**Power outages increase cardiovascular and respiratory hospitalizations among US older adults**

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**Introduction:**

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 continue to increase electricity use, outstripping supply, and causing 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 epidemiologic 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) 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 (CVD), 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 individuals’ opportunity to mitigate the impacts of power outage exposure, meaning outages may have stronger impacts in higher vulnerability communities.

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. Though power outages often occur with severe weather, most power outages do not occur during large disasters. As outages become more common with climate change, understanding the downstream health effects of power outage alone 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 cardiovascular and respiratory hospitalization rates in older adults 65+ in the US nationwide. We also conduct secondary analyses examining effect modification of the effect of power outage on hospitalization rates by age, sex, social vulnerability index (SVI) and electricity-dependent durable medical equipment (DME) use.

**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).

**Outcome assessment:**

Using enrollees’ county of residence, we tabulated the number of Medicare enrollees for all US counties in all US states. We also tabulated daily, county-level counts of urgent or emergency hospitalizations for cardiovascular or respiratory causes based on the county of residence on the hospitalized beneficiary. We identified hospitalizations as CVD or respiratory related based on the first five ICD codes recorded as hospitalization cause. We included only urgent and emergency hospitalizations since we hypothesized only emergency and urgent hospitalization rates would be impacted by power outages and resulting heat, cold, and electricity-dependent medical device disruption in the short term.

We aimed to capture hospitalizations for all cardiovascular and respiratory disease causes except for hypertension (list of ICD-10 codes included in the supplement). Hypertension is extremely prevalent in older adults, and y% of hospitalizations in our dataset included an ICD code for hypertension. By excluding hypertension, we hoped to exclude hospitalizations that were not primarily for CVD or respiratory concerns, but where the patient had a diagnosis of hypertension coded by their provider. We conducted a sensitivity analysis where we included hypertension-related hospitalizations.

We excluded counties with <500 beneficiaries due to their unstable hospitalization rates. Our final outcome dataset included county-level rates of CVD and respiratory hospitalizations among older adults for n= x, y% of US counties for all days in 2018.

**Exposure assessment:**

We used PowerOutage.us (POUS) 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 PowerOutage.us for all counties in all US states from 2018-2020, and used data from 2018. These data included the number of customers without power every hour by county.

‘Customers’ refers to residential consumers such as households or 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 from the POUS dataset. In our previous work, we conducted a simulation study to test the impacts of this missing data on an epidemiologic study modelled to represent this paper. We found that when a total of 15% of county-hours were missing from a power outage exposure dataset, results of an epidemiologic study like this one would be biased towards the null by 10%. In order to balance generalizability and bias, we excluded counties with <50% of county-hours non-missing in the POUS data. We excluded X counties due to missing exposure data, leaving Y counties covering Z% of Medicare beneficiaries. The remaining counties were missing A% of data. After excluding these counties, if there were 4 hour or less intervals of missing data, we used last observation carried forward to interpolate those hours.

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, or ending in each 24-hour period. Since we were interested in understanding the health impacts of common outages, rather than those associated with disasters, we aimed to capture power outages with prevalence. There were on average N (SD) 8+ hour power outages affecting >1% of the county in each county in 2018. Across counties with varying populations, on average, these outages impact X customers. Prior studies have also evaluated the health impacts of outages of this magnitude, and found associations between outages and cardiovascular and respiratory health outcomes in all adults and older adults.

We also conducted secondary analyses for power outages affecting >3% or >5% of county customers, to evaluate the impacts of larger, more rare outages, during which we hypothesized there might be stronger health effects.

We chose the 8+ hour power outage duration. We hypothesized that 8+ hour outages are health-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. After 8+ hours, we also hypothesized that indoor temperatures would change substantially, exposing older adults to heat and cold.

Because there is no literature on the health-relevant duration of power outage, beyond epidemiologic studies showing that outages of certain lengths have effects, we conducted a sensitivity analysis on the power outage duration evaluating the effects of 4+ hour outages and 12+ hour outages on both hospitalization rates. We also conducted a sensitivity analysis where we used a continuous metric of “daily number of hours without power” (hrs where >1% of population is without power) to determine if there were threshold effects for outages longer than a certain duration. We used distributed non-linear lag terms in the conditional Poisson model to determine the relationship between continuous number of hours without power and both outcomes.

As in all available population-level power outage datasets, counts of customers without power 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 represent exactly 1% of customers continuously experiencing 8 hours without power, rather, they represent some level of large power outage exposure among individuals in a county.

**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 rates. Conducting a case-crossover analysis with a conditional Poisson model is equivalent to conducting a traditional case-crossover study at the individual level using logistic regression, but is more computationally efficient.

We evaluated the effect of outage on CVD and respiratory hospitalizations separately in two different models. We hypothesized power outage may have different effects on these two hospitalization types, since heat, cold and dehydration effect CVD and respiratory disease differently. We selected control days for every county-day with non-zero hospitalization count, matching on county, day of week, and month to control for time-varying confounding. This matching on county, day of week, and month automatically controlled for county-level confounders like county-level SES, which could affect both hospitalizations rates and power outage rates.

However, this design does not automatically control for time-varying confounders. We controlled for wind speed, temperature, and precipitation, which can all influence both power outage and hospitalization rates. We used daily county-level maximum temperature, average wind speed, and total precipitation measures from gridMET, a dataset of daily high-spatial resolution (~4-km, 1/24th degree) surface meteorological data. We included maximum temperature flexibly in our models as a natural spline with 3 degrees of freedom. To determine how flexibly to control for wind speed and precipitation, we removed power outage exposure from models and modelled only the relationships between precipitation, wind speed, and CVD and respiratory hospitalization rates separately. We ran several test models with splines on precipitation and wind speed with varying degrees of flexibility (linear, and 2-4 degrees of freedom), and tested model fit using F tests. We controlled for these confounders in main models with the degree of flexibility that resulted in the best test model fit. In models with the outcome of respiratory hospitalizations, we controlled for precipitation linearly, and in models for CVD outcomes, with 2 degrees of freedom. Wind speed was modeled with 3 degrees of freedom across outcomes.

We hypothesized that there would be lagged effects of power outage on both CVD and respiratory hospitalizations. Other studies of power outage and CVD and respiratory outcomes have found lagged effects, and heat and cold exposure also produces lagged effects. Power outage exposure was moderately autocorrelated (R = 0.2). We included lags up to 6 days after power outage exposure, and constrained these lags. We tested 3-5 degrees of freedom on the lag dimension, since >5 degrees of freedom seemed biologically implausible. We compared model fit using F-tests, finding that for CVD outcomes, 5 degrees of freedom across the lag dimension produced the best model fit, and 3 degrees of freedom was appropriate for respiratory outcomes.

**Testing for effect modification**

We tested for effect modification of the effect of power outage exposure on CVD and respiratory outcomes by age and 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 also tested for effect modification by social vulnerability index (SVI). SVI is a

We also tested for effect modification by the percentage of Medicare beneficiaries using DME by county. We used emPOWER data to estimate the number of Medicare beneficiaries (all, not only those 65+) using DME, and the total number of beneficiaries. We calculated the percentage of DME users by county and stratified analyses by quartiles of percentage of DME users.

**Results**

We included X number of counties in our final analysis, covering Y beneficiaries. The number of county beneficiaries ranged from A to B. There were on average 5.6 county-level 8+ hour power outages affecting >1% of county customers in 2018. The total number of county-days w power outage was A, and B% of days were exposed to PO. The mean daily CVD hospitalization rate was X, and the respiratory rate was Y. The most common causes of CVD hospitalization were blank and blank, and the most common causes of respiratory hospitalization were blank and blank.

**CVD hospitalizations**

Main analysis

* In main analyses of effects of outage on CVD, we saw increases in CVD hosp with outage exposure, same day and lagged
* we saw the largest increases in hospitalization rate with power outage exposure the day of exposure, a day after exposure, and a week after exposure
* All other lags were null
* One day after power outage exposure, the CVD hospitalization rate was 1.05 times larger than on days not following those exposed to power outage.
* We also analyzed larger 8+ outages affecting >3% or >5% of county customers.
* Effects of outage on CVD hospitalization risk increased with larger outages
* For outages affecting both 3% and 5% of the population, the day of exposure, day after exposure, and a week after exposure, CVD rates were more elevated than for smaller outages.
* The day after outage exposure for outages affecting >3% of the population, CVD rates were X times those on days unexposed.
* For outages affecting 5% of the population, rates were Y times rates on days unexposed.

Sensitivity analysis

* We conducted sensitivity analyses evaluating the impact of 4+ and 12+ hour outages on CVD hospitalization rates.
* We also modelled the relationship between the daily county-level number of hours without power and CVD hospitalizations
* For 4+ hour and 12+ hour outages, we observed similar results to 8+ hour outages
* Hospitalizations were elevated the day of exposure, the day following exposure, and a week after exposure
* Effects were strongest for 12+ hour outages. Hospitalization risk was X% higher the day after 12+ hour power outage exposure.
* Effects of 4+ hour outages on CVD hospitalizations were weaker than 8+ hour outage effects
* Day after exposure, blank.
* We used distributed non-linear lag terms in the conditional Poisson model to determine the relationship between continuous number of hours without power and CVD hospitalization rates
* Tested model fit for models with a linear relationship between number of hours without power and CVD hospitalizations, and models with a natural spline on number of hours without power with 2 and 3 degrees of freedom.
* Also tested models with different flexibility on the lag dimension (3-5 degrees of freedom).
* Found that a model where number of hours without power affects hospitalization rate linearly was the best fit, with 5 dfs on the lag dimension.
* In that model, since the relationship between number of hours without power and hospitalization was linear, there was no threshold duration above which power outages began to affect CVD hosp
* Rather, the more hours without power, the stronger the effect of outage on hospitalizations
* Biggest increases were day of and day after outages, with increases a week later as well.
* Say effect size

**Respiratory hospitalizations**

* Respiratory results were similar to CVD results in that there were increases in resp hosp day of and after outage
* Largest increases were also day of and day after, and a week later, with other lags null
* However, largest effect was day of power outage, rather than day after.
* On day of power outage exposure, the resp hospitalization rate was 1.05 times larger than on days not exposed to power outage.
* For larger 8+ outages affecting >3% or >5% of county customers, lagged effects followed a similar pattern to those analyses including smaller outages, but were stronger.
* The day of outage exposure for outages affecting >3% of the population, resp rates were X times those on days unexposed.
* For outages affecting 5% of the population, rates were Y times rates on days unexposed.

Sensitivity analysis

* We conducted sensitivity analyses evaluating the impact of 4+ and 12+ hour outages on resp hospitalization rates.
* As with CVD sensitivity analyses, for 4+ hour and 12+ hour outages, we observed similar results to 8+ hour outages
* Hospitalizations were elevated the day of exposure, the day following exposure, and a week after exposure
* Effects were strongest for 12+ hour outages. Hospitalization risk was X% higher the day after 12+ hour power outage exposure.
* Effects of 4+ hour outages on CVD hospitalizations were weaker than 8+ hour outage effects
* Day after exposure, blank.
* Finally, as with CVD, we used distributed non-linear lag terms in the conditional Poisson model to determine the relationship between continuous number of hours without power and resp hospitalization rates
* models where number of hours without power affects hospitalization rate linearly was the best fit, with 5 dfs on the lag dimension, as with CVD
* means that as with CVD, there were no observed threshold effects
* Rather, the more hours without power, the stronger the effect of outage on hospitalizations
* In continuous hrs out analyses, biggest increases were day of and day after outages, with increases a week later as well.
* Say effect size

**Effect modification**

* We tested for effect modification by age, sex, SVI, and percentage of county Medicare beneficiaries who use DME
* Overall, we did not observe effect modification by age and sex or SVI
* However, the effect of power outage on respiratory hospitalizations appeared stronger in counties with smaller percentages of DME users.
* Respiratory hospitalizations remained elevated in counties int eh first quartile of DME use for two days after power outage, while in counties with fourth quartile DME use, hospitalizations were elevated only on the day of power outage.

**Discussion**

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