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Severe Weather, Utility Spending, and the Long-term Reliability of the U.S. Power System

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Abstract:
There has been a limited amount of peer-reviewed literature on long-term trends in electricity reliability including the underlying factors that impact reliability across the United States. In this analysis, we considered up to 16 years of data from 203 U.S. utilities—representing about 70% of electricity sales. Annual frequency of interruptions for an average customer—at the regional and U.S. national-level—has generally decreased over this timeframe. But we do not find that there is a statistically significant trend in the annual duration of interruptions for an average customer. We find that more explicit measures of severe weather are correlated with reliability. We are able to explain 7% and 16% of past variation in the reliability metrics system average interruption duration and frequency indices, respectively, is due to severe weather—a significant improvement over earlier studies. We find that current year spending by utilities is correlated with worse reliability and that cumulative spending over the preceding three years is correlated with better reliability. Finally, we demonstrate that using a statistical instrument to represent the annual frequency of interruptions for an average customer can greatly improve analysis of trends in the annual duration of interruptions for an average customer.

1. Introduction

Power interruptions are caused by a number of different factors including weather-related impacts, electrical equipment faults or failure, and, indirectly, spending strategies on power system infrastructure, operations, and maintenance. The U.S. Department of Energy (DOE) reports that extreme weather is the most commonly-reported cause of power interruptions with the frequency of these extreme events increasing significantly over the last two decades [1]. Power interruptions significantly impact economic activity. A recent study estimates that sustained power interruptions cost an average of $44 billion annually in the U.S. alone [2].

The 2017 Atlantic hurricane season is just one example of recent extreme weather that has caused long duration, widespread power interruptions. During this season, six hurricanes were classified as "major" (i.e., Saffir-Simpson Category three storms or higher). For perspective, the long-term average number of major hurricanes since 1851 is six per decade [3]. In August 2017, Hurricane Harvey flooded many parts of Texas and Louisiana where some locations received as much as five feet of rain, resulting in power interruptions that impacted more than 330,000 customers [4]. During this storm, substations were flooded, utility poles were toppled, and there was extensive damage to other critical energy and electricity infrastructure [5, 6]. The following month, Hurricane Irma caused widespread damage to the Florida Keys and resulted in power interruptions for nearly two million customers [7]. Less than a week later, Hurricane Maria—the second category five storm of the season—caused widespread devastation across the U.S. territory of Puerto Rico. This storm destroyed the island's electric power grid—nearly all of the island's 1.5 million customers were without power for months [8].

Not all interruptions are associated with storms. In March 2019, Venezuela experienced widespread and sporadic blackouts affecting tens of millions of people lasting days or weeks possibly due to a poorly maintained infrastructure or political sabotage [9]. In July 2019, a blackout in New York City interrupted electricity to 73,000 customers and was caused by equipment failure at a substation [10, 11]. And in what may be the first publicly-known, successful cyber-attack on an electric utility, over 200,000 customers in Ukraine lost power for up to six hours in December 2015 due to malware that infected a local energy company [12].

To this end, Lawrence Berkeley National Laboratory (LBNL) has conducted a number of studies to better understand the economic value of investments in reliability [13], current practices related to utility-reported reliability data [14], and overall trends in U.S. electricity reliability [15]. Most recently, Larsen et al. [16] evaluated the reliability of the U.S. power system—including the factors impacting reliability—using up to 13 years of data from 195 utilities located across the country. The analysis that follows is an update to the Larsen et al. [16] study by extending the timeframe of analysis and the number of utilities evaluated. More specifically, this work seeks to answer the following questions:

- Has regional or national power system reliability improved over the last 16 years?
- Are more explicit measures of severe weather activity correlated with long-term reliability? If so, how much of the past variation in U.S. power system reliability can be explained by severe weather?
- Is there a statistically significant correlation between previous and/or current year utility spending and electricity reliability?

The remainder of this paper is structured as follows. In section two, we provide background on recent literature and motivation for this paper. We describe data sources in section three and the econometric modeling framework is introduced in section four. In section five, we discuss key findings and section six concludes.

2. Motivation and Background

A number of factors motivated this update to the Larsen et al. 2016 study [16]. First, severe weather is the most common cause of power interruptions [17] and the 2017 Atlantic hurricane season is just one example of the enormous impact severe weather can have on the electric power system. Abi-Samra et al. [18] highlight a series of international extreme weather events and the significant impacts to the electric power grid. Santagata et al. [19] explored the link between extreme temperatures and disastrous power outages in Buenos Aires over a period of four decades and found increased vulnerability of the power system to heat waves compared to cold waves. Fant et al. [20] evaluate the impact of climate change on transmission and distribution infrastructure costs, but do not account for downstream reliability impacts to customers. Our earlier study took initial steps to explore how annual measures of severe weather, including “abnormal” temperature, number of lightning strikes and wind speeds, impact power system reliability. However, our findings—and subsequent research by Larsen et al. [16]—suggested that more granular measures of severe weather are needed to improve large-scale (e.g., national) models of power system reliability.

Larsen et al.'s 2016 paper [16] also highlighted the importance of exploring the statistical relationship between utility spending and changes in reliability, including operations and maintenance (O&M) and capital expenditures. Recent reports have indicated that utility spending does appear to be increasing over time—a trend that is expected to result in improved reliability. A recent study by Deloitte showed that transmission and distribution (T&D) capital expenditures have increased over the past decade, from $32 billion in 2008 to an estimated $47 billion in 2017 [21]. It was also noted that distribution system-related expenditures increased 42%—from $15.5 (2006) to $22 billion (2015). Information collected from FERC Form 1 highlights utility spending on poles, other power system infrastructure, and operations and maintenance activities. A private firm, DEFG, interviewed utility customers across the U.S. and released a study indicating that the majority (54%) of customers would opt to continue their current level of reliability instead of paying more for increased reliability [22]. This finding accentuates the challenges identified by some utilities, namely that they may have more difficulty justifying rate increases to address reliability concerns, in spite of assertions by certain parties that there is underinvestment in electricity system infrastructure. It is unclear on a national—or even regional—scale the impact of stagnant or reduced utility spending will have on power system reliability over the long-run. It is also important to note that there is a trade-off between having "perfect", or even improving, reliability and the costs that ratepayers are unwilling (or unable) to bear.

To date, there has been a limited amount of peer-reviewed literature on long-term trends in electricity reliability. Hines et al. [23] assess historic trends in large blackouts, although this study relies on a North American Electric Reliability Council (NERC) data source that have been found to be inconsistent with comparable information reported to the U.S. Department of Energy [24, 25]. For example, nine disturbance events reported to DOE were not found in the NERC data in year 2009. There have been a number of studies published detailing the vulnerabilities and the resilience of events. Schaeffer et al. [26] provide an international perspective and review of studies on the vulnerability of energy systems to climate change, stressing the need for more research that consider a changing future climate instead of studies that rely on historic precedence. Larsen et al.'s 2018 paper [13] projected future costs to U.S. electric utility customers from power interruptions using regression results from previous research [16, 27]. The Larsen et al. 2018 study [13] highlighted a key shortcoming of the 2016 Larsen et al. [16] manuscript—that severe weather only explained ~6% of the variation in the frequency and total duration of past power interruptions for an average customer.

There are very few studies in the public domain that have evaluated past changes in reliability over time for a broad geographic area (i.e., regional- or national-level). The IEEE Distribution Reliability Working Group prepares an annual reliability benchmarking study [28]. The study collected and reported annual system average interruption duration index (SAIDI), system average annual interruption frequency index (SAIFI), and customer average interruption duration index (CAIDI) statistics from 93 load serving entities (LSEs)—representing nearly 90,000,000 customers. This study shows time trend graphics of the reliability metrics going back to 2005, however, the statistical significance of these trends has not been assessed. The Council of European Energy Regulators (CEER) *Benchmarking Report on the Quality of Electricity and Gas Supply* assessed electricity service availability for 28 European Union (EU) countries including Norway and Switzerland [29]. This work highlights the challenges—described by Eto and LaCommare [14]—when assessing reliability at geographic scales beyond the utility service territory. Often, different reporting entities use different metrics for reporting reliability information and even when the metrics are the same, the underlying assumptions used to estimate these metrics vary significantly [14]. For example, CEER [29] shows how different countries use different duration thresholds to define a short and long interruption and how different definitions of planned interruptions can lead to skewed exclusions of the underlying data. The threshold for a long interruption is three minutes in most European countries in the study and five minutes in the U.S. It was also shown how different countries define exceptional events differently, which is a finding consistent with Eto and LaCommare [14]. CEER [29] reports annual duration and frequency of power interruptions by country from 2002 to 2014 and includes a graphic showing a downward (i.e., improving) trend over time. However, as with the IEEE 2018 study [28], this study conducted no formal analysis to validate the statistical significance of this long-term trend.

A number of studies have described models for assessing power system reliability (or resilience) under different hypothetical scenarios. Ouyang and Duenas-Osorio [30] use a probabilistic modeling approach for quantifying resilience to hurricanes using a suite of models for assessing hazard, component vulnerability, power system performance, and restoration. The results show the impact that varying levels of changes to these various model parameters can have on average economic losses per year. Panteli et al. [31] present a probabilistic model considering component failures due to extreme weather, with a focus on wind events and their failure probabilities. Xu et al. [32] model real-time reliability as a characteristic of system health, thereby serving as an indicator of preventative maintenance and monitoring. Adoghe et al. [33] stress the importance of power system infrastructure maintenance decisions using electricity outage data from feeders and other components. Sultana et al. [34] review the vast body of research related to optimal power system network reconfigurations as a means of improving the overall reliability of power systems. Caswell et al. [35] evaluated techniques to account for the variability of distribution system reliability due to severe weather—including measures of lightning strikes and high wind speeds.

This work builds upon two foundational reports by Berkeley Lab that laid the groundwork for assessing trends in electricity reliability across the United States. In 2012, Eto et al. [15] collected publicly-available data from over 155 utilities—representing 50% of U.S. electricity sales—and spanning up to 10 years. To the best of our knowledge, this was the first study of reliability trends of the U.S., and was informative also in that it considered power interruptions affecting customers that originated from both the distribution as well as the bulk power system. Eto et al. [15] found a modest yet statistically significant decrease in reliability at a rate of ~2% annually. They also found that installation of an OMS was correlated with a decrease in reliability, at least initially, and speculated that this was the result of reporting on interruptions becoming more accurate due to installation of an OMS. One notable shortcoming of this study was that the researchers were unable to explain what was driving this trend and further research was suggested.

Larsen et al. [16] expanded the Eto et al. [15] dataset to include 195 utilities—representing ~70% of U.S. electricity sales—covering up to 13 years of reliability performance data. This follow-on study expanded the number of potential explanatory variables to include some basic annual severe weather metrics, utility characteristics, and transmission and distribution operations and maintenance spending. This analysis corroborated the finding in the 2012 study of a statistically significant trend of decreasing reliability. A subset of the study group which were historically represented within the IEEE annual benchmark study were found, however, to have a statistically significant improvement in reliability suggesting a bi-modal population. It also extended the finding by suggesting that severe weather was the primary driver of this trend. This study also found a consistent and statistically significant correlation between lower reliability and abnormally windy years. Somewhat surprising, however, was the lack of a significant correlation between utility O&M spending and reliability. This unexpected result motivated us to further explore how current and previous year utility expenditures might be correlated with trends in long-term reliability. In this study, we expand the dataset once again—this time including 203 utilities with reliability performance metrics spanning up to 16 years.

3. Generalized Model and Data Sources

This section describes the general model framework and key data sources considered in this study.

3.1 Generalized Model

Following the lead of Eto et al. [15] and Larsen et al. [16], we evaluate the relationship between reliability and utility characteristics as well as severe weather-related explanatory variables using the following log-linear fixed effects specification:

$$\ln(Y_{it}) = \alpha + \sum_{d=1}^{N} \beta_d X_{itd} + \gamma year + u_i + \varepsilon_{it} \quad (1)$$

In this model, Y represents utility reliability expressed as SAIDI or SAIFI, with major events, indexed by *i* over utilities and *t* over year. *X* is a vector of *N* utility characteristics and weather-related variables unique to each utility and year; their effect on reliability is measured by the vector β. *u* represents the unobservable, time-invariant, utility-specific characteristics captured as fixed effects and ε is the error term. γ measures the change in reliability over time.

3.2 Summary of Key Data Considered

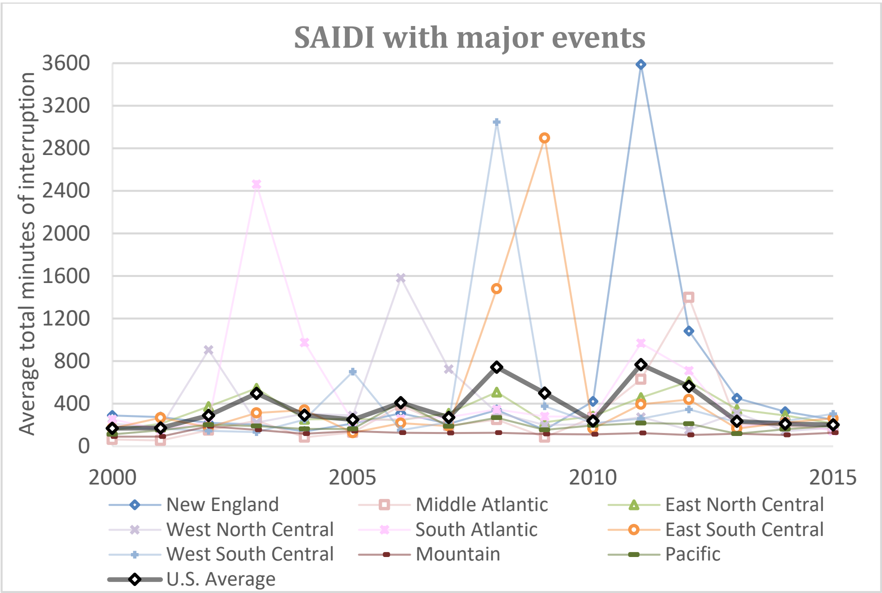
The data considered in this analysis largely follows earlier research by Larsen et al. [16]. However, key improvements involved adding: (1) three additional years of data (now through 2015); (2) more robust measures of extreme weather; and (3) additional details on annual utility capital and operations and maintenance spending. In this section, we categorize the input data into three broad data classifications—reliability metric information, utility characteristic information, and weather-related explanatory variables. Additional details about data sources can be found in the supplemental information to this paper [36-42].

3.3 Utility Reliability Metrics

The reliability data collected for this analysis include SAIDI and SAIFI. These two metrics represent two of the most commonly reported measures of reliability in the U.S. We collected data from four distinct metrics—SAIDI and SAIFI with and without major events included. SAIDI represents the number of minutes that the average customer is without power in a given year. SAIFI represents the number of sustained interruptions that the average customer experiences in a given year. Major events refer to instances when the utility experiences extreme stresses to its physical system, or, the ability to operationally respond to those stresses, representing infrequent occurrences that are often the result of severe weather. Please see IEEE Standard 1366 [43] for additional details on the formal definition of these metrics as well as the definition of major events.

The presentation in this paper focuses on analysis of SAIDI and SAIFI with major events included. Analysis of SAIDI and SAIFI with major events excluded is regularly practiced by utilities for direct comparison and evaluation of year-on-year trends in reliability because major events can vary greatly in number and severity from year to year. As a robustness check, we also evaluated trends in SAIDI and SAIFI without major events. Additional details are included as a supplement to this paper.

For this study, we collected reliability data from 203 utilities across the U.S. each representing up to 16 years of data following the same data collection approach described in Eto et al. [15] and Larsen et al. [16]. Figure 1 displays the annual customer-weighted averages of SAIDI and SAIFI with major events by Census division. The averages reported in Figure 1 are estimated by giving each utility a weight—expressed as the number of customers served—and then calculating the weighted average SAIDI (SAIFI) for each Census division and year. Weighting by the number of customers allows for a more accurate comparison of reliability metrics across regions as it prevents having a small utility serving a few thousand customers from having undue influence on the average for a region that may contain tens of millions of customers. It should be noted that the mix of utilities changes from year to year. By definition, when major events are included, both SAIDI and SAIFI are higher. We also expect and observe significantly more variance as the reported information reflects the inclusion of significant interruption events. Looking at SAIFI, at a regional level, the Middle Atlantic and Pacific regions appear to report consistently better reliability (lower values) when compared to other regions, while the West and East South Central regions show consistently worse reliability (higher values).



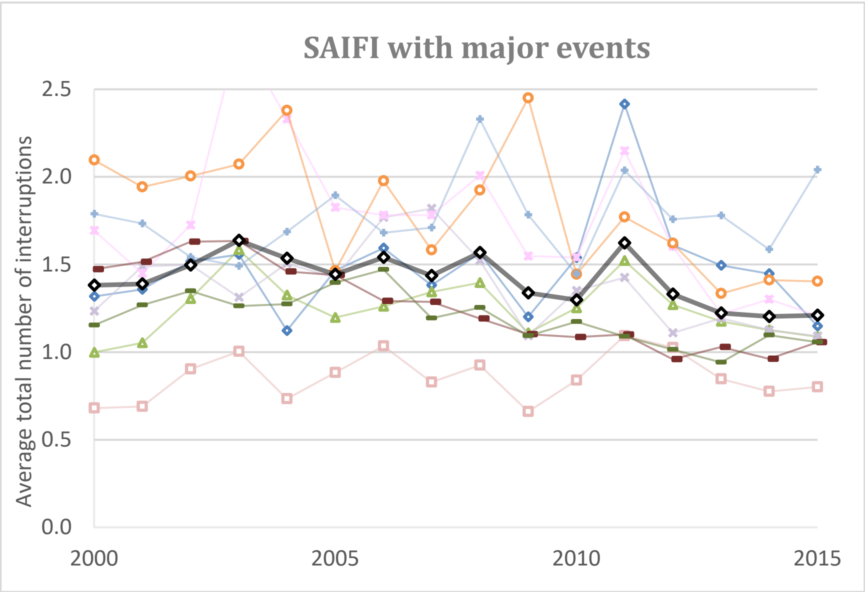


Figure 1. Annual customer-weighted average SAIDI and SAIFI with major events by U.S. Census region

3.4 Utility Characteristics

A number of utility-specific characteristics were considered as part of the econometric analysis that follows. Information for as many of the considered utilities and years were collected. Included in this sub-section is a description of the following parameters considered in the study:

- Year when the utility installed or upgraded its automated outage management system
- Annual retail electricity sales
- Total miles of distribution lines
- Annual utility expenditures on distribution
- Percentage share of the utility line miles that are underground

3.4.1 Outage management systems

Information on whether a utility had installed or upgraded an outage management systems was collected from state regulatory filings or directly from the utilities. Over the past few years, we have found that utilities have reported a significant increase in the adoption of automated detection systems or improved data capture and analysis within their distribution networks. For example, Eto et al. [15] found that 65% (100 out of 155 utilities) of utilities had installed an OMS. Larsen et al. [16] showed that this percentage increased to 75% (146 out of 195 utilities). In this study, we find that the share of utilities using OMS has increased to 85% (172 out of 203 utilities), as shown in Table 1 below.

It is worth noting that the OMS parameter we use in this study has become less effective than it was when we originally began collecting this information over a decade ago when utilities were in the midst of installing an OMS they did not already own. Since that time, most utilities have installed some form of an OMS and capturing both the initial installation and subsequent upgrades during this time period has become challenging. As a result, this metric is more effective at capturing the initial installation or major upgrade of the OMS by a utility earlier in the analysis years than in more recent years. Furthermore, the presence of OMS may have more of an impact on the accuracy of reliability metrics and less of an impact on actual improvements in reliability metrics like SAIDI [44].

Table 1. Utilities reporting the installation or upgrade of OMS by U.S. census division

Census division	Number of utilities in this study	Number of utilities studied reporting the use of OMS	% share reporting OMS
New England	35	16	49%
Middle Atlantic	21	20	95%

Census division	Number of utilities in this study	Number of utilities studied reporting the use of OMS	% share reporting OMS
East North Central	30	28	93%
West North Central	18	18	100%
South Atlantic	21	21	100%
East South Central	13	13	100%
West South Central	32	26	78%
Mountain	15	12	80%
Pacific	18	18	100%
Total	**203**	**172**	**85%**

3.4.2 Retail electricity sales

We collected retail electricity sales information from U.S. Energy Information Administration (EIA) Form 861. Annual retail sales information was assembled by utility and by census region from 2000-2015 [37] and normalized by number of customers. Table 2 shows electricity retail sales by census region for first (2000) and last year (2015) in the analysis period. In general, electricity sales per customer has generally not grown significantly across this time period.

Table 2. Retail electricity sales per customer in years 2000 and 2015

Census division	Total sales per customer—2000 (MWh per customer)	Total sales per customer—2015 (MWh per customer)
New England	17.7	17.7
Middle Atlantic	16.8	20.8
East North Central	26.9	31.3
West North Central	28.4	29.4
South Atlantic	29.8	27.3
East South Central	37.8	40.2
West South Central	35.5	28.8
Mountain	27.2	29.1
Pacific	18.9	19.3
Total	**25.1**	**27.1**

3.4.3 Utility distribution lines

For the utilities in our sample, we consider both total annual distribution line miles and the percentage share of total line miles that are underground for each utility as potential explanatory variables. This data was originally collected via FERC Form 1 and the U.S. Department of Agriculture Rural Utilities Service Form 7 and compiled via the ABB Velocity Suite platform. For more information on these sources, please see Larsen et al. [16].

3.4.4 Utility capital and O&M expenditures on distribution systems

Larsen et al. [16] indicated the importance of "collect[ing] information on annual capital spending and extend[ing] the analysis to evaluate the relationship between annual O&M and capital spending and changes in reliability." Accordingly, we used FERC Form 1 data [39] and the U.S. Department of Agriculture Rural Utilities Form 7 data—via the ABB Velocity Suite platform [38, 39]—to consider the potential impact of distribution capital *and* operations and maintenance (O&M) spending information on reliability. It should be noted that electric utility O&M spending is closely regulated by public utility commissions and that capital spending is often allocated to a number of projects, which may extend beyond efforts to specifically address power system reliability (e.g., construction of a new corporate headquarters building) [44]. In addition, these sources do not explicitly identify proactive spending (e.g., undergrounding lines) to address potential reliability problems or reactive measures that address actual reliability problems (e.g., replacing damaged poles). We converted all historical spending data to real dollars using the Handy-Whitman index of utility construction costs, divided by 1,000 to simplify the numerical analysis. We normalized this metric by line miles to yield thousands of real dollars spent by utilities per line mile because total O&M spending is correlated with the overall number of line miles (new and existing) and capital spending, which is often associated with new line miles, can also be correlated with existing line miles especially in the case of upgrading existing lines or converting existing overhead lines to underground lines. The O&M expenditures include costs associated with maintain or operating the station equipment, power lines, transformers, meters as well as load dispatching and vegetation management, among others. Figure 2 shows the average annual distribution expenditures, both capital and O&M, per line mile by region for those utilities considered in this study, noting again that the mix (and count) of utilities changes from year to year. This figure shows that distribution spending per line mile is generally decreasing for this changing mix of utilities during the analysis period—an intermediate finding that is inconsistent with Deloitte [21].

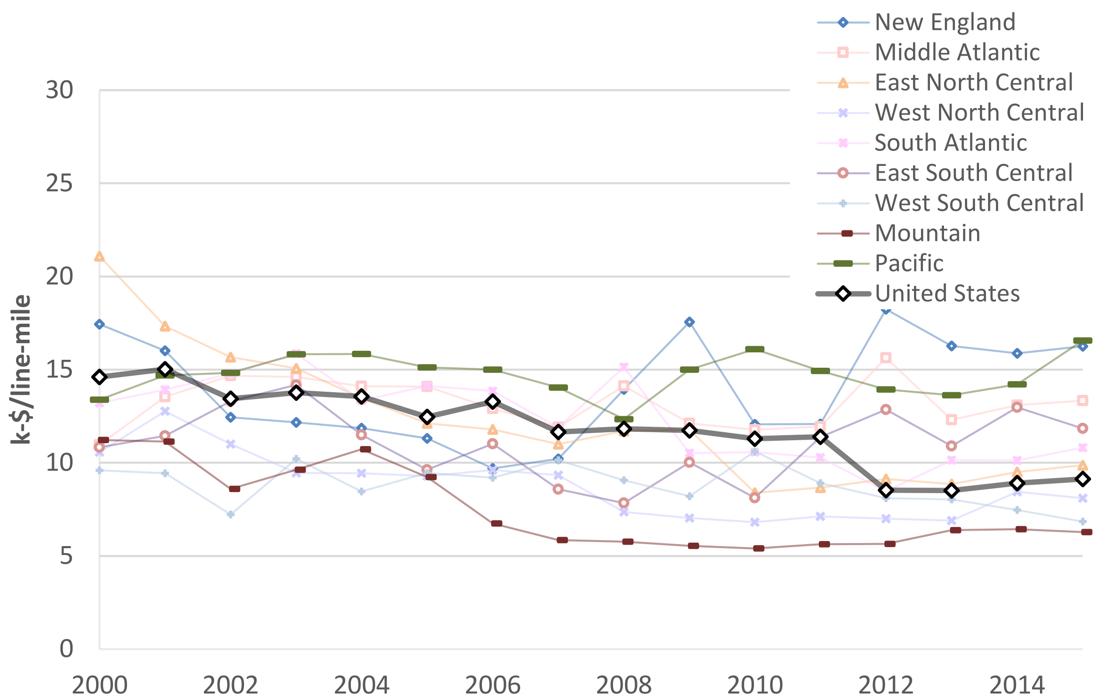


Figure 2. Annual average distribution expenditures per line mile by Census region

We hypothesize that a utility's expenditures on distribution, subject to current year budget constraints, is related to reliability in two ways: current year spending and cumulative spending in the preceding years. Current year expenditures, including immediate repairs of distribution equipment, occurs in response to a disruption; more disruptions in a given year will require more contemporaneous spending. Cumulative spending over the preceding three years, however, may involve preventative O&M practices and longer-term capital investments in distribution infrastructure, with the expectation that investments over multiple years will yield improved reliability over a longer term. It is plausible that more than three years may pass from the time that large-scale problems with reliability are identified; O&M budgets are proposed (approved); spending occurs; and reliability improvements can be measured [45]. As discussed later, utility case study-based research is needed to fully evaluate this cycle and properly account for it in long-term models of power system reliability. *CapDistExp* is annual utility-level capital expenditures on distribution systems, *OMDistExp* is annual utility-level operations and maintenance expenditures on distributions systems, *t* is year, and *i* denotes the utility. Cumulative spending is essentially the accumulation of distribution-level spending in the three years preceding the current reliability performance year, whereas current year spending is the spending observed in the current reliability performance year. We normalize both current year and cumulative spending by the number of line miles.

$$CurrentExp_{it} = CapDistExp_{it} + OMDistExp_{it} \quad (2)$$

$$CumulativeExp_{it} = \sum_{d=1}^{3} CapDistExp_{it-d} + \sum_{d=1}^{3} OMDistExp_{it-d} \quad (3)$$

3.5 Severe Weather-Related Metrics

Impacts from adverse weather are one of, it not the most, common cause of power interruptions [46, 47]. Researchers have explored the relationship of power interruptions (or system performance) to key weather metrics including wind gust speed, lightning, some combination of lightning and wind speed, precipitation, or temperature [35, 48-54]. It is clear that utilities are also interested in other environmental factors, which may lead to interruptions including the amount of vegetation near distribution lines [55]. For these reasons, both Eto et al. [15] and Larsen et al. [16] conducted a preliminary analysis of potential severe weather covariates to help explain trends in reliability. Larsen et al. [16] indicate that: "there may be additional (or alternative) annual weather parameters available that more accurately capture the impact of major events (e.g., number of days per year with wind speeds greater than 35 mph, significant drought years followed by abnormally wet years)." Consequently, we explore some alternative parameters that more closely represent influences of severe weather on electricity reliability. In addition to lightning strikes and temperature anomalies, we also include measures of wind exceeding a given threshold value (instead of a more general "abnormal" wind average), precipitation and snow accumulations greater than a given threshold (instead of deviations from a calculated average), and inclusion of a state-of-the-art metric that has been shown to capture severe storm potential (Cape x Shear)—a metric not previously considered. Due to resource and data availability constraints, we were unable to evaluate other potential explanatory factors which have been shown to cause power interruptions including, but not limited to: tree canopy density (or vegetation coverage more broadly), high moisture-content snow, icing conditions, and consecutive number of days of extreme weather metrics.

3.5.1 Lightning strikes

The lightning data used in this study is from the Vaisala National Lightning Detection Network (NLDN) [40]. We used the latitude and longitude for each strike and the utility service territory boundaries available in the ABB Velocity Suite platform to map each recorded lightning strike to each utility in our dataset. Utility lightning strikes were then aggregated to an annual total for the years 2000-2015.

3.5.2 Extreme precipitation

We used daily precipitation data collected by the National Oceanic & Atmospheric Administration's National Environmental Information Center and processed via the ABB Velocity Suite platform. ABB staff compiled the daily precipitation data (in inches) for each weather station within each utility service territory for each year of the analysis period. For each weather station, ABB staff summed the total number of days each year when rainfall was greater than two inches in a 24-hour period (and when snowfall was greater than 6 inches per day). Finally, ABB staff calculated the average total number of days with rainfall (snowfall) greater than two (six) inches using all of the weather stations within a service territory. This two (six) inch rainfall (snowfall) per day threshold was identified as a common extreme rainfall (snowfall) threshold by the National Weather Service [56]. Multiple stations within a service territory were averaged. If no weather station was located within a service territory, then the nearest station outside of the service territory was used.

3.5.3 High winds

We also used daily three-second peak wind speed data collected by the National Oceanic & Atmospheric Administration's National Environmental Information Center and processed via the ABB Velocity Suite platform. For every weather station in the U.S., ABB staff counted the number of days in each year where the daily three-second peak wind speed exceeded some threshold in miles per hour. We selected a 40 mph peak wind speed threshold based on an assessment conducted by National Weather Service branches from across the U.S. that routinely issue high wind warnings [56]. We used this refined severe weather metric to better explain the significant impact wind has on electricity reliability as documented in Larsen [27] and Larsen et al. [16], and a number of other studies. It is clear, however, that utility operations may be significantly impacted if peak wind speeds are lower than the 40 mph threshold used in this study, as other research suggests that power distribution system failure rates increase rapidly above approximately eight meters per second (or about 18 mph) [35, 52, 57].

3.5.4 Extreme temperature

Extreme hot or cold temperatures can permanently damage (or accelerate depreciation of) distribution system equipment resulting in power interruptions [58, 59]. For this reason, it is important to continue to explore the role that temperature has on electricity reliability trends. As in previous studies, we consider an annual measure of warm temperatures (cooling degree-days) and a measure of cold temperature (heating degree-days). This temperature information was collected by the National Oceanic & Atmospheric Administration's National Environmental Information Center and processed via the ABB

Velocity Suite platform. ABB staff calculated the average annual heating (cooling) degree-days using all of weather stations within each utility service territory. We develop annual proxies for abnormally warm (cold) temperatures by subtracting a utility's 16 year average HDDs (CDDs) from the annual HDD (CDD) and dividing it by the utility's 16 year average (see Larsen et al. [16] for more information on this technique).

3.5.5 Severe storm potential

For the first time, we also include a metric—herein referred to as CAPE x Shear—to capture the potential for severe storms. Seeley and Romps [60] indicate that "it has been recognized for quite some time that convective available potential energy (CAPE) and deep-layer wind shear—as well as other measures of wind shear, such as helicity—have skill in predicting the severity of thunderstorms in the case that such storms develop at all". Seeley [42] provided processed CAPE x Shear data from the NARR Reanalysis of NOAA SPC Archive. This annual mean product of CAPE and wind shear, which is in half-degree grid cells, was mapped to utility service territories and then averaged across these service territories to produce a single CAPE x Shear value for each utility and year.

4. Economic Analysis

We report the results from three models: 1) a basic time trend model to determine whether utility-level reliability is changing over time; 2) a model to identify the factors correlated with changes in SAIFI; and 3) a model to identify the factors correlated with changes in SAIDI. As noted in Section 3.3, all analyses were conducted using SAIDI and SAIFI with major events included. We also evaluated reliability trends and covariates using metrics not including major events and find that most of the models' predictive power decreases, particularly for SAIDI.

All models are weighted by the annual average number of customers for individual utilities from 2000 to 2015, inclusive. This transformation results in a model that represents the experience of reliability across the grid at the customer- rather than utility-level. In other words, the reliability of a utility with five million customers will have 1,000 times more influence on the model compared to a utility with only 5,000 customers. Weighted specifications improve model fit substantially for both SAIFI and SAIDI. For SAIFI, there is no change in coefficient signs and miles of distribution lines is significant in the unweighted specification. For SAIDI, signs also do not change. In the unweighted SAIDI model the estimates of two parameters change significance: lagged expenditures are not significant and the share of distribution lines that are underground is significant.

4.1 Time Trend Specification

We start with a simple regression model to assess whether, across utilities, there is a trend in reliability over time. This model does not identify the factors influencing reliability, only whether reliability is changing or not using the full sample of utilities. We use the following log-linear fixed effects specification to evaluate this time trend:

$$\ln(Y_{it})W_i = \alpha + \beta yearW_i + u_iW_i + \varepsilon_{it} \quad (4)$$

Reliability, represented by *Y*, is measured as the log of SAIDI or SAIFI, with major events. Subscript *i* represents individual utility and *t* indexes the year. *u* represents the unobservable, time-invariant, utility-specific characteristics captured as fixed effects. *Year* captures the utility characteristics, severe weather, and any other factors that may change over time across all utilities (e.g., interest rates) and *β* measures their effect on reliability. W_i is a vector of weights using a utility's average number of customers from year 2000 to 2015, inclusive.

4.2 Results and Preferred Model Selection

We estimate two types of models: a basic time trend analysis and explanatory variable analysis. We estimate the time trend models using Stata's -xtreg- procedure and the explanatory variable models using Stata's -xtivreg2- procedure [61]. The following section presents the results from both.

4.2.1 Basic time trend models

Table 3 shows the results from the simple time trend models of SAIFI and SAIDI for all regions pooled as well as by individual regions. The average utility had 10.5 years of reliability metrics in the panel dataset used to evaluate the time trends.

Nationally, and for every Census division except for West South Central, there is a statistically-significant decrease in SAIFI (i.e., improved). Across all utilities, there are, on average, 1.8% fewer interruptions for an average customer. The trend ranges from less than a 1% decrease in New England to more than a 4% decrease in the Mountain Census division. West South Central is the only region that has experienced a statistically significant increase in SAIFI, with 0.9% more interruptions per year for an average customer.

After pooling all regions, we do not find evidence for a decrease or increase in SAIDI. East South Central and Mountain have experienced statistically significant decreases in SAIDI of 6.6% and 1.3% per year, respectively. Customers in the West South Central division are experiencing—on average—6% increases in SAIDI. As with SAIFI, the West South Central part of the country is the only region experiencing statistically significant increases in SAIDI.

Table 3. Time Trends of SAIFI and SAIDI

	All Regions	East North Central	East South Central	Middle Atlantic	Mountain	New England	Pacific	South Atlantic	West North Central	West South Central
					SAIFI					
Year	-0.0180***	-0.0135***	-0.0316***	-0.00284	-0.0443***	-0.00705*	-0.0198***	-0.0223***	-0.0254***	0.00947*
Adjusted r-squared	0.109	0.087	0.160	0.003	0.495	0.010	0.196	0.113	0.147	0.023
					SAIDI					
Year	0.00394	0.00660	-0.0664**	0.0256	-0.0128**	0.00757	0.00595	-0.0127	-0.0241	0.0595***
Adjusted r-squared	0.001	0.003	0.058	0.019	0.045	0.002	0.003	0.005	0.023	0.184
Obs. (n)	1,663	252	118	86	142	352	220	215	111	167

Notes:

(1) *** represents coefficients that are statistically significant at the 1% level

(2) ** represents coefficients that are statistically significant at the 5% level

(3) * represents coefficients that are statistically significant at the 10% level

4.2.2 Explanatory variable models

To evaluate the relationships between severe weather variables, utility characteristics, and reliability measures, we compare the performance of models with a set of severe weather variables, then a set of utility characteristic variables, and then both included. We follow the same process outlined in Larsen et al. [16] to determine model preference based on performance, which considers fit statistics, parsimonious specification, and the consistency of parameter estimates across specifications.

Parameter estimates and model fit statistics for the models of SAIFI are reported in Table 4. Standard errors are clustered at the utility-level and all models include year. We developed a series of model specifications by grouping related explanatory variables such as weather or operating characteristics, evaluating the effect their inclusion has on model performance criteria.

Model A includes variables capturing extreme weather events: deviation from the average number of cooling degree days, the annual number of days with peak wind speed greater than 40 miles per hour, the number of days with rainfall exceeding two inches, and CAPE x Shear (i.e., storm potential). Abnormally warm weather was identified by Larsen et al. [16] as a significant determinant of reliability; the other variables are new measures of extreme events.

Model B includes only utility characteristics: thousands of miles of distribution lines, current year expenditures on distribution per line mile, the previous three years' expenditures on distribution per line mile, and percentage share of underground line miles.

Model C includes both severe weather and utility characteristics along with a dummy for the number years after the OMS was first installed.

Model D is identical to Model C, except it omits the dummy for OMS to evaluate how the correlation between OMS and year affects model performance.

Table 4. Models of SAIFI

Coefficients	**A**	**B**	**C**	**D (preferred)**
Year	-0.0247***	-0.0310***	-0.0265*	-0.0350***
Abnormally warm weather	0.00191***		0.00207***	0.00200***
# of days peak wind speed > 40 mph	0.00623***		0.00506**	0.00520***

Coefficients	A	B	C	D (preferred)
# of days rainfall > 2” per day	0.0307***		0.0274***	0.0276***
CAPE x Shear (storm potential)	6.13e-05***		5.49e-05*	5.69e-05*
Lightning strikes per line mile	0.00296***		0.0160	0.0131
Distribution line miles (thousands)		0.00274	0.00267	0.00249
% share line miles underground		-0.00473*	-0.00430**	-0.00426**
Distribution expenditures ($1,000 per line mile) (“Current year spending”)		0.0127***	0.0150***	0.0145***
Previous three years of distribution expenditures ($1,000 per line mile) (“Preceding years cumulative spending”)		-0.00330**	-0.00335**	-0.00312*
Years since OMS first installed			-0.00967	
Constant	49.49***	62.42***	52.98*	70.14***
Observations	1,180	634	610	610
R-squared	0.194	0.286	0.355	0.353
Count of utilities	114	86	82	82
Root mean square error (RMSE)	0.203	0.169	0.163	0.163
Bayesian Information Criterion (BIC)	-373.3	-427.2	-426.9	-431.6

Omitting the OMS dummy variable has little effect on model performance, but does affect the significance of the coefficient on year. This is unsurprising, given the close correlation between the two variables. It is not possible to disentangle the effects of the time trend and OMS dummy, so we omit this variable in our final model. Model D includes the share of distribution miles underground, which is associated with a small, but statistically significant decrease in SAIFI, slightly improved R^2, and somewhat less strong BIC. *Model D is the preferred model for SAIFI.*

The SAIDI model results are reported in Table 5. Our approach with SAIDI models mirrors our approach with SAIFI, using a model with just weather variables (A), just utility characteristics variables (B), and both weather and characteristics variables (C), and Model C without the OMS dummy (D). As with the SAIFI model, we evaluate the inclusion of OMS separately because it is collinear with year, affecting the model’s ability to estimate the effects of both variables separately.

We find that a utility that experiences higher SAIFI also tends to experience higher SAIDI and vice versa. Before an interruption of any duration can occur, the interruption must occur. To account for this inherent relationship between SAIFI and SAIDI, we developed a two-stage least squares model that uses instrumental variable of SAIFI as a predictor of SAIDI. Accordingly, for SAIDI, we also include a two-stage least squares (2SLS) approach using deviation from normal cooling degree days and year as instruments to allow us to include an instrument for SAIFI that is used as a predictor of SAIDI (E).

Like the SAIFI models, including both weather and operational characteristics improves model performance. Omitting the OMS dummy (Model D) has a large effect on the coefficient for year, little effect on the other parameter estimates, and little effect on overall model performance. *Among the single-stage models (A-D) of SAIDI, we prefer Model D*. Model E, using year and abnormally hot weather (cdd_pos_dev) as instruments for the natural log of SAIFI, has substantially improved model performance across all three metrics we evaluate: adjusted R^2, root mean square error, and the BIC. The magnitude and statistical significance of the second stage coefficients remain qualitatively unchanged.

Table 5. Models of SAIDI

Coefficients	**A**	**B**	**C**	**D (preferred)**	**E (2SLS)**
Year	-0.0173	0.0224	0.00758	-0.0425***	
Abnormally warm weather	0.00243		0.00140	0.00100	
# of days peak wind speed > 40 mph	0.0250***		0.0218***	0.0226***	0.0162***
# of days rainfall > 2” per day	0.0583**		0.0680**	0.0688**	0.0339
CAPE x Shear (storm potential)	0.000151**		0.000151	0.000159	6.37e-05
Lightning strikes per line mile	0.00804***		0.0351	0.0213	0.0176
Distribution line miles (thousands)		0.0144**	0.0155**	0.0146*	0.0119**
Distribution expenditures ($1,000 per line mile) (“Current year spending”)		0.0463***	0.0525***	0.0497***	0.0325***
Previous three years of distribution expenditures ($1,000 per line mile) (“Preceding three years cumulative spending”)		-0.0143***	-0.0117**	-0.0106**	-0.00774**
% share line miles underground		-0.00757	-0.00600	-0.00574	-0.000328
Years since OMS first installed		-0.0591**	-0.0562**		
SAIFI instrument (year, abnormally warm weather					1.263***
Constant	39.01*	-40.12	-11.54	88.73***	
Observations	1,171	628	605	605	603
R-squared	0.106	0.074	0.181	0.173	0.512
Count of utilities	114	86	82	82	80
RMSE	0.537	0.500	0.477	0.479	0.392

Coefficients	A	B	C	D (preferred)	E (2SLS)
BIC	1905	942.4	887	880.2	553.6

5. Key Findings

5.1 Has Regional or National Power System Reliability Improved Over the Last 16 Years?

The annual number of interruptions the average customer experiences (SAIFI) has decreased nationally and within most regions during the 2000-2015 study period (see Figure 3). Overall, we find that SAIFI has decreased by 1.8% per year during this period. This pattern holds in most regions, ranging from a 4.0% annual decrease in the Mountain region to a 0.7% annual decrease in New England. However, in the West South Central region, we find that the number of interruptions has increased by 0.1% per year for the average customer.

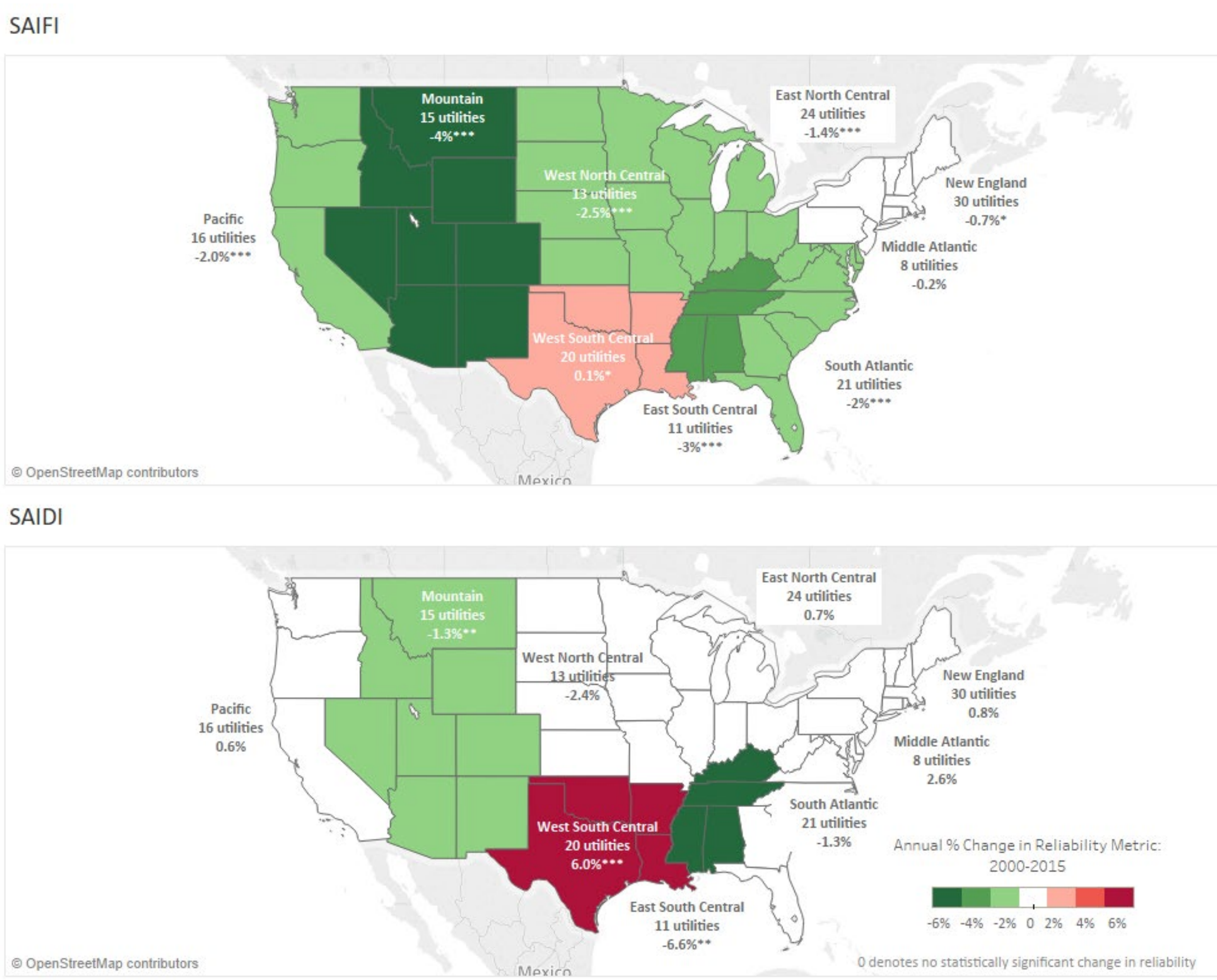


Figure 3. Average annual changes in reliability, 2000-2015 (top=SAIFI, bottom=SAIDI). Statistical significance of the coefficients is denoted by * (p<0.01), ** (0.01≤p≤0.05), or * (0.05≤p≤0.10).**

For the entire U.S., we do not find a statistically significant trend in the annual amount of time that an average customer is without power (SAIDI). Two regions have experienced consistently lower trends in SAIDI over time: In the East South Central region SAIDI averages 6.6% lower per year and in the Mountain region it is 1.3% lower per year. In the West South Central region, however, SAIDI has increased by ~6.0% annually.

5.2 Are More Explicit Measures of Severe Weather Activity Correlated with Long-Term Reliability? How Much of the Past Variation in Reliability Can be Explained by Severe Weather?

We find that SAIFI is strongly correlated with abnormally hot, windy, and high precipitation weather, and somewhat less strongly correlated with the high storm potential variable (CAPE x Shear). SAIDI, on the other hand, is strongly correlated with high wind speeds, but no other severe weather metrics. Increased lightning strikes are correlated with lower SAIDI. This finding is counterintuitive. We suspect it may indicate that lightning strikes are correlated with an unobserved variable correlated with shorter interruptions. But, we believe it also may be attributable to the aggregation of data over a year, which obscures the direct relationship between a specific storm (or major event) and reliability. Further research is necessary to better understand this counter-intuitive result.

Model performance measures indicate the weather variables included in these models more effectively capture the correlations between extreme weather and reliability than previous Berkeley Lab studies that evaluated reliability with major events included. Using methods outlined in Larsen et al [16], we find that extreme weather accounts for 16% of variation in SAIFI and 7% of variation in SAIDI. This is a substantial improvement compared to our previous national, econometric models of power system reliability. It suggests that measures of extreme events more accurately capture the relationship between weather and reliability than annual deviation from norms, which is what we used in our previous studies [15, 16]. In other words, because the older covariates we used are aggregated both over an entire service territory and over the entire year, they do not adequately capture the reliability impacts associated with individual extreme weather events at a particular locations and times within the year. The large year-to-year variations in reliability shown in Figure 3 are symptomatic of this issue.

5.3 Is there a Statistically Significant Correlation between Previous and/or Current Year Utility Spending and Electricity Reliability?

We find that distribution-related expenditures are higher in years with lower reliability, both in terms of SAIFI and SAIDI. We hypothesize that this correlation is due to current year spending as utilities respond to immediate repair and maintenance needs. The magnitude of the correlation is very similar for both SAIFI and SAIDI: for every additional $1,000 spent per line mile in a particular year, SAIFI is 1.5% higher and SAIDI is 3.3% to 5.0% higher in that same year.

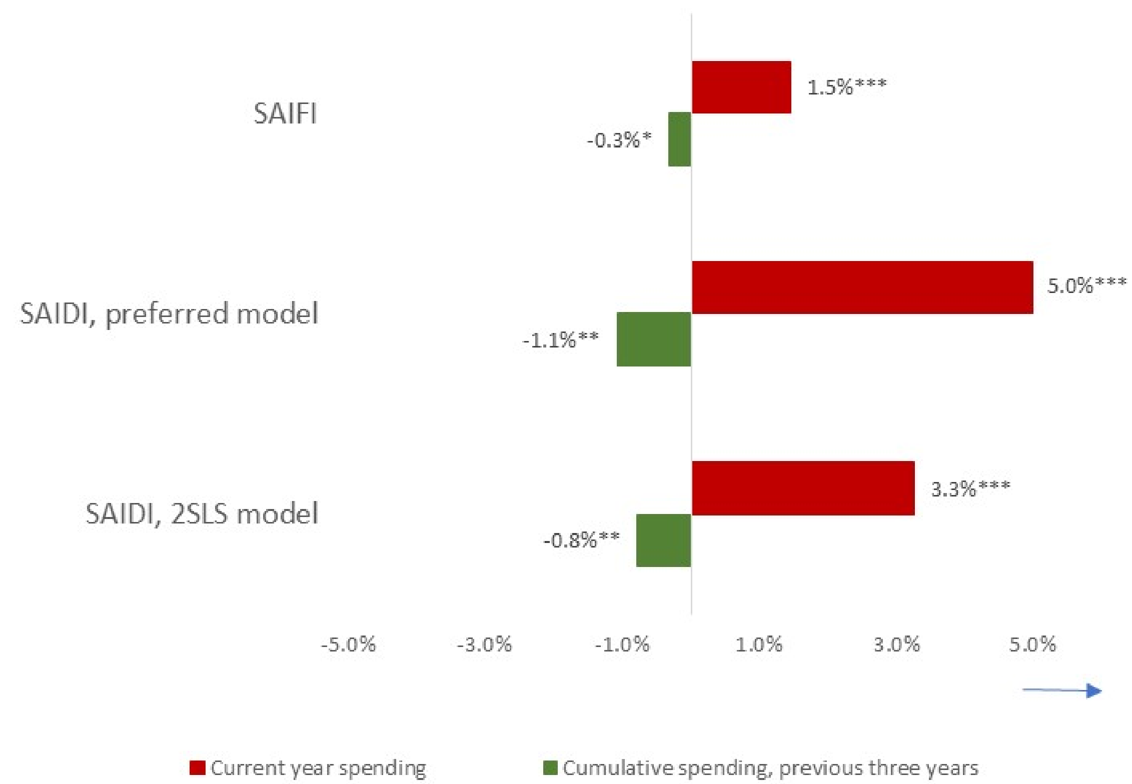


Figure 4. The relationship between cumulative spending over the previous three years and current year spending and reliability. Statistical significance of the coefficients is denoted by * (p<0.01), ** (0.01≤p≤0.05), or * (0.05≤p≤0.10).**

Cumulative spending over the previous three years on distribution systems is correlated with statistically significant reductions in SAIDI ranging from -0.8% to -1.1% as shown in Figure 4. A similar correlation is not found for SAIFI. Instead, we find only a marginally statistically significant correlation between previous years' spending on distribution and SAIFI (0.3% decrease for every $1,000 spent per line mile).

To begin teasing out whether there are differences in effects of capital versus O&M spending, we calculated the correlations between SAIDI and SAIFI, and capital and O&M spending. We find statistically significant negative correlations between capital spending and SAIDI and SAIFI in the same year, strongly so for SAIDI and marginally so for SAIFI. We find a marginally significant positive correlation between SAIFI and same year O&M spending and no correlation between SAIDI and same year O&M spending.

These findings suggest that longer-term, ongoing spending on distribution lines may be correlated with reductions in the average total duration of interruptions (SAIDI), but are not correlated whether or not interruptions occur in the first place. The three previous years' spending does not necessarily reflect how quickly utilities invest in reliability-improving technologies after a major event. Additionally, the timing of disaster response funds affect when utilities make capital investments and O&M spending, further complicating the temporal relationship between spending and reliability.

5.4 SAIFI is Strongly Correlated with SAIDI

This analysis finds that these two measures of reliability, which before have been modeled independently, are closely and positively correlated with one another. We explored this relationship because it is possible that reductions in SAIFI might be correlated with *increases* in SAIDI. For example, investments in underground electricity infrastructure might generally lead to a lower frequency of interruptions, but repairing underground lines might take more time than repairing overhead lines (i.e., in this example, the relationship between SAIFI and SAIDI would be negative). Bouford [45] suggested another example where utilities—possibly at the direction of local policymakers—spend more resources to reduce interruptions in densely-populated areas. In these types of locations, fault detection and repair may be faster in comparison to sparsely-populated, rural customers who continue to experience longer interruptions. In this specific example, SAIFI may improve while SAIDI may worsen.

To account for this relationship between SAIFI and SAIDI, the two-stage least squares (2SLS) model uses SAIFI as a predictor of SAIDI. The two-stage model is a novel strategy to link these two reliability measures statistically and provides an opportunity to evaluate their interdependence. The two-stage model provides strong evidence that SAIFI is one of the larger and more significant factors correlated with SAIDI. A 1% increase in SAIFI is correlated with a 1.3% increase in SAIDI (i.e., a positive relationship between the two). Specification tests conducted support the hypothesis that SAIFI drives SAIDI, and not vice versa.

5.5 Percentage Share of Underground Line Miles is Correlated with Lower SAIFI, but Inconclusive Relationship with SAIDI

This analysis finds that higher shares of underground line miles are correlated with lower SAIFI—or less frequent interruptions over the course of a year for an average customer. But we found an inconclusive relationship between SAIDI—the total amount of time that an average customer is without power over the course of a year—and the share of underground line miles.

6. Concluding Discussion

Table E-1 in the supplemental information includes the covariates used in earlier studies, the sign of the covariate coefficients, the overall fit of each model, and whether or not each covariate was statistically significant. This comparison allows us to confirm that more sophisticated measures of extreme weather (e.g., number of days with peak wind speed > 40 mph) increases the explanatory power of models when compared to less sophisticated extreme weather measures (e.g., % above annual average wind speed). In addition, this type of econometric modeling is able to consistently identify long-term trends in annual power system reliability. Interestingly, earlier studies, which were based on a shorter timeframe and smaller number of utilities, showed that U.S. power system reliability was getting worse over time [15, 16]. In this study, however, we find that reliability—when measured in terms of the average annual frequency of interruptions—has improved for customers at the regional and U.S. national-level. We also find no statistically significant trend in the annual duration of interruptions at the regional or U.S. national-level. We find that a statistically significant positive correlation between SAIFI and SAIDI and, further, we developed a two-stage least squares model that uses instrumental variable of SAIFI as a predictor of SAIDI. Interestingly, many of the technologies employed by utilities (e.g., AMI; OMS; Fault Location, Isolation, and Service Restoration—FLISR) primarily target decreasing the duration of interruptions once they have been detected. Our research support what many utility planners already know: "grid hardening" activities such as undergrounding lines, increasing the strength of distribution system poles, and aggressive vegetation management have important implications for both SAIFI *and* SAIDI. Future research should be directed to further evaluate how SAIFI affects SAIDI.

Using a smaller sample of utilities, we also find that measures of severe weather activity (e.g., annual number of days with wind speeds greater than 40 mph, annual number of days with rainfall greater than 2") are better correlated with long-term reliability than measures of weather based on annual averages. We are able explain 7% and 16% of past variation in the reliability metrics SAIDI and SAIFI, respectively, is due to severe weather—a significant improvement over earlier studies. More specifically, we find that SAIFI is strongly correlated with abnormally hot, windy, and high precipitation weather, and somewhat less strongly by the high storm potential variable (CAPE x Shear). SAIDI, on the other hand, is strongly correlated with high wind speeds, but not with other severe weather metrics that were considered in this study.

Coarse spatial and temporal data limits our ability to test our hypothesis that the majority of power system reliability is correlated with local severe weather and event-specific spending patterns. The “bottoms-up” modeling approach—as discussed here—could test this hypothesis. Due to resource constraints, we were unable to evaluate other temporally and geographically detailed explanatory factors which are known to affect power interruptions including, but not limited to: tree canopy density (or vegetation coverage more broadly), high moisture-content snow, icing conditions, more accurate lightning metrics [6, 46] and the presence of FLISR and other distribution automation technologies. For this reason, we suggest assembling recorded information on storms and other severe weather events from utilities and regulators; news media; and other sources. Reviewing various facets of these types of events, including restoration times, causal information, and the original condition of power system infrastructure could improve future model specifications and data sources. Alternative means of categorizing different types of utilities, such as retail sales divided by energy usage and percentages of customer classes served, could help understand reliability trends for different market segments.

We find that current year capital and O&M distribution system spending by utilities is correlated with lower current year reliability and that cumulative capital and O&M distribution spending—spending over the previous three years—is correlated with better reliability. This finding, in particular, provides further evidence for the important role that cumulative spending may play in influencing power system reliability. To better understand what types of spending are most effective, we recommend case study evaluations into utility O&M (e.g., spending specifically for vegetation management) as well as capital spending patterns that are directly relevant to reliability.

The novelty of this work can be expressed in the following ways: (1) it is the most comprehensive and statistically-rigorous analysis of reliability trends conducted in the U.S.; (2) it builds on earlier work by showing that metrics that better capture extreme events provide more explanatory power compared to earlier studies; and (3) it highlights the limitations with using annual data at the service territory-level—thus arguing for a new set of reliability performance metrics and explanatory variables that are more local in geographic scale and reported more frequently than at the annual-level. These lessons learned could be useful for researchers in other countries—as well policymakers/planners in the U.S. and abroad—as they begin to initiate similar analyses and/or require utilities to report more granular information.

This study seeks to update information on whether reliability—as experienced by the customer—is getting better or worse as well as the factors that are closely correlated with changes in reliability over time. There are, however, broader issues related to power system *resilience* that were not addressed in this study on power system reliability. Utility spending on investments in long-term resilience, including storm hardening activities that are more expansive than typical investments in reliability, is an emerging area of research. Although power system reliability appears to be improving—at an annual- and service territory-level—there are numerous examples of parts of power systems being without power for longer periods of time due to catastrophic weather (e.g., Hurricane Harvey, Hurricane Sandy). The impacts of these types of events on customers are not fully captured using annual, system-wide measures of reliability. Nonetheless, it is our hope that the findings from this study provide insights for policymakers, researchers, utility planners, and other stakeholders that will ultimately influence the future reliability of power systems in the U.S. and beyond.

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Supplemental Information

A.1 Summary of Key Data Considered

Table A-1 provides a summary of the data considered in this study, which is reported annually and at the service territory-level.

Table A-1. Summary of Data Considered for this Study

Description	Data Type	Unit	Source
SAIDI	Reliability metric	Average total minutes per year	Compiled in the LBNL Electric Reliability Metrics dataset [40]
SAIFI	Reliability metric	Average number of interruptions per year	Compiled in the LBNL Electric Reliability Metrics dataset [40]
Outage management system (OMS)	Utility characteristic	Annual indicator if OMS is present	Compiled in the LBNL Electric Reliability Metrics dataset [40]
Electricity retail sales	Utility characteristic	Megawatt hours	U.S. DOE/EIA Form 861 [41]
Distribution line miles	Utility characteristic	Line miles	FERC Form 1 and U.S Department of Agriculture Rural Utilities Form 7 via ABB Velocity Suite [42, 43]
Capital and O&M distribution expenditures per line mile	Utility characteristic	$1,000 per line mile	FERC Form 1 and U.S Department of Agriculture Rural Utilities Form 7 [42, 43]
Share of underground line miles to overhead line miles	Utility characteristic	Percentage of line miles undergrounded	FERC Form 1 and U.S Department of Agriculture Rural Utilities Form 7 via ABB Velocity Suite [42, 43]
Lightning strikes	Weather	Number of strikes within service per line mile	National Lightning Detection Network and processed by LBNL [44]
Precipitation	Weather	Annual number of days with more than 2 inches of rainfall in 24 hours	NOAA National Center for Environmental Information via ABB Velocity Suite [45]
Heating and cooling degree-days	Weather	Annual degree-days	NOAA National Center for Environmental Information via ABB Velocity Suite [45]

Description	Data Type	Unit	Source
Wind speed	Weather	Annual number of days with peak wind speed greater than 40 miles per hour	NOAA National Center for Environmental Information via ABB Velocity Suite [45]
Snowfall	Weather	Annual number of days with more than 6 inches of snow in 24 hours	NOAA National Center for Environmental Information via ABB Velocity Suite [45]
Mean sea level pressure	Weather	Annual number of days when mean sea level falls below 30 millibars	NOAA National Center for Environmental Information via ABB Velocity Suite [45]
CAPE x Shear	Weather	Amount of energy measured in Joules per kilogram of air (J kg−1)	Seeley [46]

B.1 Representativeness of Utilities Studied

The middle pie chart of Figure B-1 shows that 75% of the 203 utilities are investor-owned utilities (IOUs), with a significantly smaller share of information coming from electric utility cooperatives (Coop) (15%) and municipals (Muni) (8%). For comparison, IOUs, cooperatives, and municipals provide 87%, 1%, and 2%, respectively, of total U.S. electricity sales in 2015, as shown on the right side of Figure B-1.

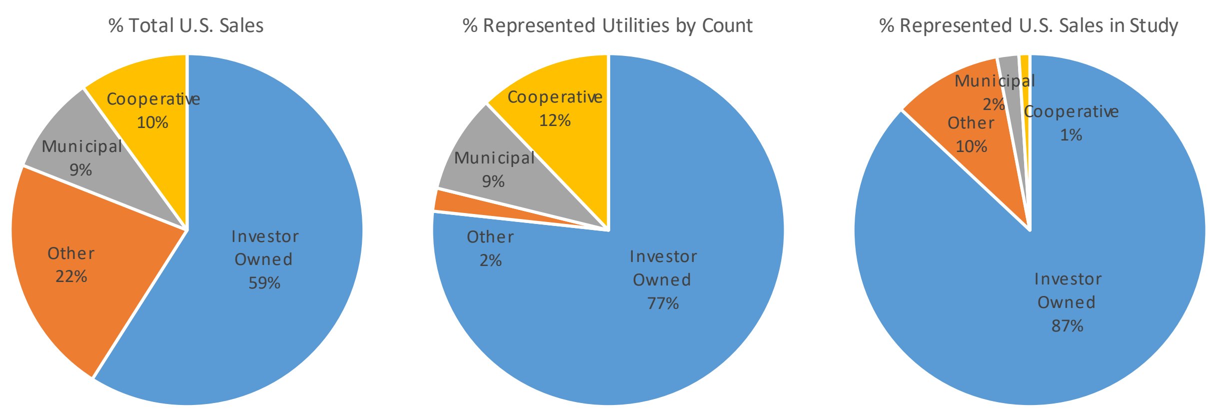

Figure B-1. Share of total U.S. sales (left), share of represented count (middle), and share of represented sales (right) by ownership type, year 2015

Figure B-2 is a map of the U.S. Census regions, including the represented share of U.S. regional electricity sales and the number of utilities we collected data for in each region. Table B-1 shows the total and sample of electricity sales by Census region. In general, we have a good representation of data across the U.S. with the exception of East South Central. In total, the collected utilities account for nearly 70% of total U.S. electricity sales (and 71% of U.S. electricity customers), which is similar to the overall coverage in Larsen et al.'s 2016 study [24].

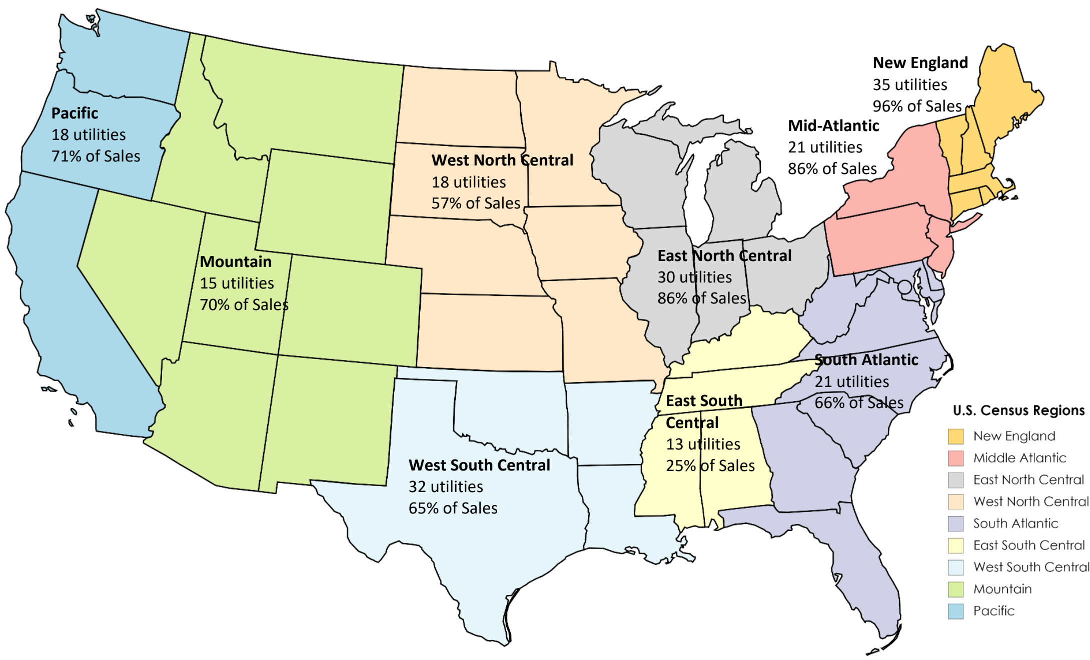

Figure B-2. Map of U.S. Census regions with share of represented sales

Table B-1. Representation of utilities by retail electricity sales by Census division

Census division	Represented electricity sales in study (TWh)	Total electricity retail sales in 2015 (TWh)	Percentage of region represented in study	Percentage of U.S. represented in study
New England	111.1	120.2	96%	3%
Middle Atlantic	317.1	370.7	86%	8%
East North Central	482.3	563.5	86%	13%
West North Central	168.7	294.8	57%	4%
South Atlantic	537.2	815.5	66%	14%

East South Central	79.2	313.2	25%	2%
West South Central	382.1	591.8	65%	10%
Mountain	193.7	275.0	70%	5%
Pacific	295.5	414.2	71%	8%
Total	2,570.7	3,759.0	68%	68%

C.1 Data Cleaning and Transformations

Following Larsen et al. [24], we investigated extreme outliers to determine if utilities may have incorrectly reported any of the reliability performance metrics. SAIDI and SAIFI values were flagged for further analysis as statistically extreme outliers if the reported value was less than the 1st percentile or greater than the 99th percentile value for that particular reliability metric. We replaced missing covariate values with utility-specific means[1]; and removed utilities with less than four years of consecutive and sporadic reporting, which caused the regression software to fail. We did not observe substantial changes in coefficient values when we did not replace missing values. The initial regression dataset contains 176 utilities spanning up to sixteen years (2000-2015). The preferred SAIFI and SAIDI models include 82 utilities. The utilities included in the SAIFI model account for 49 percent of sales, on average, ranging from a low of 35 percent of sales in 2008 and a high of 65 percent of sales in 2015. Across regions, the Middle Atlantic utilities in the sample account for the smallest share of regional sales (21%) and the Pacific utilities included in the model account for the largest share of regional sales (75%). The average utility includes 8.6 years of data. Robustness checks found the parameter estimates did not meaningfully change when only utilities with at least twelve years of data were included. We used augmented Dickey-Fuller tests for the presence of unit roots in SAIFI and SAIDI and reject the null hypothesis that all panels contain unit roots.

D.1 Accounting for the Relationship between SAIDI and SAIFI

We conducted several tests to determine the appropriateness of using a 2SLS and the selection of the SAIFI instruments. The model passes tests of endogeneity, under-identification, and over-identification,

[1] Replacing missing values with utility-specific means for three covariates – share of miles underground, total distribution expenditures per mile, and number of customers – affected 68, 47, and 51 utilities, respectively. For utilities with missing records for the share of miles underground and total distribution expenditures per mile, an average of seven years of data were replaced. For utilities missing total customers, an average of two years of data were replaced.

providing support for using a 2SLS approach and the strength of our selected instruments, cdd_pos_dev and year. Although SAIFI is the single strongest predictor of SAIDI, it is endogenous to several other variables that explain SAIDI. Therefore, to include SAIFI as an explanatory variable, we need to create an instrument using variables that are statistically correlated with SAIFI, but not SAIDI. To meet these criteria, we use the following specification:

$$\ln(Y_{it})W_i = \alpha + \sum_{d=1}^{N} \beta_d X_{itd} W_i + \beta_3 \ln(\widehat{SAIFI}) W_i + u_i W_i + \varepsilon_{it} \tag{1}$$

where:

$$\ln(\widehat{SAIFI}) W_i = \alpha + \delta_1\, yearW_i + \delta_2\, cdd\_pos\_devW_i + u_i W_i + \varepsilon_{it} \tag{2}$$

In the first stage, we create an instrument for SAIFI using abnormally warm temperature and year. Next, we use the predictions of this instrumental variable as a covariate within the SAIDI regression. We carry out several tests to evaluate whether these assumptions hold.

Table D-1. Specification tests performed on the two-stage least squares model of SAIDI

	Test statistic	p-value	Null hypothesis	Conclusion
Endogeneity	7.639	0.0057	ln_saifi is exogenous	Reject null; cannot include SAIFI as regressor of SAIDI
Kleibergen-Paap LM	15.818	0.0004	Instruments are not strong predictors of ln_saifi (under-identification test)	Reject null; selected instruments are strong predictors of *ln_saifi*
Hansen J statistic	0.926	0.3358	Instruments are correlated with error term (over-identification test)	Cannot reject null; instruments are not correlated with other ln_saidi regressors

A test of the endogeneity of *ln(SAIFI)* to the other regressors in Model E rejects the null hypothesis that *ln(SAIFI)* is exogenous, providing support for creating instruments for *ln(SAIFI)* rather than including it directly into the model. According to the Kleibergen-Paap LM test for whether the instruments (*cdd_pos_dev* and *year*) are sufficiently correlated with *ln(SAIFI)*, we can reject the null that they are not strong predictors of the endogenous regressor. The Hansen J statistic s 0.926 (p-value=0.3358), so we cannot reject the null hypothesis that the instruments (*cdd_pos_dev* and *year)* are over-identified (i.e., correlated with the error term). In other words, the over-identification restrictions (the instruments are uncorrelated with the error term and are correctly excluded from the estimated regression) are appropriate and we have confidence that these are valid instruments.

The following figures present residual plots for the most preferred models for SAIFI and SAIDI.

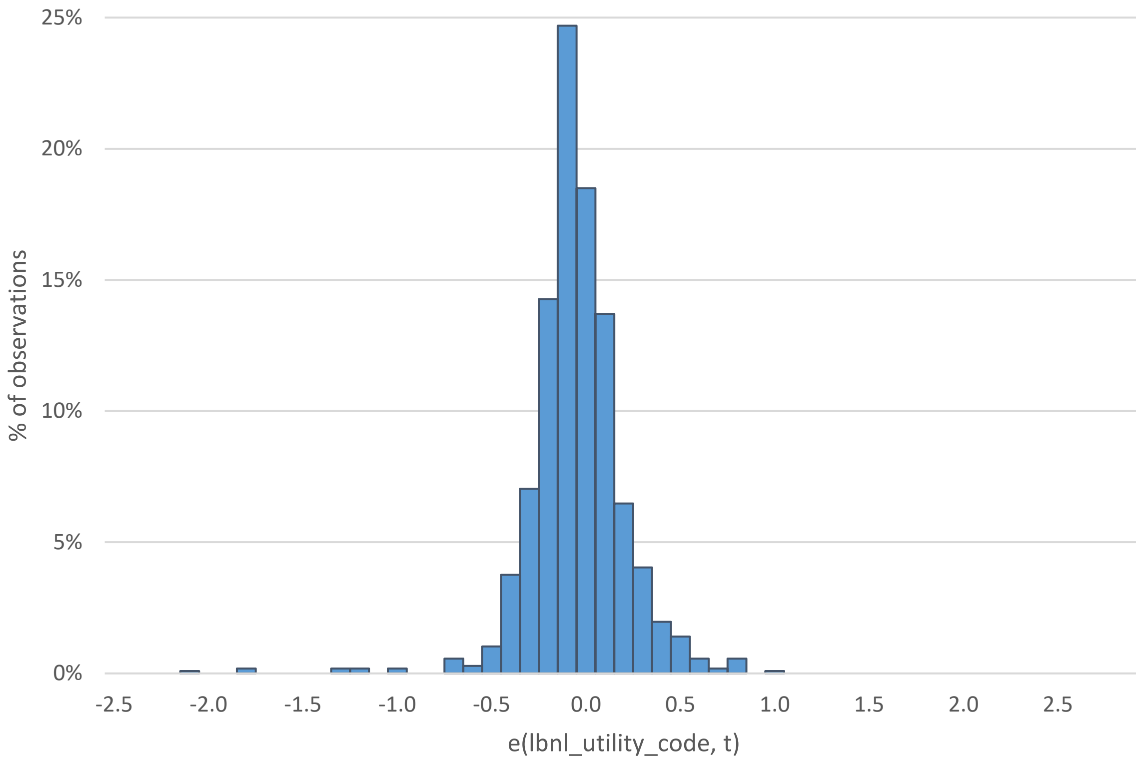

Figure D-1. Residual plot of most preferred SAIFI model with MEDs

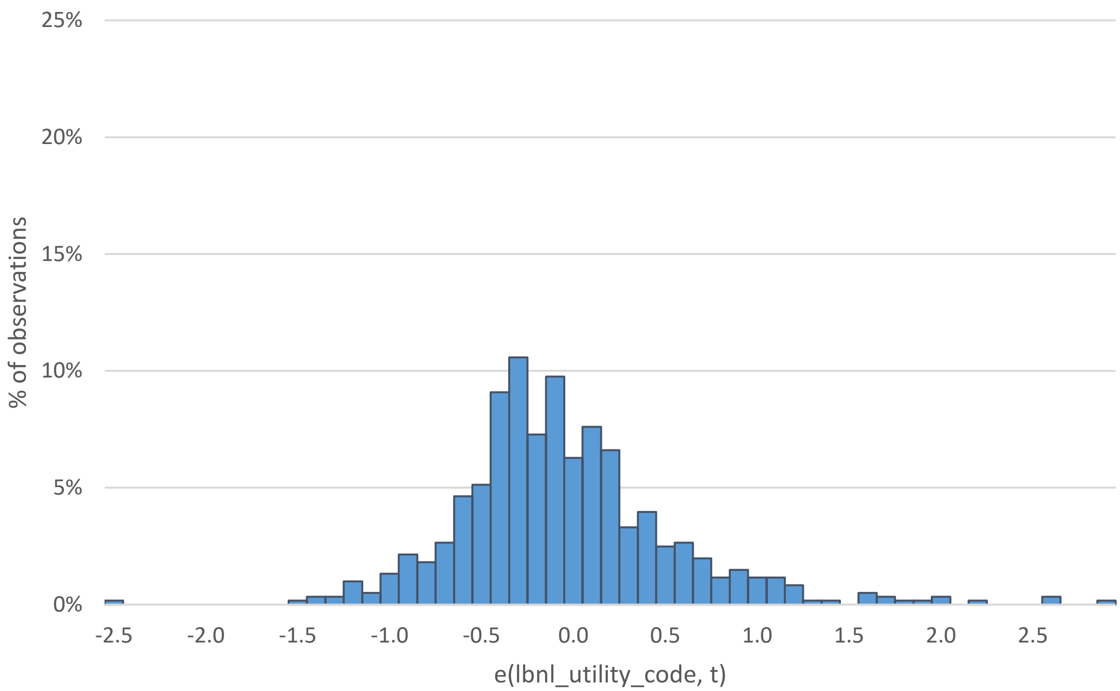

Figure D-2. Residual plot of most preferred single stage SAIDI model with MEDs

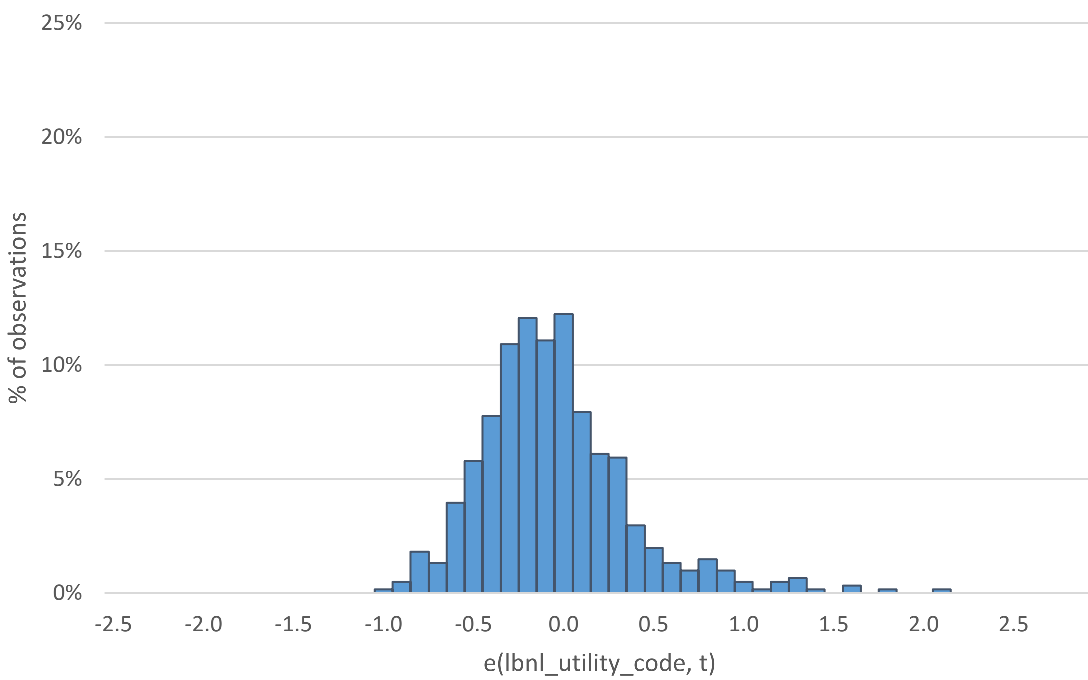

Figure D-3. Residual plot of most preferred two-stage SAIDI model with MEDs

The following two tables present the model results for SAIFI and SAIDI without major events included. In general, the predictive power of the models decreases when major events are not included. Perhaps most importantly, we found no statistically significant correlation between utility spending and improvements in utility reliability when major events are excluded.

For SAIFI when major events are not included, summarized in Table D-2 below, abnormally warm weather and lightning strikes remain strong predictors, and the size of the time trend is still significant, but of a smaller magnitude when compared to SAIFI with major events included.

Table D-2. Models of SAIFI without MEDs

Coefficients	**A**	**B**	**C**	**D**
Year	-0.0182***	-0.0199***	-0.0169***	-0.0200***
Abnormally warm weather	0.00130***		0.00117***	0.00114***
# of days peak wind speed > 40 mph	0.00233		0.00160	0.00171
# of days rainfall > 2" per day	0.0146***		0.00976	0.00968
CAPE x Shear (storm potential)	2.07e-05**		1.92e-05*	1.95e-05*
Lightning strikes per line mile	0.00110		0.0166**	0.0161**
Distribution line miles (thousands)				
% share line miles underground		-0.00259	-0.00250	-0.00247
Distribution expenditures ($1,000 per line mile) ("Current year spending")		-0.00115	-0.00217	-0.00236
Previous three years of distribution expenditures ($1,000 per line mile) ("Preceding years cumulative spending")		0.00141	0.000674	0.000773
Years since OMS first installed			-0.00396	
Constant	36.44***	40.04***	33.92***	40.28***
Observations	1,798	967	941	941
R-squared	0.180	0.270	0.284	0.283
Count of utilities	137	101	96	96
Root mean square error (RMSE)	0.157	0.132	0.131	0.131
Bayesian Information Criterion (BIC)	-1515	-1144	-1085	-1090

For SAIDI, the models' predictive power particularly diminishes.

Table D-3. Models of SAIDI without MEDs

Coefficients	**A**	**B**	**C**	**D**	**E (2SLS)**
Year	-0.00980*	-0.00888	-0.0130*	-0.0105	
Abnormally warm weather	0.00172***		0.000964	0.000992	
# of days peak wind speed > 40 mph	0.00805***		0.00596**	0.00584**	0.00563
# of days rainfall > 2" per day	0.0171*		0.0185**	0.0186**	0.0125*
CAPE x Shear (storm potential)	1.53e-05		1.47e-05	1.46e-05	2.63e-06
Lightning strikes per line mile	0.00145*		0.0170	0.0172	0.00957
Distribution line miles (thousands)		-0.000835	-0.00280	-0.00277	-0.00153
Distribution expenditures ($1,000 per line mile) ("Current year spending")		-0.00190	-0.00144	-0.00129	0.000984
Previous three years of distribution expenditures ($1,000 per line mile) ("Preceding three years cumulative spending")		0.000448	-0.000815	-0.000871	-0.00199
% share line miles underground		-0.00344	-0.00323	-0.00324	-0.00190
Years since OMS first installed		-0.00280	0.00323		
SAIFI instrument (year, abnormally warm weather					0.547
Constant	24.17**	22.69	30.95**	25.87	
Observations	1,829	966	940	940	931
R-squared	0.051	0.047	0.073	0.073	0.340
Count of utilities	137	101	96	96	96
RMSE	0.228	0.218	0.209	0.208	0.185
BIC	-183	-168.3	-216.6	-223.1	-538.9

E.1 Comparison of past studies to current study

Table E-1. Comparison of past studies to current study with all models including major event days

Study:	Eto et al. (2012)		Larsen et al. (2016)		Current Study		
Metric:	**SAIFI**	**SAIDI**	**SAIFI**	**SAIDI**	**SAIFI**	**SAIDI**	**SAIDI (2SLS)**
Intercept	−	−	−	−	+	+	
Electricity delivered (MWh per customer)	−	−	−	+			
Heating degree-days (#)	−	−	N/A	N/A			
Cooling degree-days (#)	+	+			N/A	N/A	
Outage management system?	−	+	−	+			
Years since outage management system installation	−	−	+	−			
Year	+	+	+	+	−	−	
Abnormally cold weather (% above average HDDs)			+	+	N/A	N/A	N/A
Abnormally warm weather (% above average CDDs)			+	−	+	+	
Abnormally high # of lightning strikes (% above average strikes)			+	+			
Abnormally windy (% above average wind speed)	N/A		+	+			
Abnormally wet (% above average total precipitation)			+	+	N/A	N/A	
Abnormally dry (% below average total precipitation)		N/A	+	+			
Abnormally windy squared			−	−			

Study:	Eto et al. (2012)		Larsen et al. (2016)		Current Study		
Metric:	**SAIFI**	**SAIDI**	**SAIFI**	**SAIDI**	**SAIFI**	**SAIDI**	**SAIDI (2SLS)**
Lagged T&D expenditures ($2012 per customer)			−	+			
Number of customers per line mile			+	+			
Share of underground T&D miles to total T&D miles			−	−	−	−	−
# of days peak wind speed > 40 mph					+	+	+
# of days rainfall > 2” per day					+	+	+
CAPE x Shear (storm potential)					+	+	+
Lightning strikes per line mile					+	+	+
Distribution line miles (thousands)			N/A	N/A	+	+	+
Distribution expenditures ($1,000 per line mile) (“Current year spending”)					+	+	+
Previous three years of distribution expenditures ($1,000 per line mile) (“Preceding years cumulative spending”)					−	−	−
SAIFI instrument (year, abnormally warm weather)					N/A	N/A	+
Period of analysis	2000-2009	2000-2009	2000-2012	2000-2012	2000-2015	2000-2015	2000-2015
R-squared (adjusted or generalized)	0.031	0.049	0.710	0.14	0.353	0.173	0.512

Notes: Shaded cells represent covariates that are significant at $p < 0.10$; + or – represent the sign of the covariate coefficient; 2SLS is two-stage least squares approach using deviation from normal cooling degree days and year as instrument for SAIFI; N/A is not applicable—covariate was not included in model