**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 initially included a total of 33,242,414 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. To identify CVD hospitalizations, we used all codes beginning with I, and for respiratory hospitalizations, all codes beginning with J. To identify hypertension-related hospitalizations, we used codes I10-I169 (a list of all ICD-10 codes used is included in the supplement). Hypertension is extremely prevalent in older adults, and 36% 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 (178 counties had <=500 benes). Our final outcome dataset included county-level rates of CVD and respiratory hospitalizations among older adults for n= 2,964, or 94% 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 the study conducted in 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 804 counties due to missing exposure data. After excluding counties with low beneficiary counts and missing data, our analytic dataset included 2,161 counties (69%) covering 71.06% of Medicare beneficiaries (N = 23,622,770). The remaining counties were missing 7% of power outage county-hours. 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 7.3 (28.29) 8+ hour power outages affecting >1% of the county in each county in 2018. Across counties with varying populations, on average, these outages impact >109 fee-for-service Medicare beneficiaries in our study population. 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, when measuring exposure to 8+ hour power outages affecting >1% of the population, it is not guaranteed that >1% of county customers are experiencing 8 consecutive hours of power outage. Though we aim to capture individuals’ exposure to power outage with this definition, there is substantial error. These outages 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 association 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 poverty status. We calculated the proportion of county households making less than the federal poverty income using 2018 ACS data, and created quartiles of this measure. We stratified analyses by quartile.

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 2,161 number of counties in our final analysis, covering 71.06% of beneficiaries. The number of county beneficiaries for included counties ranged from 501 to 252,004. There were on average 7.3 county-level 8+ hour power outages affecting >1% of county customers in 2018. The total number of county-days w power outage was 15990, and 2.02% of days were exposed to an 8+ hour power outage affecting >1% of customers. The mean daily county-level CVD hospitalization rate was 3.23, and the respiratory rate was 2.25. The most common non-hypertension causes of emergency CVD hospitalization were atherosclerotic heart disease (I25.10), acute on chronic diastolic (congestive) heart failure (I50.33) and unspecified atrial fibrillation (I48. 91). The most common causes of emergency respiratory hospitalization were acute respiratory failure with hypoxia (J96.01), acute COPD exacerbation (J44.1), and unspecified COPD (J44.9).

**CVD hospitalizations**

Main analysis

In our main analysis testing the effect of power outage exposure on CVD hospitalization rates, we found the largest increases in CVD-related hospitalizations 1-3 days after exposure and 6 days after exposure. Exposure was not associated with increased hospitalizations on other lag days. One day following power outage exposure, the CVD hospitalization rate was on average 1.02 (CI: 1.00, 1.01) times higher than on unexposed days.

* 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
* **Also conducted sensitivity analysis including hypertension hosp**
* **Results**

**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**

Qualitative summary:

* Study of 23 million fee-for-service Medicare benes aged 65+ enrolled in 2018 across US
* 8+ hour power outages affecting > 1% of county customers increased emergency hospitalizations for both cvd and respiratory-related hospitalizations
* For CVD effects were greatest day after
* For respiratory hospitalizations, effects were greatest day of
* We also looked at outages affecting greater percentages of the county customers (3%, 5%) and found stronger effects for larger outages. (say what the effects were)
* In sensitivity analyses designed to test the effects of outages of different durations, we modelled the relationship between the number of hours without power in each county-day with hospitalizations, as well as outages that were 4+ hours and 12+ hours long.
* Linear relationship between number of hours of PO and CVD outcomes
* Both sensitivity analyses about outage duration supported the conclusion that there were no threshold effects where outages caused CVD health effects after a certain duration. Effects were larger for longer outages, but were still present for shorter outages.
* Need to add resp part here once models are finalized
* Power outages increasing due to climate change
* 8+ hour ower outages we looked at are prevalent (county avg 7 outages per year), shorter outages even more prevalent
* Big public health problem

Comparison to existing lit

* Several studies using data from New York State have evaluated the effects of outage on CVD and respiratory hospitalizations (cite dominanni)
* Shao lin et al:
  + Found increases in adult respiratory visits using sparcs data with outages day of and after
* Deng show CVD hosp and resp hosp increased w PO in all adults
  + Cvd hosp increase largest day after
  + Resp day of, as in our study
  + Effect stronger in older adults
* Measured outage with similar but not identical definitions to ours, threshold but different thresholds with smaller spatial units
* Do et al. found evidence for increased CVD emergency hosp in the medicare beneficiaries in NYS, measuring outage with different data but with the same older adult population for outcome
* Altogether our results agree with the results from these studies showing effects of po on hospitalizations – similar effect sizes and lag patterns
* Because we’re working with national data we had more power to detect effects of po on hospitalizations – many more exposed counties and beneficiaries
* Some qualitative work has shown that older adults are concerned about the health consequences of power outages.
* Overall our results and prior studies are showing that this is concern is warranted. More work is needed to prevent hospitalizations from outages in older adults.
* Bio plausibility/mechanism
* Think effects are happening through heat and cold exposure and through loss of electricity to DME
* Possible air pollution changes (air purifiers out, generators in, ac/heat/ventilation off)
* If these are indeed mechanisms, it matters that power outages often co-occur with other climate hazards like storms, floods, heat, and cold
* Do et al showed this
* In this analysis we controlled for these factors rather than looking at effect modification or mediation
* Future studies need to address this
* Dominianni, Deng, Lin results suggest they might be, seeing effect modification of PO on health with floods and storms
* New national datasets of po exposure could help us look at effects of regional hazards
* Talk about county-level exposure as well
  + We also saw larger effects with larger outages
  + Could be for a couple reasons
  + One: larger outages might just be measured better in our dataset
  + When we classify county as exposed if >5% of pop is without power, then less exposure misclassification
  + Marking fewer people exposed when they are not
  + Also could be that larger outages affect health differently. If outages are localized, people might be able to go to a neighbor’s house for electricity, heat, or AC. Larger outages might mean larger community disruption and might be harder for people to cope with

Effect mod

* No effect mod by sex, surprising bc women more effects from temp, possible but CIs are overlapping
* No effect modification by age – also surprising because adults >75 rely more on DME and mobility devices, more isolated, more underlying conditions
* No effect mod by poverty
* Hypothesized there would be because of adaptive capacity
* Could be because we’re measuring poverty at the county level, all counties with high poverty also have areas with a lot of wealth
* Difficult to get at this construct with county-level data
* Some effect mod on respiratory hosp by DME use. Looks like counties with higher prevalence of DME use have lower hospitalization rates
* Surprising bc we thought DME use would be strong, main hypothesis for mechanism
* Could be that DME users are more prepared for outages
* Could be mortality
* We’re also unable to distinguish between types of DME
* Here we measured quartiles for all DME users, but these include people who use wheelchairs and adjustable beds, not just life-sustaining DME like oxygen tanks and ventilators.
* Effects of power outage on DME users might vary by type of DME
* Unfortunately national data on oxygen use/life sustaining DME not available for years we have power outage data – good future direction
* Limitations
* Sixth day lag – possible result of the modelling strategy or delayed effects of air pollution and temperature
* Or delays in care
* But we don’t know
* County-level measures for PO and effect mod
  + Best available data but still coarse
  + Exposure misclassification inherent in definition of power outage
  + Not tracking the same customers
  + Unclear what direction this would bias results to have this measure at county-level
  + Would need individual data to know this better
  + Possible not observing effect mod bc of county-level measures of poverty and DME use
  + As in any observational study, confounding but we tried our best and the design controlled for a lot of confounders but there could be residual
* Missingness – bias towards the null and generalizability issues
  + Selection bias excluding rural counties
  + Other studies have shown differential effects by rural status
  + Important to address in future work
* Strengths:
  + Generalizability (large study pop, covered a lot of benes)
  + power
  + Confounders well controlled for by design
* Conclusion:

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