevated cardiovascular and respiratory hospitalizations up to one week after power outage exposure,[[14]](#endnote-14),[[15]](#endnote-15),[[16]](#endnote-16) and associations may be stronger when outdoor temperatures are extreme. During power outages, loss of electricity to life-sustaining medical devices like at-home ventilators and oxygen tanks can be life-threatening. During longer outages, loss of electricity to refrigerators, elevators, wheelchairs, and water disruptions can result in stress, isolation, dehydration, or injury. These pathways may explain associations between power outages and cardiorespiratory hospitalizations, injury hospitalizations, and mortality.

Older adults (those aged 65+) may be particularly vulnerable to stroke, myocardial infarction, chronic obstructive pulmonary disease (COPD) exacerbation, and other adverse cardiorespiratory outcomes following power outage exposure. 70-86% of older adults already live with cardiovascular disease, making them vulnerable to disease exacerbations from outage exposure. 3.5% of older adults use electricity-dependent medical equipment such as ventilators and oxygen tanks at home to treat conditions like COPD, and this equipment may become unusable during outages. Because of aging-related thermoregulation changes, heat and cold exposure cause more health consequences in older adults compared to younger adults. Older adults also have higher rates of other underlying health conditions, increased reliance on mobility devices and elevators, and are more socially isolated than younger adults. Therefore, they may have fewer opportunities to seek out electricity, air conditioning, or heat, putting them at higher risk for health consequences from power outage.

Social vulnerability can also impact

Despite the clear risks of power outage to vulnerable populations such as older adults, research on power outage exposure and health has been limited by exposure data availability. Population-level datasets of power outage exposure beyond New York State, the site of most epidemiologic studies of outage and health, have only recently become available. The remaining studies of outage and health use large-scale events such as single hurricanes or other disasters that disrupted power as a surrogate for the timing of power outage exposure in specific locations. These studies consider everyone in a city or county exposed to the power outage in the hours, days, or weeks following the index event. In these studies, it is difficult to disentangle health effects of outage from health effects of the disaster, however qualitative work on outages during disasters has reported that older adults are concerned about outage exposure and report health effects from exposure. As outages become more common with climate change, understanding the downstream health effects of power outage can inform prevention efforts.

In our preliminary work, we assembled the first nationwide dataset describing hourly county-level power outage exposure from 2018-2020, based on data from poweroutages.us. In this paper, we leverage these data together with Medicare hospitalization data to describe the relationship between daily county-level power outage exposure and daily cardiorespiratory hospitalization risk in older adults 65+ in the US nationwide. Should I write some sentences about effect mod here??

Maybe add sentence about SVI as an effect modifier earlier in the intro and then talk about effect mod in the last paragraph.

Methods:

Study population:

Our study population included all fee-for-service Medicare enrollees age 65+, enrolled for at least one month between January 1st, 2018 and December 31st, 2018. From the Medicare enrollee record file, we obtained age, sex, county, and state of residence for all enrollees in our study. We included a total of N enrollees.

We used the Medicare Provider Analysis and Review (MEDPAR) file to access inpatient claims data on all hospitalizations in our study population in 2018 from the Center for Medicare and Medicaid Service (CMS). We accessed the date of hospitalization, type of hospitalization (emergency, urgent or planned), and cause of hospitalization (ICD-10 codes).

* Fee-for-service Medicare enrollees aged 65+
* Enrolled for at least one month between January 1st, 2018 – December 31st 2018
* Age, sex, and county and state of residence from the Medicare enrollee record file
* N total enrollees
* Inpatient claims data on all hospitalizations in this population in 2018 from Center for Medicare and Medicaid Service (CMS)
* date of hospitalization, type of hospitalizations (emerg vs urgent vs. planned) and ICD-10 codes for each hospitalization from the Medicare Provider Analysis and Review (MEDPAR) file

Outcome assessment:

* analysis at county-day level on hospitalization rates.
* Obtained number of Medicare enrollees by county based on county of residence
* Tabulated daily county-level counts of ‘urgent’ or ‘emergency’ hospitalizations for cardiovascular or respiratory concerns based on county of residence of hospitalized individual
* we hypothesized power outage would increase urgent and emergency hospitalizations not planned ones, so included those
* Aimed to capture all hospitalizations for CVD or respiratory causes
* Identified hospitalization cause based on first five ICD codes included
* List of cvd and resp codes in supplement
* Excluded hospitalizations including hypertension bc of its prevalence in the top five codes. Thought that we might capture hospitalizations for other stuff where the person had hypertension
* Conducted a sensitivity analysis for CVD including hypertension.
* Ended with daily county-level rate of cardiovascular hospitalizations and respiratory hospitalizations for each county-day in 2018
* Excluded counties with <500 benes from analysis (N counties had <500 benes)
* Conducted sensitivity analysis where we looked at only the 1st icd code as well. (wait until they ask)

Exposure assessment:

* We used PowerOutages.us nationwide county-level power outage data to assess county-day power outage exposure
* PowerOutages.us has scraped data from public electric utility websites using utility providers’ application programming interfaces (API), as these websites have reported the number of customers without power in the areas they serve in real time.
* We purchased power outage data from PowerOutages.us for all counties in all US states from 2018-2020, and use data from 2018.
* These data included the number of customers without power every hour by county.
* ‘Customers’ refers to residential consumers such as households/families and non-residential consumers such as businesses.
* Estimates of customers served by county from POUS were unreliable. We used EIA estimates of customers served by state to determine total customers in each state. We then used census estimates of the number of households and establishments by county to determine the proportion of state customers in each county, and allocated state customers to each county based on this proportion, estimating the number of customers served by county.
* There was substantial exposure data missing in the POUS dataset.
* We excluded counties with <50% of county-hours covered by the POUS dataset.
* X number of counties were excluded due to missing exposure data, leaving Y counties covering Z% of Medicare beneficiaries.
* If there were <=4 hours of data missing we used LOCF to interpolate it but did not interpolate past this.
* Counties left had A% missing data.
* Conducted a simulation paper to look at the magnitude and direction of bias potentially introduced in a study like this one from missing data, found bias would be minimal.
* Trying to find a balance between generalizability and bias by excluding counties w poor coverage but trying to keep some in for generalizability
* We considered a county-day exposed to power outage if >1% of county customers were without power for 8 or more consecutive hours in each 24-hour period.
* We also conducted additional analyses for power outages affecting >3% or >5% of county customers.
* Consistent with outages looked at in prior studies that have been shown to have health effects
* We wanted to capture outages that have some prevalence, interested in understanding common outages
* While smaller in magnitude they would have larger overall population health effects because of there prevalence,
* Want to know if more moderate outages are related to health outcomes, rather than sweeping blackouts or disasters + outages/one-off events
* But then we also looked at larger outages….
* Find out how many people this is
* As in many population-level power outage datasets, counts of customers without power (henceforth, “customers out”) reported in this dataset do not necessarily track the same customers: if 10 customers are reported out in two subsequent hours in one county, the data do not contain information about whether the same 10 customers lacked power or if, for example, 10 customers were without power in the first hour and a different 10 customers were without power in the second hour, meaning 20 customers were without power for 1 hour each.
* Therefore, these outages don’t mean exactly 1% of customers being out for 8+ hours, rather, they represent some level of large power outage exposure among individuals in a county.
* We chose to look at 1, 3, 5% because we hypothesized effects might be stronger when more people were affected in larger scale outages, so wanted to also examine larger outages.
* We hypothesize that 8+ hour power outages are clinically relevant to older adult hospitalizations because batteries for most electricity-dependent medical equipment last 8 hours. During a power outage, electricity-dependent medical device users might experience adverse health effects without their equipment immediately after losing power to the equipment
* Without air conditioning or heat, indoor temperatures may also begin to change over the course of 8 or more hours, though we have no literature on the speed of indoor temperature change.
* also no literature on the health-relevant duration of power outage.
* Conducted a sensitivity analysis with other durations, and a secondary analysis where we looked at continuous metric of daily number of hours without power (hrs where >1% of population is without power) to determine if there were threshold effects.

Statistical analysis:

* We used a case-crossover design with a conditional Poisson model to analyze the association between daily county-level power outage exposure and CVD and respiratory hospitalization risk separately in two different models, as we hypothesized power outage may have different effects on these different types hosp.
* This method is an extension of a case-crossover design using a logistic regression model, that affords extra computational efficiency
* It is equivalent to conducting a traditional case-crossover study using logistic regression.
* selected control days from same county for every county-day with non-zero hospitalization count, matching on day of week and month to control for time-varying confounding.
* By matching on county, day of week, and month, county-level factors like county-level SES which could affect hospitalization rates and power outage rates, are automatically controlled for
* We still needed to control for some time-varying confounders like temperature, wind speed, and precipitation, because hot temperatures can cause outages and also hospitalizations, and so do storms, and could still induce an association even though we are using this matching
* Controlled using gridmet, which is a dataset of daily high-spatial resolution (~4-km, 1/24th degree) surface meteorological data
* Used mean county-level maximum temperature, wind speed, and total mm of precip for 2018
* Included max temp in the model as a natural spline w 3 dfs.
* Chose how to model relationship between precip and wind speed and hospitalizations by removing power outage from the model, leaving covariates in, and modelling the relationship between precip and windspeed and hosp as linear or with natural splines w 2-3 of freedom, and picking the best model fit using an anova.
* We chose wind speed 3 dfs and precip linear for respiratory hospitalizations and with 2 dfs for cvd hospitalizations.
* Included lag terms because we though there would be lagged effects of power outage since temp has lagged effects on cvd and resp, and other studies have reported this
* Moderate autocorrelation in outage exposure (0.2 correlation between lags 0 and 1).
* Constrained our lags.
* Tested various dfs for lags and picked best model using anova. Tested 3-5 dfs, 5 was best fit for cvd and 3 was best fit for respiratory.
* Included an offset for county customers.

Effect modification analyses:

* Tested for effect modification by age, sex, number of durable medical equipment users in a county, and county poverty.
* Number of underlying health conditions, mobility, susceptibility to heat and cold, and social isolation all increase with age so we thought adults 75 + might be more affected by outage exposure than those <75
* Heat and cold effects also differ by sex, so we tested for effect mod by sex
* We stratified analyses by age, for those age 75+ and <75, and by sex (male and female, there is no gender reporting or option to record sex as intersex in CMS records).
* We used empower data to get the percentage of Medicare benes using DME by county in 2018 (this did include some beneficiaries under 65). We created quartiles of this measure and ran stratified analyses for quartiles 1-3 and 4.
* Could potentially add back poverty or AC or SVI if we for some reason feel like it

Results:

* Something about pop
* Something about exposure
* Something about covariates
* And table 1
* Can we say how many counties experienced a 8+ hour power outage
* On average the num of county-days with outage was A%.
* There were on average 5.6 county-level 8+ hour power outages affecting >1% of county customers in 2018
* Total number of county-days w power outage was A, and B% of days were exposed to PO.
* Number of county benes ranged from A to B, mean number
* Mean CVD hospitalization rate was X, and the resp rate was Y
* Most common causes of CVD hosp were blank, and most common causes of respiratory hosp were blank.

CVD main analysis and sensitivity

* We saw effects at lags 0, 1, 6 and the rest were null
* Give an example of one or two lags (biggest one and say that it was the largest in order not to cherry pick) (eg lag 1 was 1.5 or whatever it is)
* We also looked at larger outages affecting 3% and 5% or more of the population
* Found stronger effects that increased with the size of outage
* Increased with increasing severity of power outage
* Give example of lags (largest one)
* Because we didn’t know the health relevant duration of outage we did two sensitivity analyses
* Looked at 4, 8, 12
* Looked at continuous measure of outage
* The results showed that a linear model was the best fit
* That there were no threshold effects of outage duration
* We also looked at different durations

Respiratory main analysis and sensitivity

Effect modificiaton

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2. U.S. Energy Information Administration, “U.S. Electricity Customers Experienced Eight Hours of Power Interruptions in 2020,” November 10, 2021, https://www.eia.gov/todayinenergy/detail.php?id=50316#. [↑](#endnote-ref-2)
3. Vivian Do et al., “Spatiotemporal Distribution of Power Outages with Climate Events and Social Vulnerability in the USA,” *Nature Communications* 14, no. 1 (April 29, 2023): 2470, https://doi.org/10.1038/s41467-023-38084-6. [↑](#endnote-ref-3)
4. Joan A. Casey et al., “Power Outages and Community Health: A Narrative Review,” *Current Environmental Health Reports* 7, no. 4 (December 2020): 371–83, https://doi.org/10.1007/s40572-020-00295-0. [↑](#endnote-ref-4)
5. “The US Has More Power Outages than Any Other Developed Country. Here’s Why.” (Popular Science, August 18, 2020), https://www.popsci.com/story/environment/why-us-lose-power-storms/. [↑](#endnote-ref-5)
6. Washington Post, “Nation at Risk of Winter Blackouts as Power Grid Remains under Strain,” n.d., https://www.washingtonpost.com/business/2023/11/08/power-grid-blackouts-texas/. [↑](#endnote-ref-6)
7. United States Environmental Protection Agency, “Climate Change Impacts on Energy,” n.d., https://www.epa.gov/climateimpacts/climate-change-impacts-energy. [↑](#endnote-ref-7)
8. Casey et al., “Power Outages and Community Health.” [↑](#endnote-ref-8)
9. Marriele Mango, Joan A. Casey, and Diana Hernández, “Resilient Power: A Home-Based Electricity Generation and Storage Solution for the Medically Vulnerable during Climate-Induced Power Outages,” *Futures* 128 (April 2021): 102707, https://doi.org/10.1016/j.futures.2021.102707. [↑](#endnote-ref-9)
10. Brian Stone et al., “Compound Climate and Infrastructure Events: How Electrical Grid Failure Alters Heat Wave Risk,” *Environmental Science & Technology* 55, no. 10 (May 18, 2021): 6957–64, https://doi.org/10.1021/acs.est.1c00024. [↑](#endnote-ref-10)
11. Yu-Chun Wang and Yu-Kai Lin, “Temperature Effects on Outpatient Visits of Respiratory Diseases, Asthma, and Chronic Airway Obstruction in Taiwan,” *International Journal of Biometeorology* 59, no. 7 (July 2015): 815–25, https://doi.org/10.1007/s00484-014-0899-0. [↑](#endnote-ref-11)
12. Nidhi Singh et al., “Heat and Cardiovascular Mortality: An Epidemiological Perspective,” *Circulation Research* 134, no. 9 (April 26, 2024): 1098–1112, https://doi.org/10.1161/CIRCRESAHA.123.323615. [↑](#endnote-ref-12)
13. G. Brooke Anderson et al., “Heat-Related Emergency Hospitalizations for Respiratory Diseases in the Medicare Population,” *American Journal of Respiratory and Critical Care Medicine* 187, no. 10 (May 15, 2013): 1098–1103, https://doi.org/10.1164/rccm.201211-1969OC. [↑](#endnote-ref-13)
14. Shao Lin et al., “The Joint Effects of Thunderstorms and Power Outages on Respiratory-Related Emergency Visits and Modifying and Mediating Factors of This Relationship,” *Environmental Health Perspectives* 132, no. 6 (June 2024): 067002, https://doi.org/10.1289/EHP13237. [↑](#endnote-ref-14)
15. G. Brooke Anderson and Michelle L. Bell, “Lights Out: Impact of the August 2003 Power Outage on Mortality in New York, NY,” *Epidemiology* 23, no. 2 (March 2012): 189–93, https://doi.org/10.1097/EDE.0b013e318245c61c. [↑](#endnote-ref-15)
16. Christine Dominianni et al., “Health Impacts of Citywide and Localized Power Outages in New York City,” *Environmental Health Perspectives* 126, no. 6 (June 15, 2018): 067003, https://doi.org/10.1289/EHP2154. [↑](#endnote-ref-16)