**Assessing potential sources of bias in measuring power outage exposure with simulations**

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**Structured abstract:**

Background: Power outages are increasing with climate change and pose serious health risks to vulnerable groups such as older adults. However, the relationship between power outage exposure and health outcomes is understudied due to lack of exposure data. Though new national exposure data have become available since 2020, exposure measurement challenges remain. Available datasets are missing large percentages of observations, and the health relevant duration of power outages is unknown. Incorrect assumptions about health relevant duration of power outage, and missing power outage exposure data could bias results of future epidemiological studies of power outage and health outcomes. Bias from missing data may be so severe that exposure data are unusable.

Objective: We aimed to determine if currently available datasets are complete enough to produce usable effect estimates in epidemiological studies, and quantify bias introduced by wrong assumptions about health-relevant duration of power outage.

Methods: We conducted simulations representing a national county-level study of daily power outage exposure and daily hospitalizations. We simulated and then estimated the effect of daily power outage exposure on hospitalization rates. We measured the magnitude and direction of bias introduced when the researcher made incorrect assumptions about the health-relevant duration of power outage (underestimated or overestimated) and when increasing amounts of exposure data were missing.

Results: In scenarios where the researcher underestimated the health-relevant duration of power outage, results of our simulated epidemiolocal study of power outage and hospitalizations were substantially biased downward, while overestimating the health-relevant duration of power outage resulted in minimal bias. When 40% of person-time of exposure data was missing or more, results were substantially biased downward. With fewer data missing, results were minimally biased.

Significance: With appropriate sensitivity analyses testing assumptions about the health-relevant duration of power outage, and with careful examination and treatment of missing data, it is possible for researchers to leverage available power outage data to get minimally biased effect estimates in epidemiological studies of power outage and health outcomes.

**Impact statement:** Research on power outages and health outcomes has been constrained by lack of reliable exposure data. We developed a strategy to measure power outage exposure with newly available power outage exposure datasets, which are missing large amounts of data. We conducted a simulation study assessing bias from missing data, as well as bias from incorrect assumptions about the health relevant duration of power outage. We found that missing data and incorrect assumptions about health relevant duration of outage did introduce substantial bias, but it was possible to obtain reasonable effect estimates from available datasets with appropriate sensitivity analyses, meaning the existing data are still useful to study power outage and health outcomes. We made recommendations to future researchers about how to measure power outage exposure and minimize bias when using power outage exposure data to study outage and health outcomes.

**Keywords:** power outages, simulation, exposure measurement, bias, electrical customers, poweroutages.us

**Introduction:**

Power outages are becoming more common.[[1]](#endnote-1),[[2]](#endnote-2) Climate change has increased the frequency and intensity of extreme weather, such as heat, wind, and precipitation.[[3]](#endnote-3),[[4]](#endnote-4),[[5]](#endnote-5) Aging grid components and have not been modernized to withstand these previously rare severe weather events.[[6]](#endnote-6),[[7]](#endnote-7),[[8]](#endnote-8) As a result, US electrical customers experienced an average of 8 hours without power in 2020, the longest duration on record.[[9]](#endnote-9)

Power outages pose serious health risks to vulnerable people. For those who use electricity-dependent medical equipment such as at-home ventilators and oxygen tanks, loss of electricity can be life-threatening.[[10]](#endnote-10) In children, outages can increase accidents and injuries related to generator, natural gas, and candle use.[[11]](#endnote-11),[[12]](#endnote-12),[[13]](#endnote-13) Power outages can render air conditioners, heaters, and tap water unavailable, resulting in heat exposure, cold exposure, and dehydration. Older adults are especially susceptible to stroke, myocardial infarction, chronic obstructive pulmonary disease (COPD) exacerbation, and other adverse cardiorespiratory outcomes following such exposures.[[14]](#endnote-14),[[15]](#endnote-15),[[16]](#endnote-16),[[17]](#endnote-17)

Despite the health risks of power outages, data describing power outage exposure are extremely limited,[[18]](#endnote-18),[[19]](#endnote-19) constraining research. To our knowledge, only one US-based dataset describes outage exposure across space and time at a sub-county spatial scale, covering only New York State.[[20]](#endnote-20) This dataset has allowed for evaluation of the impact of power outages on health.[[21]](#endnote-21),[[22]](#endnote-22),[[23]](#endnote-23),[[24]](#endnote-24),[[25]](#endnote-25) However, almost all published studies of power outages to date rely on this single dataset,[[26]](#endnote-26) meaning results are specific to New York State and may not be generalizable. 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.[[27]](#endnote-27),[[28]](#endnote-28) These studies consider everyone in a city or county exposed to the power outage in the hours, days, or weeks following the index event. Unfortunately, studies based on single climate hazard events cannot disentangle the health effects of power outage exposure from simultaneous severe weather exposure, and they cannot be used to estimate exposure-response relationships between the severity power outages and health. This would require the measurement of power outage exposure by spatial unit over time.

Quantifying the health risks and costs associated with power outages can influence energy policy decisions. If power outages cause significant morbidity and mortality, improving grid infrastructure, community solar power, electricity storage, and electricity reliability could cost-effectively improve community health. Power outages may mediate the effects of climate hazards such as heat waves and storms on health, and improving electricity reliability during these events could lessen their health impacts and improve climate resilience. Knowing the health risks of power outages can also motivate interventions in vulnerable populations to prevent adverse health outcomes.[[29]](#endnote-29)

In our previous work, we created a new national dataset of hourly power outage exposure by county in the continental United States[[30]](#endnote-30) (the PowerOutages.us dataset, or POUS dataset). This dataset will allow researchers to characterize exposure-response relationships between power outage and health outcomes nationally, by region, and within vulnerable populations.

However, even with these new data, major challenges with exposure assessment remain. First, there is no established strategy to measure health-relevant power outage exposure in the literature.[[31]](#endnote-31) Power outage is not a spatially continuous exposure, like air pollution or heat exposure. Individual households or grid connections in the same area may not experience power outages at the same time. However, the only data currently available to measure power outage (the POUS and New York State datasets) are counts of customers without power by hour at the spatial unit level, which can be interpreted in multiple ways. When assessing spatial unit level exposure, researchers must pick a cut point (a percent of customers in a community without power) after which an area is considered exposed to power outage. They must also consider and define the duration of power outage: how long does an outage need to last for a spatial unit to be exposed? A single strategy to describe power outage exposure would allow comparability and pooling of results across studies.

Second, the health-relevant duration of power outage matters for exposure assessment. Many existing studies examine outages of a specific length (ex. 8+ hours).[[32]](#endnote-32) However, we are not aware of literature or other knowledge describing how long power outages must last to cause adverse health outcomes. There are likely threshold effects: power outages longer than a certain duration may increase risk of an adverse health outcome, but shorter outages may not. For example, 8+ hour power outages may affect the health of those using oxygen tanks and at-home ventilators if device batteries die after 8 hours of power outage, while shorter outages may have no effect. Incorrect assumptions about the health-relevant duration can potentially bias the results of epidemiological studies of power outages and health outcomes.

Finally, both the New York State and POUS datasets are missing large percentages of observations,[[33]](#endnote-33),[[34]](#endnote-34) with some counties in POUS missing data on up to 70% of county-hours. In the POUS dataset, data are missing if utilities did not have a website or if utility websites were offline or unscrapable for long periods of time (months or years), since information in this dataset comes from scraping utility company websites. In these cases, imputing missing values is nearly impossible because no data exist from which to draw information. Researchers face decisions about how and when to exclude data, while trying to maintain generalizability and minimize bias.

In this paper, we aimed to address these exposure measurement issues. First, we developed a strategy for measuring power outage exposure. Then, we ran simulations to address two other potential sources of bias: incorrect assumptions about the health-relevant outage duration and exposure misclassification from missing data. We quantified the magnitude and direction of bias introduced when researchers assumed a certain length of power outage (for example, 8+ hours) caused adverse health outcomes, but outages of a different length (for example, 4+ hours) were the correct health-relevant exposure duration. To deal with missing data, we used simulations to identify patterns of missing data that would (potentially severely) bias outage-health effect estimates. We tested the sensitivity of simulation results to effect size and study design, across effect sizes estimated by previous studies of power outage and health outcomes, and across study designs we imagine researchers could use to conduct epidemiologic studies of power outage and health outcomes.

Our results contribute to the power outage and health literature with recommendations for consistently defining and measuring power outage exposure, using the datasets currently available, while minimizing potential bias in future epidemiological studies. Our results also inform the interpretation of previous studies conducted with these existing power outage exposure datasets.

**Methods:**

**Power outage datasets**

In our previous work, we purchased raw power outage data from PowerOutages.us and created a national county-level hourly dataset of power outage exposure[[35]](#endnote-35) (the POUS dataset). Most utility websites report the number of customers without power by neighbourhood or city in real-time. PowerOutages.us compiled these data by scraping counts of customers without power from utility website APIs covering the continental US in real-time every hour from 2018–2020.[[36]](#endnote-36) We used this compilation to produce the hourly county-level POUS dataset.[[37]](#endnote-37)

The POUS dataset contained hourly counts of customers without power for US counties (n = 2,447 [78%]) from January 1st, 2018, to December 31st, 2020. Utilities define a ‘customer’ as a grid connection, which can correspond to a household, apartment building, or business.[[38]](#endnote-38) 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.

The New York State power outage dataset (NYS dataset) is structured similarly – counts of customers without power are reported every 30 minutes by power operating division.[[39]](#endnote-39),[[40]](#endnote-40) Power operating divisions (n = 1,865) are geographic units varying in size but similar to ZIP codes throughout the state.

**Strategy to measure power outage**

Data from POUS is continuous: POUS contains counts of customers without power by hour. When using POUS to study power outage exposure and health outcomes, researchers could relate county-level daily or hourly customer-hours without power to health outcomes. However, ‘customer-hours without power’ is not a well-defined measurement of exposure. It is two-dimensional – it captures the number of customers without power, and also the duration of outages. If one county-day has 1000 customer hours without power, this could mean that 100 customers were without power for 10 hours, or 1000 customers were without power for 1 hour in that county on that day. These two scenarios would likely have different consequences for health.

Because customer-hours without power is not well-defined, it would be difficult to interpret the meaning of effect estimates from a study using this exposure measurement, or shape policy based on this exposure measurement. In our proposed strategy to measure power outage, we aimed to summarize continuous counts of customers without power so that we captured both dimensions of area-level power outage exposure: the magnitude of outage (how many customers are affected) and the duration (for how long).

To determine if a county-day was exposed to a power outage (**Figure 1**), we first considered each hour alone. We considered a county-hour exposed to a power outage if the percentage of customers without power in county *i* during hour *j* exceeded an arbitrary cut point *k%* —for example, 10% of county customers. In this example, we would define a county *i* exposed to a power outage during hour *j* if more than 10% of customers served in county *i* were without power. Then, we chose a health-relevant duration *d* (for example, *d* = 8 hours). *d* could be any duration specified by the researcher. We summarized to the daily level, and considered a county-day as exposed if there were at least 8 consecutive hours of ‘power outage on’ (>*k*% customers out in county *i*) in that county on that day or ending on that day.

When a county is exposed to an 8+ hour power outage according to this definition, it does not necessarily mean that 10% (or another specified *k*%) of people in that county were without power for at least 8 hours that day. One customer can represent many people, and individual customers are not tracked over time. Therefore, an 8+ hour outage affecting 10% of customers indicates that at least 10% of customers in a spatial unit were without power for 8+ hours that day. Therefore, this is an aggregate spatial unit-level exposure definition rather than an individual-level one.

Exposure misclassification is inherent in this definition. When the county is considered exposed, some customers in the county will be without electricity (at least *k*%), and others will still have electricity. Other studies of power outage exposure using a similar exposure definition have handled this exposure misclassification by conducting sensitivity analyses varying the cut point *k* above which a spatial unit is considered exposed to power outage. For example, Northrop et al. considered a spatial unit exposed to power outage if more than 10% of the customers served in that unit were without power, and conducted two sensitivity analyses using cut points at 20% and 30%.[[41]](#endnote-41) As the cut point percentage increases, the number of customers incorrectly identified as exposed decreases, and the specificity of this definition of power outage improves.

Here, we propose using this strategy for measuring power outage exposure, while always conducting a sensitivity analysis on the percentage out cut point.

**Simulation design**

**Overview**

We designed a simulation representing an epidemiological study measuring the association between power outage exposure and hospitalization rates. This study is meant to mimic a study that could be conducted using the POUS data. The outcome of ‘hospitalizations’ is intentionally vague and could be any count health outcome hypothesized to be caused or exacerbated by power outages. We simulated daily binary power outage exposure for 100 US counties for one year and daily county-level hospitalization rates for these counties over the same period. We generated effect estimates of power outage exposure on hospitalization under a zero-bias scenario and then in scenarios representing incorrect assumptions about the health-relevant power outage exposure duration and including missing data. We conducted all simulations using two different study designs to test the consistency of results to different model specifications.

**Exposure and outcome data**

We populated each county with electrical customers, drawn from the empirical distribution of customers served by county in the POUS dataset. To generate hourly counts of customers without power, we drew from the empirical distribution of counts of customers without power in the POUS dataset.

We chose the health-relevant duration of power outage for our study: 8 hours or longer (8+ hours). This was somewhat arbitrary—in a real study, the health-relevant duration would depend on the actual outcome being studied and how power outages were thought to affect that outcome. However, we do hypothesize that 8+ hour power outages matter for electricity-dependent medical device users, so we chose to use 8+ hours in the simulation. We applied our definition of power outage exposure to the simulated exposure data and identified county-days exposed to 8+ hour power outage. This produced a one-year daily time-series of binary power outage exposure data for each county.

We generated outcome data based on these exposure data. We drew hospitalization counts for each county-day based on a Poisson distribution with a base daily hospitalization rate of 0.1%. We increased this hospitalization rate for county-days exposed to 8+ hour outage by 1%, for a total hospitalization rate of 0.101%, based on reported effect sizes in the literature.[[42]](#endnote-42),[[43]](#endnote-43) This produced a one-year time series of daily hospitalization rates for each county. We repeated this procedure twice, in two additional simulations, with base hospitalization rates of 0.1% and rates on exposed days of 0.105% and 0.15%, to test the sensitivity of results to effect size.

**Simulation study design**

First, we used a base case (unbiased) scenario to estimate the true simulated effect of county-day 8+ hour power outage exposure on county-level hospitalization counts. We used a case-crossover design with a conditional Poisson model.[[44]](#endnote-44) Within each county, we chose control days for each day with non-zero hospitalization count (i.e., each case day). We included these case and control days in a conditional Poisson model relating power outage exposure to hospitalization rates. In this model, we included an offset for customers served by county. Again, we repeated this procedure twice, in two additional simulations, with base hospitalization rates of 0.1% and hospitalization rates on exposed days of 0.105% and 0.15%, to test the sensitivity of results to effect size.

We also repeated the simulation using a different study design to test if the simulation results were sensitive to study design. We implemented a study design representing an augmented difference-in-differences design,[[45]](#endnote-45) where multiple counties exposed at different times are each compared to unexposed counties. Because we did not simulate any confounding, we did not choose counties with parallel trends during pretreatment periods, rather, we randomly chose a control county for each exposed county. We used the same exposure and outcome data generated for the case-crossover simulation. For each county-day exposed to a power outage, we chose a control county-day not exposed to a power outage. We ran a conditional Poisson model including these case and control days from all 100 counties. We used exposure and outcome data created 100 times for the case-crossover design to repeat the difference-in-differences analysis 100 times and for effect sizes of 0.5% and 5%.

**Testing wrong assumptions about the health-relevant duration**

We developed a set of simulations meant to model a researcher making wrong assumptions about the health-relevant duration of power outage. We assessed the magnitude and direction of the resulting bias. These simulations model a case in which the researcher assumed 8+ hour outages caused health effects, but the truly relevant exposure window was actually 4+ hours.

To model this scenario, first, we created an additional power outage exposure dataset for each simulated county. Using the measurement strategy above, we identified county-days exposed to 4+ hour power outages instead of 8+ hour outages. We generated an additional dataset of outcome data, increasing hospitalization rates when counties were exposed to 4+ hour outages. We used the same hospitalization rate of 0.1%, with a 1% rate increase on power outage-exposed days. Then, we mismatched the exposure and outcome data: we paired exposure data indicating when counties were exposed to 8+ hour power outages with outcome data generated based on 4+ hour outages, inducing non-differential exposure misclassification.

We repeated the study we conducted above in the base case/unbiased scenario, using the mismatched datasets. We used a case-crossover design with conditional Poisson models. We chose control days for each day with non-zero hospitalization count. We ran conditional Poisson models to generate effect estimates for the mismatched scenario. We repeated this set of simulations 100 times.

We also repeated this simulation an additional 100 times, substituting 12+ hour power outages for 4+ hour power outages. This created an additional scenario where we misclassified exposure by using 8+ hour power outage exposure data rather than 12+ hour data. Finally, we repeated these simulations for two additional effect sizes, where hospitalization on exposed days were 0.105% and 0.15%.

We repeated the 4+ and 12+ hour simulations using both the case-crossover and the difference-in-differences designs to test whether results were sensitive to the study design in similar analyses as described under the zero-bias scenario.

We calculated bias in all these simulations, using the absolute difference between the estimated and true simulated effects (β\*−β, where β\* is the estimated effect and β is the true simulated effect). We also assessed coverage of confidence intervals in each of the simulations.

**Testing bias due to missing data**

To test bias due to missing exposure data, we created nine additional exposure datasets for the 100 simulated counties, with varying levels of missingness. In each dataset, increasing percentages of county-hours were removed, to model missing data (**Table 1**). In the scenario with the least missing data, 20% of counties were missing 20% of county-hours, and in the worst case, 80% of counties were missing 80% of county-hours. To create missingness, we randomly removed county-hour observations from the original dataset according to each assumed missingness percentage. We treated missing observations as though they indicated no power outage exposure (0 customers without power) since this is the mean, median, and modal value of customers without power by county-hour in the POUS dataset. We applied our definition of power outage exposure to these nine datasets with missingness to create daily binary power outage exposure data based on a power outage duration of 8+ hours.

We then modeled the relationship between 8+ hour power outage exposure measured in the nine datasets with missing data and hospitalization counts generated based on an 8+ hour power outage exposure in the complete dataset without missingness. We used both the case-crossover study and the difference-in-differences designs as above. We repeated the simulations 100 times for the main hospitalization effect of 1% and for 0.5% and 5%.

We calculated bias in each of the four cases with increasing missingness using the absolute difference between the estimated effects and simulated effects (β\*−β, where β\* is the estimated effect and β is the simulated effect). We also assessed coverage of confidence intervals.

**Results**

We ran a simulation representing an epidemiological study of power outage and hospitalizations. We created 100 counties populated with electrical customers, and simulated daily power outage exposure for these customers for 1 year. We simulated increased hospitalizations resulting from these power outage exposures. The simulated counties contained an average of 360,000 electrical customers, who experienced a yearly average of 5.6 8+ hour power outages.

With these simulations, we aimed to quantify the bias introduced in this epidemiology study when there was exposure misclassification in power outage exposure, and when there was missing power outage data. We found some evidence of bias in these simulations. On average, results from both exposure misclassification and missing data scenarios were biased downward.

**Health-relevant duration**

In the simulation scenarios representing a researcher making wrong assumptions about the health-relevant duration of power outage, when the health-relevant duration of power outage assumed by the researcher (8+ hours) was longer than the true simulated health-relevant duration (4+ hours), results were slightly biased downward (**Figure 2**). In this case, the effect estimates returned from the simulation were on average ~80% of the true simulated relative risk across study designs and effect sizes. The magnitude of bias was the similar for all effect sizes and study designs.

However, when the health-relevant duration of outage assumed by the researcher (8+ hours) was *shorter* than the true simulated duration (12+ hours), results were substantially biased downward. In this case, effect estimates returned by the simulation were on average ~50% of the true simulated relative risk across study designs and effect sizes—the largest bias of all the simulation cases. Again, magnitude of bias was similar for all effect sizes and study designs.

In scenarios modelling incorrect assumptions about the health-relevant duration, coverage varied widely by effect size and was different between the two exposure misclassification scenarios (**Figure 3**). In all scenarios, the expected coverage of 95% confidence intervals was 95%. In the simulation case where 4+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects, coverage for models with simulated effect size 0.05% was close to 100%. For effect size of 5%, coverage was close to 65%.

In the second health-relevant duration simulation, when 12+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects, coverage for models with simulated effect size 0.05% was close to 80%. However, for the effect size of 5%, coverage was 0%.

**Missing data:**

In those simulations where missing data were introduced, as more data were missing, the estimated relative risk was biased further towards the null (**Figure 4**). When 20% of data were missing in 20% of counties, effect estimates returned from the simulation were on average about 90% of the true simulated relative risk, across effect sizes and study designs (**Table 2**). When 50% of data were missing from 50% of counties, effect estimates returned from the simulation were on average about 75% of the true simulated relative risk, and when 80% of data were missing from 80% of counties, effect estimates were on average about 50% of the true simulated effect. The magnitude of bias was not sensitive to study design or effect size.

In these scenarios, coverage was high when effect sizes were small (**Figure 5**). When 20% of data were missing from 20% of counties, and the effect size was 0.05%, coverage was >95%. Coverage dropped substantially in all cases as effect size increased. When 20% of data were missing from 20% of counties and effect size was 5%, even though results were minimally biased, coverage was about 30%.

Coverage in missing data scenarios also decreased as the proportion of missing data increased, and also depended on effect size. Coverage was close to 95% in all missing data scenarios when effect size was .5%, but decreased substantially as effect size increased and as more counties were affected by missing data. Coverage was similar between study designs.

In summary, the largest bias was introduced from wrong assumptions about health-relevant duration of power outage. There was also substantial bias when 40% or more data were missing. Results from other simulation scenarios were minimally biased.

**Discussion:**

We developed a strategy to define and measure power outage exposure to support epidemiologic research. We measured bias from misidentifying the health-relevant length of power outage and missing data in simulations. Our measurement strategy and simulation results will allow researchers to use available datasets to consistently measure power outage exposure while minimizing potential bias in future epidemiological studies. Based on our results, we recommend that researchers avoid underestimating the health-relevant duration of power outage, as this can introduce substantial bias. We also recommend researchers use an analytic dataset missing less than 40% of observations overall, if possible.

We found evidence of bias in simulations where we modeled incorrect assumptions about the health-relevant duration of power outage and where we modelled missing data. Results were the most biased in those simulations representing a researcher making wrong assumptions about the health-relevant duration of power outage. Bias was largest when researchers assumed that the health-relevant duration of power outage was shorter (8+ hours) than the true simulated health-relevant duration (12+ hours). However, when the researcher assumed that the health-relevant duration of outages was longer (8+ hours) than the true health-relevant duration (4+ hours), there was minimal bias. When large proportions of exposure data were missing (50% missing from 50% of counties – 80% missing from 80% of counties), there was substantial bias, but results were minimally biased in scenarios with fewer missing data (ex: 20% missing from 20% of counties missing). The magnitude of bias did not depend on study design or effect size. However, coverage was low when the simulated effect size was larger and effect estimates were substantially biased, since results were more precise than in simulations with smaller effect sizes.

All studies using the NYS power outage dataset have used similar (but not identical) definitions of power outage exposure to the one we propose here, including Northrop et al. 2024.[[46]](#endnote-46) These studies have all used a cut point-based definition where spatial units are exposed to power outage when >*k*% of customers are without power, though details about the duration of power outage or the cut point have varied. Northrop et al. assumed that the health-relevant duration of power outage for unintentional pediatric injury hospitalizations was 4+ hours. According to our results, if longer duration outages were actually more relevant, effect estimates in Northrop et al. could be biased substantially downward. If slightly shorter outages were actually relevant, which could be possible since injuries might be related to darkness or increased candle or natural gas use, the original results could be slightly biased downward. Finally, if spatial units in the NYS dataset used in Northrop et al. had substantial missing data, effect estimates may have been biased towards the null.

If researchers are unsure of the health relevant duration of power outage for their outcome, we recommend conducting sensitivity analyses varying the health-relevant duration or using a continuous measure of the daily number of hours without power to identify the health-relevant duration of outage. Researchers should avoid underestimating the health-relevant duration, as this could result in substantial bias.

To minimize bias from missing data, which our results show can introduce substantial bias, researchers may exclude counties with high percentages of missing data. However, ignoring missing data or excluding counties with high percentages of missing data could result in selection bias, or affect generalizability. We suggest that researches do not conduct studies using datasets with high levels of missingness, as these levels of missing data do substantially bias results, but we also suggest that researchers carefully compare characteristics of included vs. excluded counties to assess generalizability, and interpret any results accordingly. Researchers could also conduct sensitivity analyses, where they compare results from models including only counties high person-coverage to results including all counties.

**Limitations**

First, in this study, we only assessed bias from missingness completely at random. In the POUS dataset, data may not be missing at random. Anecdotally, we have noticed some utility company websites are unavailable during large outages, suggesting that data could be missing more often from the POUS dataset during large outage events. We did not examine bias from non-random missingness, and bias could be substantial in either direction. Future research should explore this possibility in order to provide improved recommendations for handling missing power outage data.

Second, studies using existing datasets measuring power outage exposure need to use aggregate, spatial unit measures of power outage to estimate effects, as there are no large-scale individual-level power outage datasets available. We did not assess how aggregating measurements from the individual level to spatial unit level could bias effect estimates. Future studies are needed to address this question.

Third, we opted to construct a binary power outage exposure variable. This construct captures the two dimensions of power outage exposure (magnitude and duration), and aligns with how many people think about power outages, making it easily interpretable and policy-relevant. For some questions, a continuous measure of power outage exposure in a spatial unit (i.e., number of hours of power outage) might make more sense. Specifically, when there is no prior hypothesis on the health-relevant exposure duration, use of a continuous exposure (i.e., hours out) could facilitate identification of a potential threshold point. Researchers will need to select the best definition of power outage for their particular research question.

**Conclusion:**

Currently, power outage is understudied exposure, but power outages are increasing in frequency and duration with climate change. Researchers and the public are recognizing the importance of power reliability and the health consequences of outages, especially for vulnerable populations such as children, older adults, and people who rely on life-sustaining electricity-dependent medical equipment. When outages are caused by climate-driven severe weather events, such as extreme heat or cyclones, health risks may be even greater.[[47]](#endnote-47),[[48]](#endnote-48)

To date, data availability has constrained research on power outages and health. We developed a new national dataset of power outage exposure, the POUS dataset, which could expand the study of power outage and health outcomes. Because there is substantial missing data in the POUS dataset, and no established method to measure power outage exposure in the literature, we developed a strategy to measure power outage exposure. Then, we used simulations to test how much incorrect assumptions about health-relevant duration of power outage and missing data could bias the results of epidemiological studies of power outage and health outcomes.We found that there was substantial bias introduced in some cases, when the health-relevant duration of outage was assumed to be shorter than the true, and when more than 40% of exposure information was missing in a county. Our results show that while bias is likely, sensitivity analyses and careful choices of health-relevant duration can help researchers describe the range of plausible effect estimates in epidemiological studies of power outage and health.

Despite the high percentage of missing data in the POUS dataset, the dataset is still high resolution, with hourly measurements in 2,447 US counties over 3 years. Even after excluding counties missing >50% of exposure data, to produce a dataset where 25% of counties are missing 30% of data and the rest are more than 90% complete, the dataset covers about 70% of the US population. We hope researchers can use our results to define and measure power outage exposure in future epidemiological studies based on the POUS and NYS datasets available, while minimizing potential bias.

**Data availability:**

The power outage data examined in this study are available for purchase from PowerOutage.us at <https://PowerOutage.us/products>. Code to generate the exposure and outcome dataset used in this simulation, as well as the data themselves, are available at <https://github.com/heathermcb/power_outage_exposure_simulation>.

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**Author contributions:**

Heather: made contributions to the conception/design of the work, the analysis and creation, analysis, and interpretation of the simulation data, and draft of the work.

Joan: made contributions to the conception/design of the work, review of the simulation analysis, and draft of the work.

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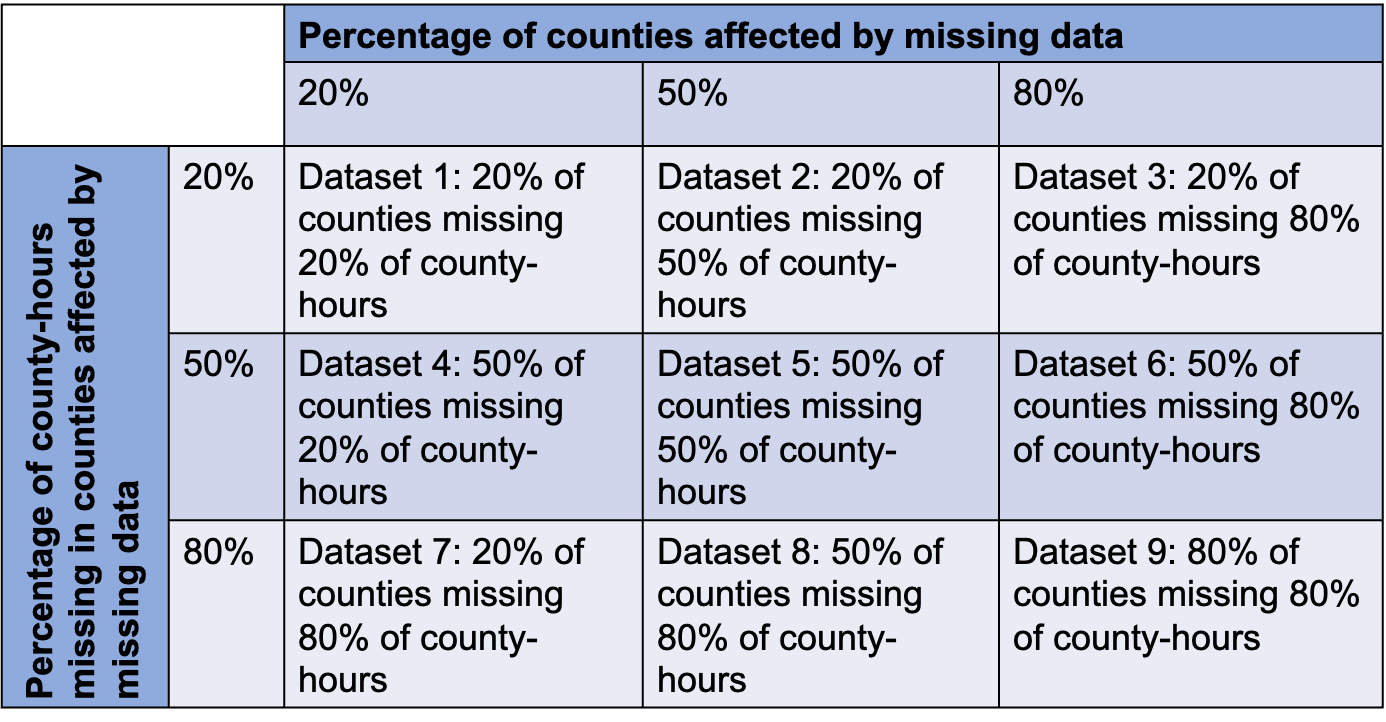
**? NIA?**

**Ethics approval:** this work does not involve human subjects, human material, or human data, only thoughts, therefore ethics approval was not required.

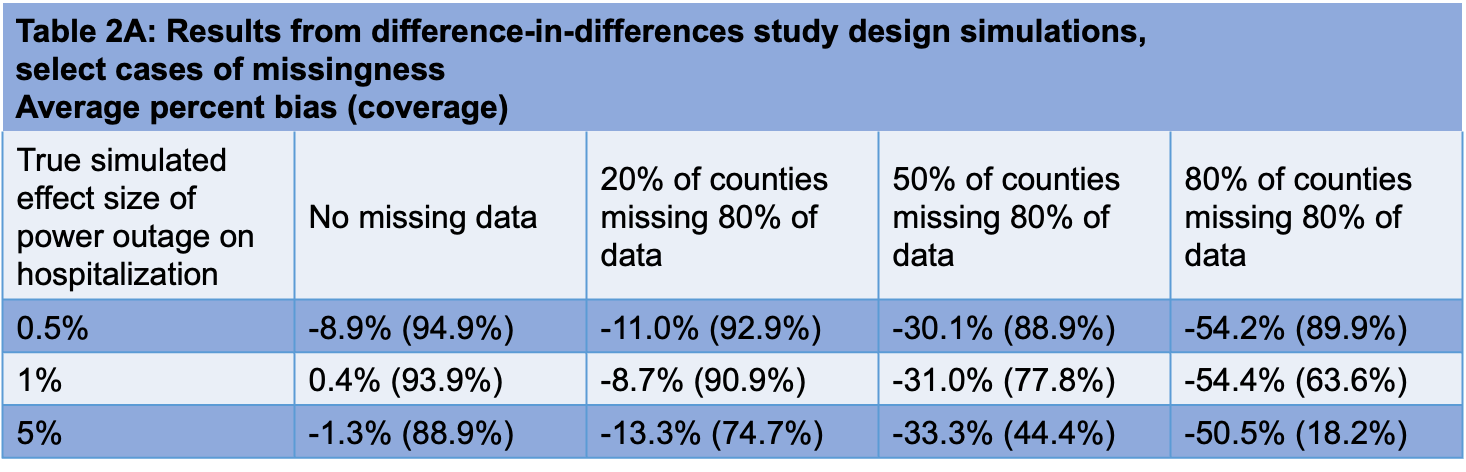
**Competing interests:** The authors declare no competing interests.

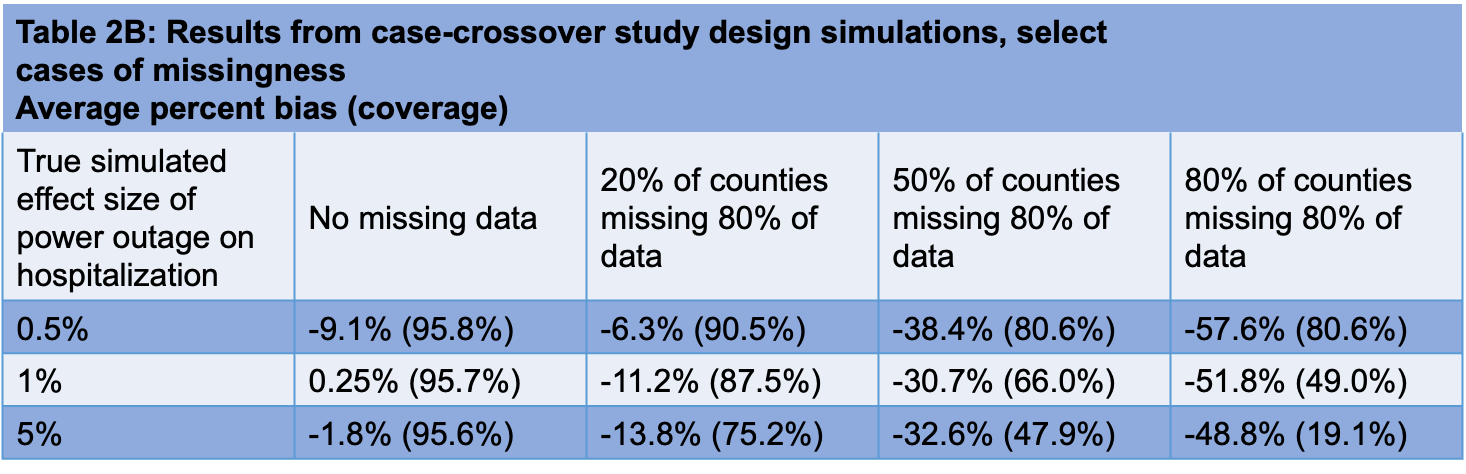
**Tables:**

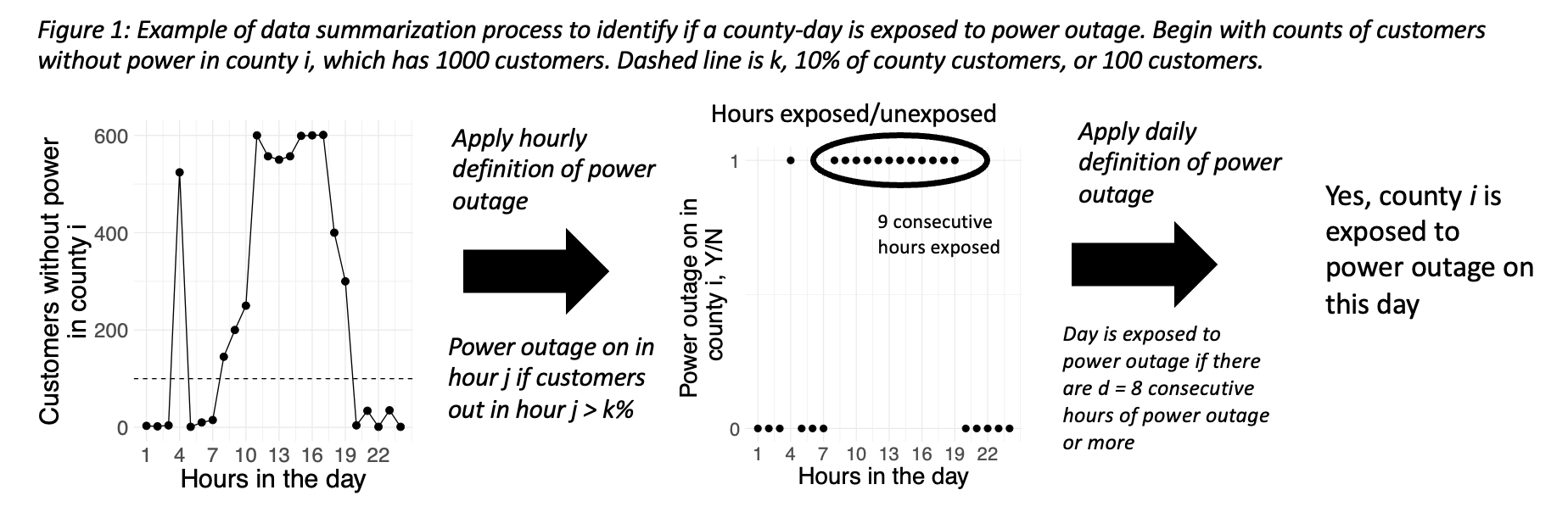
**Table 1:** Datasets created to model missing data scenarios in simulation of epidemiological study of power outage exposure and hospitalizations

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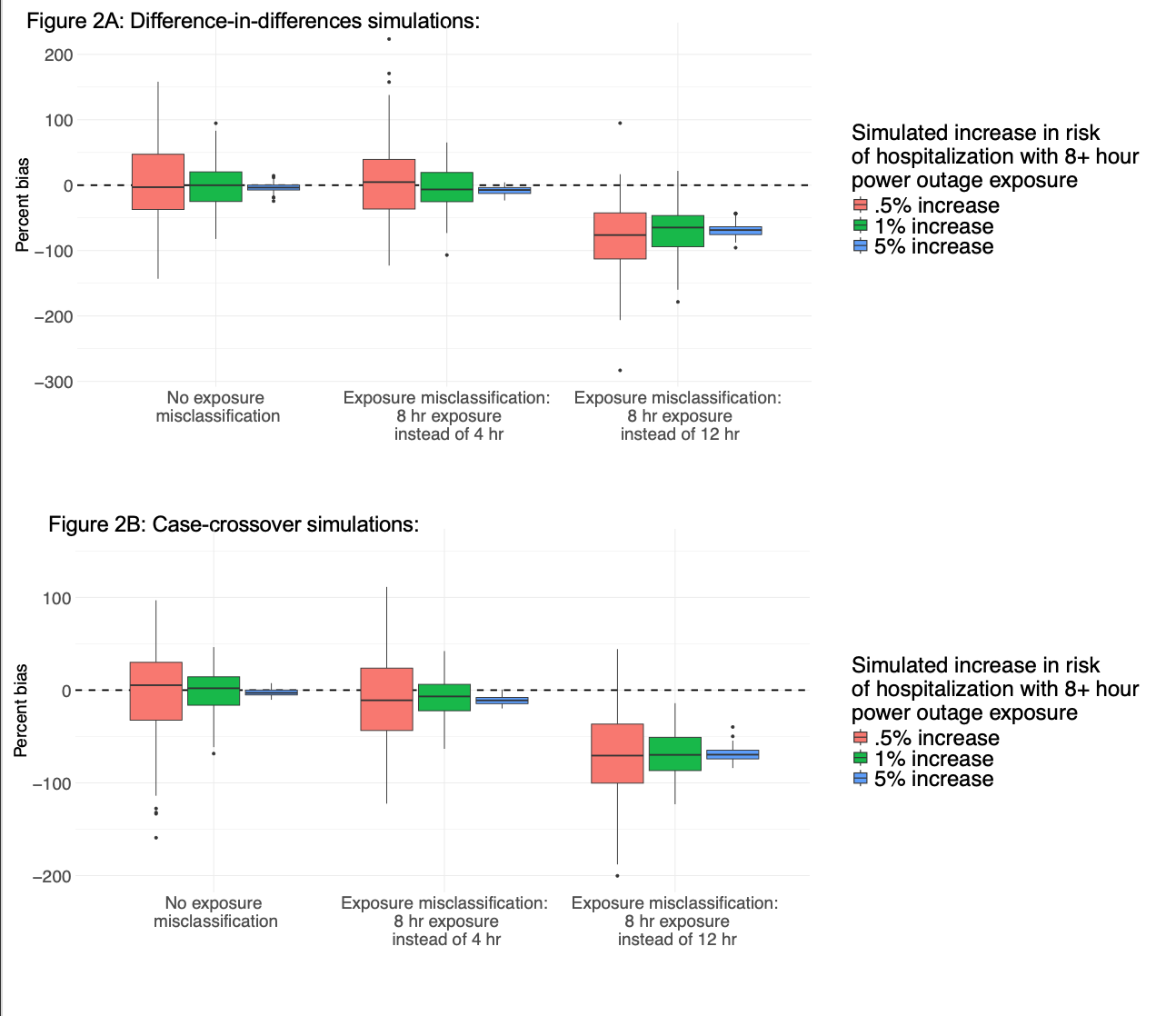
**Table 2:** Results from simulations representing missing data. Results correspond to column 3 of **Figure 4**

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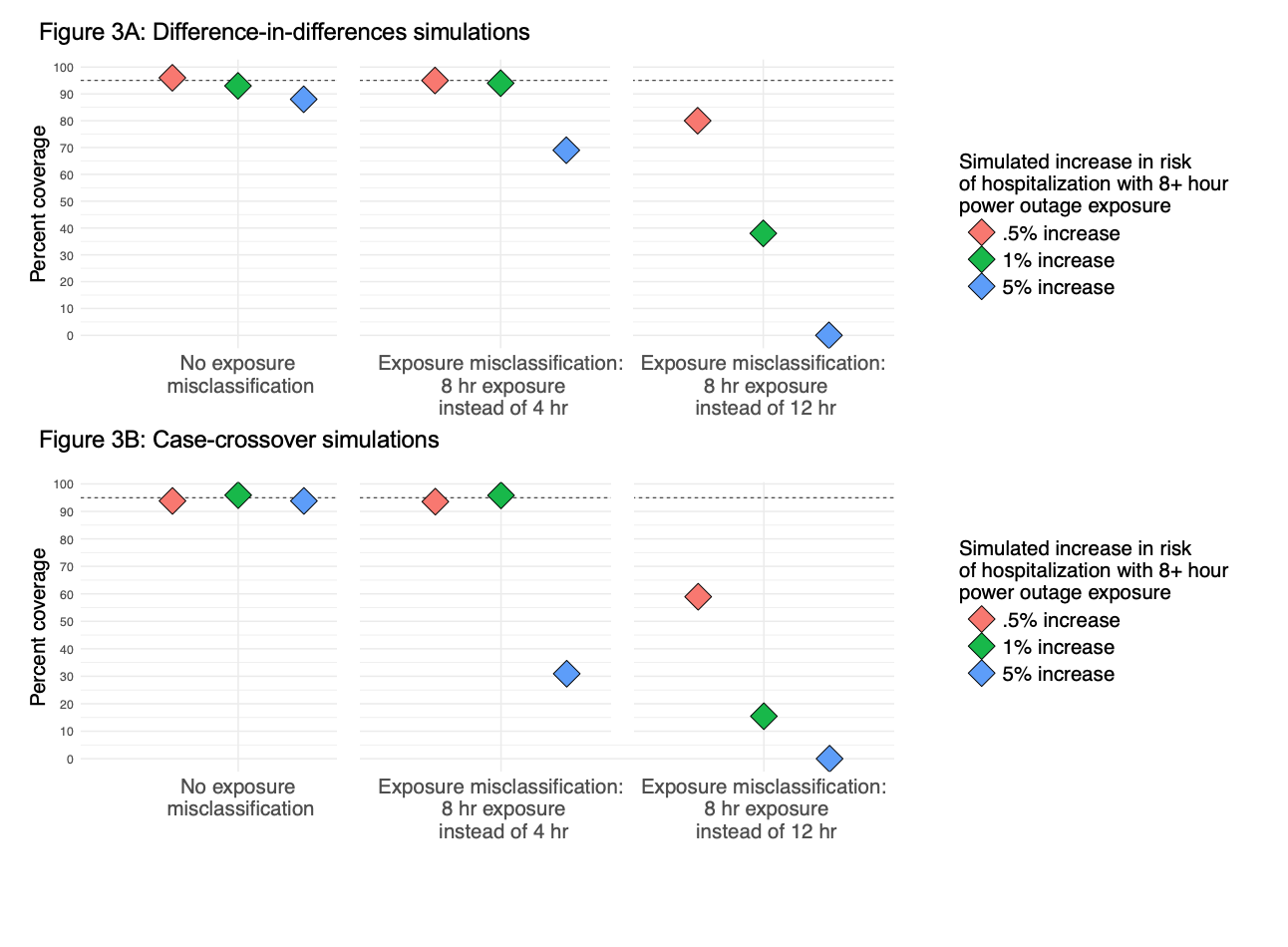
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**Figures:**

**Figure 1**: Example of data summarization process to identify if a county-day is exposed to power outage. In this example, county *i* has 1000 customers. The leftmost plot shows counts of customers without power in county *i* for each hour of the day in question. The dashed line on the leftmost plot represents *k*,the cut point after which an hour is considered exposed to power outage (10% in this case, or 100 customers).

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**Figure 2**: Simulation results from scenarios modeling incorrect assumptions about health-relevant duration. Boxplots show the distribution of the percent bias of effect estimates in each simulation scenario, for simulations representing a study of daily county-level power outage exposure and daily county-level hospitalizations in 100 simulated US counties for 1 year. Simulations were repeated 100 times. Percent bias was calculated as *{*(*𝛽*ˆ−*𝛽) / 𝛽 } \* 100*. Figure 2A includes results from simulations using a difference-in-differences study design, while Figure 2B includes results from the case-crossover design. Colors correspond to the true simulated effect size, and the x-axis titles describe each simulation case. There is a dashed line at 0.

**Figure 3**: Simulation results. Plots describe the percent coverage of 95% confidence intervals in each simulation case. Coverage is calculated as the percentage of 95% confidence intervals including the true simulated effect estimate. Figure 3A includes results from simulations using a difference-in-differences study design, while Figure 3B includes results from the case-crossover design. Colors correspond to the true simulated effect size, and the x-axis titles describe each simulation case. There is a dashed line at 95%.



**Figure 4**: Simulation results from scenarios modeling missing exposure data. Boxplots show the distribution of the percent bias of effect estimates in each simulation scenario, for simulations representing a study of daily county-level power outage exposure and daily county-level hospitalizations in 100 simulated US counties for 1 year. Simulations were repeated 100 times. Percent bias was calculated as *{*(*𝛽*ˆ−*𝛽) / 𝛽 } \* 100*. Figure 4 includes results from simulations using a difference-in-differences study design. Results from case-crossover design are similar and are included in the supplement. Colors correspond to the true simulated effect size, and the x-axis titles describe each simulation case. There is a dashed line at 0. Results in column 3 correspond to **Table 2**.

**Figure 5**: Simulation results. Plots describe the percent coverage of 95% confidence intervals in each simulation case. Coverage is calculated as the percentage of 95% confidence intervals including the true simulated effect estimate. Figure 5 includes results from simulations using a difference-in-differences study design. Results from case-crossover design are similar and are included in the supplement. Colors correspond to the true simulated effect size, and the x-axis titles describe each simulation case. There is a dashed line at 95%

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