Recent Trends in Power System Reliability and Implications for Evaluating Future Investments in Resiliency

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Abstract

This study examines the relationship between annual changes in electricity reliability reported by a large cross-section of U.S. electricity distribution utilities over a period of 13 years and a broad set of potential explanatory variables, including weather and utility characteristics. We find statistically significant correlations between the average number of power interruptions experienced annually and above average wind speeds, precipitation, lightning strikes, and a measure of population density: customers per line mile. We also find significant relationships between the average number of minutes of power interruptions experienced and above average wind speeds, precipitation, cooling degree-days, and one strategy used to mitigate the impacts of severe weather: the amount of underground transmission and distribution line miles. Perhaps most importantly, we find a significant time trend of increasing annual average number of minutes of power interruptions over time—especially when interruptions associated with extreme weather are included. The research method described in this analysis can provide a basis for future efforts to project long-term trends in reliability and the associated benefits of strategies to improve grid resiliency to severe weather—both in the U.S. and abroad.

Keywords: electricity reliability, power interruptions, severe weather, major event, reliability metrics

1. Introduction

In the U.S. and abroad, recent catastrophic weather events; existing and prospective government energy and environmental policies; and growing investments in smart grid technologies have drawn renewed attention to ensure the reliability of the electric power system (Schaeffer et al., 2012; Blumsack and Fernandez, 2011). Over the past 15 years, the most well-publicized efforts to assess trends in electric power system reliability have focused only on a subset of all power interruption events (Amin, 2008; Campbell, 2012) —namely, the very largest events, which trigger immediate emergency reporting to federal agencies and industry regulators. Anecdotally, these events are believed to represent no more than 10% of the power interruptions experienced annually by electricity consumers. Moreover, a review of these emergency reports has identified shortcomings in relying upon these data as accurate sources for assessing trends, even for the reliability events they target (Fisher et al., 2012).

Recent work has begun to address these limitations by examining trends in reliability data collected annually by electricity distribution companies (Eto et al., 2012). In principle, all power interruptions experienced by electricity customers, regardless of size, are recorded by the distribution utility. Moreover, distribution utilities have a long history of recording this information, often in response to mandates from state public utility commissions (Eto and LaCommare, 2008). Thus, studies that rely on reliability data collected by distribution utilities can, in principle, provide a more complete basis upon which to assess trends or changes in reliability over time.

Eto et al. (2012) was one of the first known studies to apply econometric methods to account for utility-specific differences among electricity reliability reports. This study found that the annual average amount of time and frequency customers are without power had been increasing from 2000 to 2009. In other words, reported reliability was getting worse. However, the Eto et al. (2012) paper was not able to identify statistically significant factors that were correlated with these trends. The authors suggested that "future studies should examine correlations with more disaggregated measures of weather variability (e.g., lightning strikes and severe storms), other utility characteristics (e.g., the number of rural versus urban customers, the extent to which distribution lines are overhead versus underground), and utility spending on transmission and distribution maintenance and upgrades, including advanced ("smart grid") technologies" (Eto et al., 2012). Alvehag and Söder (2011) describe a reliability model that correlate two severe weather metrics (lightning, wind speed) to distribution system failure rates (SAIFI) and restoration times (SAIDI) in Sweden. The aforementioned authors found that the "stochasticity in weather has a great impact on the variance in the reliability indices" (Alvehag and Söder 2011, p. 910). However, the Alvehag and Söder (2011) study does not consider other factors, which may contribute to reliability including utility spending and the presence of outage management systems—among other things.

This paper seeks to extend the Eto et al. (2012) and Alvehag and Söder (2011) analyses along exactly these lines. This paper attempts to identify statistically significant factors, including various aspects of "abnormal weather", but also other utility characteristics, using up to 13 years of information on power interruptions for a large cross-section of U.S. electricity distribution utilities. These utilities, taken together, represent approximately 70% of both total U.S.

electricity sales and customers. We also consider the possibility that utility operations and maintenance spending may impact reliability and that weather and reliability have a non-linear relationship. Following Hoen et al. (2009), we employ a sequential modeling approach to ensure model (1) performance; (2) parsimony; and (3) coefficient stability is achieved prior to interpretation.

In this work, we seek to answer the following questions:

- Are warmer/cooler, wetter/drier, and/or windier than average years correlated with changes in the annual average number of minutes and/or frequency of power interruptions?
- Are the number of customers, annual sales of electricity, share of underground lines, or the presence of outage management systems (OMS) correlated with changes in the annual average number of minutes and/or frequency of power interruptions? Is previous year T&D operations and maintenance (O&M) spending correlated with changes in the annual average number of minutes and/or frequency of power interruptions in the following year?
- Are there trends in the annual average number of minutes and/or frequency of power interruptions over time, which we cannot explain by considering the above factors?

Answers to these questions have important implications for efforts to project long-term trends in reliability and the associated benefits of strategies to improve grid resiliency to severe weather—both in the U.S. and abroad.

2. Causes of power outages and data used in this study

2.1 Reported causes of power outages

Utilities in the U.S. publicly report a number of causes associated with increased frequency and duration of outages. This section reviews causes of reliability events as reported by a subset of the U.S. electric utilities evaluated in the broader econometric analysis. The following utility reliability reports were consulted to determine the causes of past reliability events: Florida Public Utilities Company (2012); Rocky Mountain Power (2011); Interstate Power and Light Company (2013); Jersey Central Power & Light (2013); Madison Gas and Electric Company (2013); Pacific Gas & Electric Company (2009); Portland General Electric (2012); PSE&G Services Corporation (2013); and AEP Southwestern (2012). Table 1 provides information on the range of categories used by a selected number of utilities introduced above. Weather, equipment failure, human error, vegetation, other/unknown, and wildlife are factors which typically affect the frequency and duration of power interruptions. These causes, which have been documented by the utilities, informed the choice of explanatory variables used in this model of power system reliability.

Table 1. Causal categories for a selected number of electric utilities

Utility name	Reporting year	Metric	Causal categories	Comments
Madison Gas & Electric Company (Wisconsin USA)	2012	SAIFI	Cable failures; equipment failures; storm-related; substations; tree-related; wildlife-related; other	Reported by worst performing circuit.
Florida Public Utilities Company (Florida USA)	2012	Number of outages	Named storm; animal; vegetation; other; corrosion; unknown; transformer failure; lightning; vehicle	Reported by two geographic divisions within service territory.
Rocky Mountain Power (Wyoming USA)	2011	SAIDI (% share); SAIFI (% share)	Weather; animals; environment; equipment; interference; loss of supply; operational; other; planned; trees	

Interstate Power & Light (Iowa/Minnesota USA)	2012	% of outage minutes	Earthquake; equipment; error; lightning; major event; overload; public/other; scheduled; supply; trees; unknown; weather; wildlife	Percentage of outage minutes by cause was reported for 2008-2012.
Jersey Central Power & Light (New Jersey USA)	2012	Number of customer hours	Animals; equipment-related; lightning-related; other/unknown; trees (preventable); trees (not preventable); vehicle	Reported by entire service territory, northern region, and central region.
PSE&G (New Jersey USA)	2012	Number of customer hours	Trees; construction (underground); construction (overhead); supply and station equipment; other; lightning; outside plant equipment; external; animals; weather	Causes were reported from 2003-2012 and across four divisions within service territory.
Portland General Electric (Oregon USA)	2012	Frequency of outage; outage duration (hours)	Equipment; lightning; loss of supply (substation); loss of supply (transmission); other; planned; public; unknown; vegetation; weather; wildlife	Causes were broken down by feeder and with more granularity than the general categories reported in this table.
AEP Southwestern Electric Power (Texas USA)	2011	% of interruptions	Animals and birds; people; unknown; utility-owned equipment; other; vegetation; weather (including lightning)	

2.2 Electricity reliability metrics considered in this study

The measures of electricity reliability used in this study are the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI).

SAIDI represents the total minutes that electricity customers, on average, are without power over the course of a year. Equation 1 shows that annual SAIDI for a utility is calculated by summing all annual minutes of customer interruption and dividing this number by the total number of customers served. In this equation, the total number of minutes of each interruption event in a given year is represented by $Time_t$, the number of customers affected by all interruptions in a given is $Affected_t$, and the total number of customers served by the utility in a given year is $Customers_t$.

$$SAIDI_t = \frac{\sum Time_t \times Affected_t}{Customers_t} \tag{1}$$

SAIFI represents the number of times that electricity customers, on average, experiences power interruptions over the course of a year. Equation 2 shows that annual SAIFI for a utility is calculated by summing all annual customer interruptions and dividing this number by the total number of customers served. In this equation, the number of customers affected by an event is Affected_t and the total number of customers served by the utility in a given year is Customers_t.

$$SAIFI_t = \frac{\sum Affected_t}{Customers_t} \tag{2}$$

Some utilities report these metrics with the inclusion of what are known as “major events”, which represent times during the year when the utility is subjected to significant, yet generally infrequent stresses, often due to severe weather. The number of major events experienced by a utility in any given year can vary considerably, yet because they are large events they have a disproportionate effect on reported reliability. In order to facilitate year-to-year comparisons of utility reliability performance, SAIDI and SAIFI are often reported without inclusion of the interruptions associated with major events. For more information on major events and how the IEEE defines major events days as well as more information on reliability metrics please refer to the IEEE guideline (IEEE, 2012).Our analysis considered each of the four distinct ways of reporting reliability performance separately. That is, we conducted separate analyses of: (1)

SAIDI without major events; (2) SAIDI with major events; (3) SAIFI without major events; and (4) SAIFI with major events.

The primary source for utility-reported reliability performance information was state utility regulatory commissions, because many require the utilities they regulate (generally speaking, these are investor-owned utilities) to report these data, and these commissions typically make this information publicly available (Eto and LaCommare, 2008).[1] In order to collect data on utilities not under the jurisdiction of state utility commissions (e.g., municipal utilities and cooperatives) or when the commissions either do not require or make these data publicly available, we also obtained reliability performance data via online press releases, reports posted by the utility or through direct contact with the utility.

Ultimately, we collected reliability data for 195 different utilities, representing both 70% of total U.S. electricity sales and total U.S. electricity customers. Of these, 152 of the utilities are investor-owned utilities and 43 are either municipals or electricity cooperatives. Figure 1 shows the geographic coverage of the utilities we obtained data for represented by Census region.

[1] Previous work by Eto and LaCommare reviewed state utility commission reporting practices across the U.S. (Eto and LaCommare, 2008).

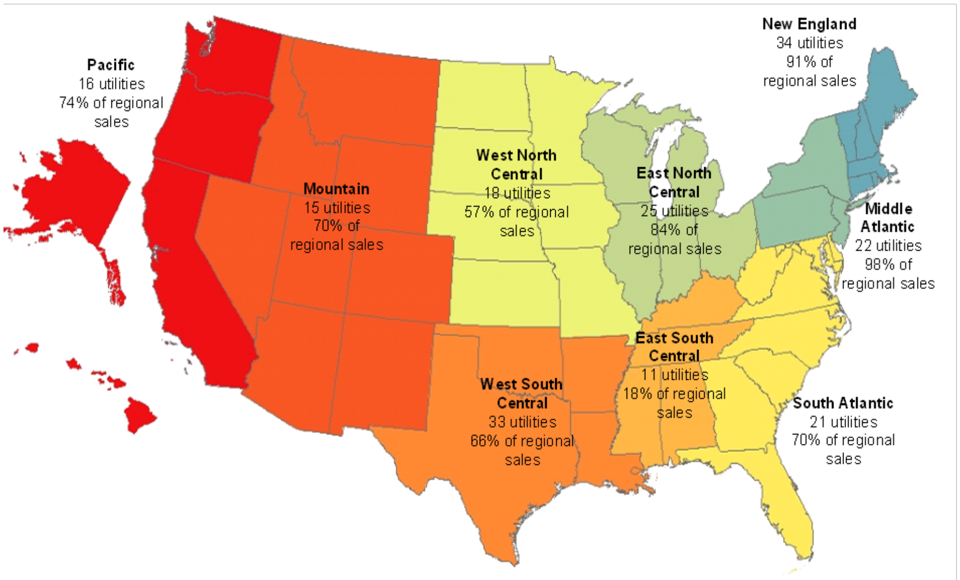


Figure 1. Geographic coverage of utilities included in this study

Figure 2 and Figure 3 show the middle 50% range of SAIDI and SAIFI values, both with major events (left) and without major events (right) included, respectively. The top and bottom line of each gray-shaded area represent the 75th and 25th percentiles, respectively, and the line through the box indicates the median value for that year. For the set of data without major events included, the average annual duration of customer interruptions (SAIDI) is slightly more than 140 minutes (2 hours and 20 minutes) per year and, for the set of data with major events included, slightly more than 370 minutes (6 hours and 10 minutes) per year—this difference represents a ~260% increase in the duration when major events are included. Bear in mind that these averages refer to two different sets of utilities both averaged over all years of data.

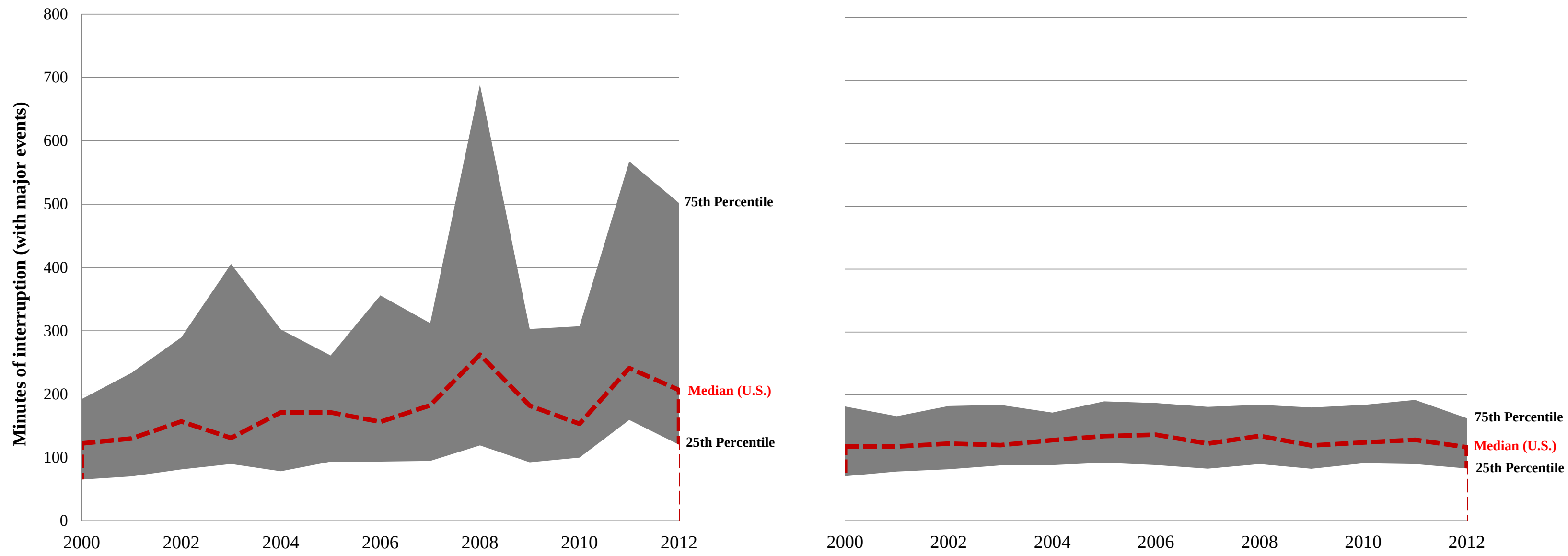


Figure 2. Average minutes of interruption (SAIDI) with (left) and without (right) major events included

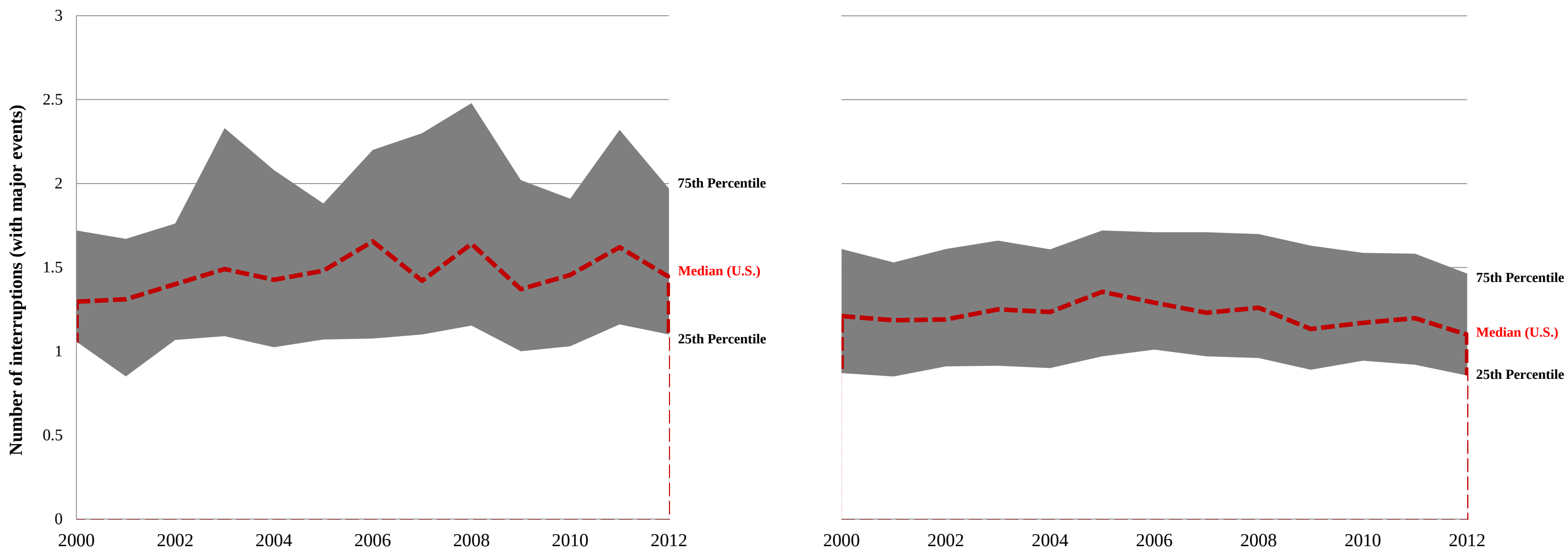


Figure 3. Average number of interruptions (SAIFI) with (left) and without (right) major events included

As utility reporting practices vary, we were not able to collect SAIDI and SAIFI both with and without major events from all 195 utilities for all 13 years. A complete dataset (for all years 2000–2012) was obtained for more than 80 utilities for SAIDI and SAIFI without major events and for more than 50 utilities for SAIDI and SAIFI with major events included. Figure 4 shows the number of utilities we have data for use in this study by the length of the time series.

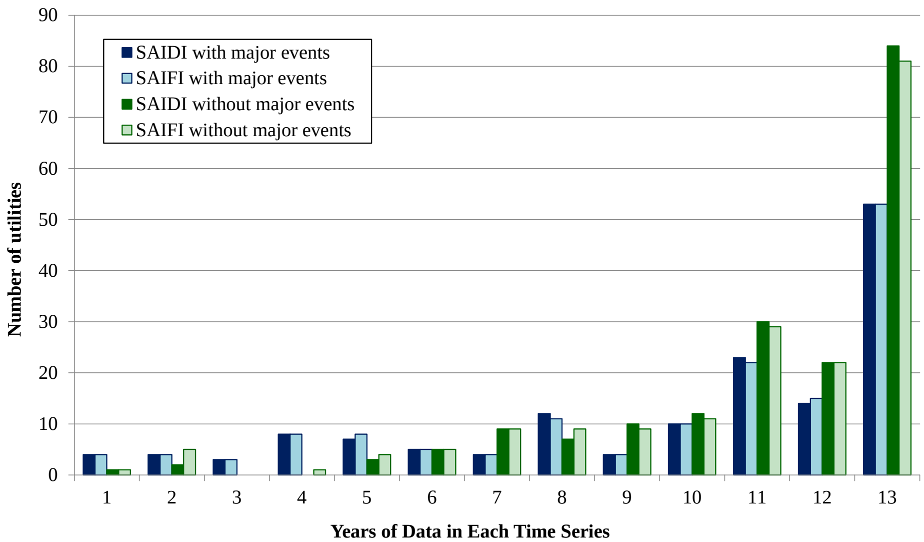


Figure 4. Number of utilities with each number of years of successive data

2.2 Weather and utility characteristics

We also collected information for a number of potential explanatory variables for use in the econometric analysis.

Table 2 describes the granularity and source of information used in this study.

Table 2. Data granularity and source

Data	Granularity	Source
Reliability metrics (SAIDI/SAIFI)	195 utilities spanning years 2000-2012 (70% of U.S. sales)	Direct communication and/or web search of public utility commissions and utilities
Presence of outage management system (OMS)	Information as of 2012 for each utility	Direct communication and/or web search of public utility commissions and utilities
Adoption of IEEE Standard 1366	Information as of 2012, but not evaluated, for each utility	Direct communication and/or web search of public utility commissions and utilities
Retail electricity sales	Information as of 2012 for each utility	U.S. Energy Information Administration (EIA) via Form 861 (EIA, 2013)
Heating/Cooling degree-days	Utility-level	National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) (NCDC/Ventyx, 2014)
T&D line miles—including underground share	Total for each utility by year	FERC Form 1; U.S. Department of Agriculture Rural Utilities Service Form 7(FERC/RUS/EIA/Ventyx, 2014)
T&D O&M expenditure data	Total for each utility by year	FERC Form 1; U.S. Department of Agriculture Rural Utilities Service Form 7 (FERC/RUS/EIA/Ventyx 2014)
Lightning data	Strike count summed to each utility by year	Vaisala National Lightning Detection Network (NLDN, 2013)
Wind speed	Average for each utility by year	National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) (NCDC/Ventyx, 2014)
Precipitation	Average for each utility by year	National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) (NCDC/Ventyx, 2014)

3. Econometric analysis method

We used the following regression equation to analyze the relationship between utility-specific attributes and weather variability on the duration (SAIDI) and frequency (SAIFI) of power interruptions:

$$\ln(Y_{it}) = \beta_1 + \sum_{d=2}^{e} \beta_d X_{dit} + \sum_{f=1}^{g} \gamma_f Z_{fi} + \delta T + \varepsilon_{it} \tag{3}$$

The general model specification described in equation (3) above follows the general form used in earlier energy-related multivariate panel regressions (Erdogdu, 2011 and Eto et al., 2012). In equation (1), annual utility reliability (measured by SAIDI or SAIFI with or without major events included) is represented by the log of the dependent variable: Y_{it}. Electric utility and reporting year are represented by subscript $_i$ and $_t$, respectively. Subscripts $_d$ and $_f$ are used to differentiate between observed and unobservable variables, respectively. X_{di} and Z_{fi} represent observed and unobservable variables. For example, variables in X may include annual T&D O&M spending and variables in Z might include non-observable factors that vary across the utility. Finally, ε_{it} represents the model error term and T is a variable that captures an annual time trend.

As indicated, the array of Z_{fi} variables are unobservable. Accordingly, we define a new term, α_i, which represents the combined effect of the unobservable variables on the dependent variable, Y_{it}. Equation 4 describes the reduced form empirical model used in this analysis.[2]

[2] The presence of the α_i component within this model is "crucially important" (Erdogdu, 2011) because it enables the regression to estimate the combined effect of all the explanatory variables that have not been captured in the array of X observable variables. If one could determine, in advance, that all explanatory variables have been fully captured in the array of observable variables, then the α_i term could be eliminated from the model and a pooled ordinary least squares (OLS) regression technique would be appropriate (Erdogdu, 2011). However, this determination can rarely be made prima facie in analyses of this type. The key point is we do not know this in advance, with any degree of precision or consistency. For this reason, it is essential to include an α_i term in the model and conduct the econometric analysis assuming the presence of unobservable fixed (or random) utility effects.

$$\ln(Y_{it}) = \beta_1 + \sum_{d=2}^{e} \beta_d X_{dit} + \alpha_i + \delta T + \varepsilon_{it} \tag{4}$$

3.1 Data characteristics, treatments, and selected transformations

The data used in this study represent many utilities (roughly 100, depending on whether SAIDI or SAIFI with or without major events included is examined) but for each utility comparatively fewer data points in terms of years (no more than 13 for any utility). Colloquially, this is referred to as a “short” dataset (Cameron and Trivedi 2009). In addition, because we do not have 13 years of data for each utility and because some possible explanatory variables may be missing for some of the utilities, the dataset is also considered “unbalanced” (Wooldridge 2002). These features of the data set can impact the regression performance, selection, and results.

Table 3 and Table 4 contain summary statistics for the raw datasets without and with major events, respectively.

Table 3. Raw summary statistics for SAIDI and SAIFI without major events

Variable (units)	Number of observations	Min	Mean	Median	Max	Standard Deviation
SAIDI (minutes)	2,062	0[3]	143.1	125.6	1,015.1	86.9
SAIFI (# of events)	2,026	0.0[4]	1.4	1.2	20.9	0.9
HDD (# of degree days)	2,210	198	4,807.1	5,020.7	9,697.0	2,023.7
CDD (# of degree days)	2,210	0	1,319.6	1,026.0	4,313.0	894.9
Lightning strikes (strikes per customer)	2,181	0	0.5	0.1	189.9	5.2
Precipitation (inches)	2,210	1.8	35.9	37.9	79.3	14.9
Wind speed (mph)	2,210	3.4	7.3	7.0	12.7	1.5

[3] The minimum reported SAIDI value (without major events) of zero was determined to be incorrectly coded by one utility. Accordingly, the minimum value used in the econometric analysis was 1.18.
[4] Raw value reported is 0.003.

Variable (units)	Number of observations	Min	Mean	Median	Max	Standard Deviation
T&D lines (customers per line mile)	2,024	0	172.2	23.3	8,942.6	672.8
Share of underground line miles (%)	840	0.1%	22.2%	20.4%	89.8%	15.3%
Delivered electricity (MWh per customer)	2,288	1.1	26.7	25.0	181.7	14.4
T&D O&M spending ($2012 per customer)	2,084	$4.4	$883.0	$239.8	$52,261.0	$2,328.4

Table 4. Raw summary statistics for SAIDI and SAIFI with major events

Variable (units)	Number of observations	Min	Mean	Median	Max	Standard Deviation
SAIDI (minutes)	1,438	1.2	372.2	173.0	14,437.6	825.8
SAIFI (# of events)	1,440	0[5]	1.8	1.5	37.3	2.0
HDD (# of degree-days)	1,794	198	5,160.8	5,329.0	9,136.0	2,000.6
CDD (# of degree-days)	1,794	0	1,168.1	897.0	4,921.0	874.6
Lightning strikes (strikes per customer)	1,748	0	0.5	0.1	189.9	5.8
Precipitation (inches)	1,794	1.8	34.9	37.1	73.2	13.6
Wind speed (mph)	1,794	3.2	7.0	6.9	12.1	1.6
T&D lines (customers per line mile)	1,471	0.0	148.2	27.9	3,832.1	409.9
Share of underground line miles (%)	648	0.6%	24.6%	23.4%	89.8%	16.1%
Delivered electricity (MWh per customer)	1,856	1.1	27.3	24.2	257.3	22.8
T&D O&M expenditures ($2012 per customer)	1,499	$4.4	$734.6	$235.1	$11,076.0	$1,659.2

The raw data were subjected to two screening evaluations, which led to the exclusion of some of the utilities from the analysis. The first screen is a requirement of the software we used to analyze the data. The second is a manual process we implemented to remove extreme outliers

[5] The minimum reported SAIFI value (with major events) of zero appeared to be incorrectly coded by one utility. In this case, the minimum value used in the econometric analysis was 0.003.

from the analysis.[6]

It is possible that utilities make decisions related to day-to-day reliability partially based on normal (i.e., average) weather conditions. For this reason, we hypothesized that warmer/cooler/wetter/drier/windier/etc.-than-average years will be correlated with measurable changes in the annual average total duration and/or frequency of power interruptions. To evaluate this assumption, a number of metrics were developed to capture "abnormal" atmospheric conditions. We develop a metric to capture "abnormal" atmospheric conditions in order to explore the possibility that warmer/cooler, wetter/drier, windier/less windy etc. than average years were correlated with changes in the annual average total duration and/or frequency of power interruptions. We transformed the weather variables ($\vec{W}$) into pairs of positive (see equation 5) and negative (see equation 6) deviations from the 13-year average.

$$\overset{+}{\Delta}\vec{W}_{\text{it}} \begin{cases} \dfrac{\left(W_{it} - \overline{W}_i\right)}{\overline{W}_i}\times 100: & \dfrac{\left(W_{it} - \overline{W}_i\right)}{\overline{W}_i}\times 100 > 0 \\ 0: & \dfrac{\left(W_{it} - \overline{W}_i\right)}{\overline{W}_i}\times 100 \le 0 \end{cases} \tag{5}$$

$$\overset{-}{\Delta}\vec{W}_{\text{it}} \begin{cases} 0: & \dfrac{\left(W_{it} - \overline{W}_i\right)}{\overline{W}_i}\times 100 \ge 0 \\ \dfrac{\left(W_{it} - \overline{W}_i\right)}{\overline{W}_i}\times 100: & \dfrac{\left(W_{it} - \overline{W}_i\right)}{\overline{W}_i}\times 100 < 0 \end{cases} \tag{6}$$

[6] Additional information detailing the analytical techniques used in this type of analysis can be found in Larsen et al. (2015) and Larsen (2016).

For example, positive deviations in annual HDDs and CDDs were calculated by subtracting the HDDs (or CDDs) in a given year from the 13-year average. Accordingly, a pair of abnormally cold (or hot) temperature deviations was created to test this hypothesis. If the HDDs (or CDDs) in a given year were less than the 13-year average, the positive deviation variable was coded with a zero. This procedure was applied to the annual lighting strike, average wind speed, and annual precipitation data and repeated for positive and negative deviations.

The Eto et al. (2012) analysis did not consider the possibility that weather and reliability may be related in a non-linear fashion. Accordingly, we also transformed the weather variables to explore the possibility that the relationship between weather, including temperature, precipitation, and wind—and the annual average total duration and frequency of power interruptions—is non-linear. Hitz and Smith (2004) surveyed the literature on the shape of weather-related infrastructure damage curves and concluded that the curves were nonlinear. Larsen et al. (2015) argued that using non-linear indicators may be a "more appropriate" choice for estimating damages to infrastructure.

We transformed the weather variables by expressing them as second-order polynomials. McIntosh and Schlenker (2006) show how transforming quadratic functional forms *within fixed effects groupings* is preferred to developing global quadratic terms across units. Assuming the presence of unobservable fixed (or random) effects, we follow the lead of McIntosh and Schlenker (2006) by "first demeaning the covariate and then squaring it, rather than squaring then demeaning."

We did not, however, transform the weather variable involving lighting strikes, because we could not envision a plausible scenario in which there could be a non-linear relationship. That is, it seemed to us that changes in the number of lightning strikes could only affect reliability in a linear fashion since each strike is associated with a unique, i.e., separate, impact on reliability.

Finally, we lagged T&D O&M spending variables by one year to test the hypothesis that operations and maintenance spending in a given year would not have an effect on reliability performance metrics until the following year (see equation 7).[7] Accordingly, lagged fixed and variable transmission (i.e., TFC, TVC) and distribution O&M expenses (i.e., DFC, DVC) were combined into total lagged annual transmission and distribution expenses,[8] multiplied by the Handy-Whitman utility cost index (HW), and normalized by number of customers (see Equation 7).

$$Expenditures_{it\text{-}1} = \left(\frac{TFC_{it\text{-}1} + TVC_{it\text{-}1} + DFC_{it\text{-}1} + DVC_{it\text{-}1}}{Customers_{it}} \right) \times \left(\frac{HW_{2012}}{HW_{t\text{-}1}} \right) \tag{7}$$

4. Model performance and selection

We developed a sequence of model specifications (each a distinct regression equation following

[7] Comprehensive information describing annual utility-level capital spending patterns was not easily accessible and therefore not included in this study.

[8] At first glance, the inclusion of utility spending in a model of reliability implies that there may be a correlation between spending and the error term of the model, which is a violation of the OLS assumption of exogeneity. For example, *current* year spending could influence *current* year reliability and vice versa. Ericsson (1991) notes that "invalid exogeneity assumptions may lead to inefficient or inconsistent inferences and result in misleading forecasts and policy simulations. Valid exogeneity assumptions may permit simpler modeling strategies, reduce computational expense, and help isolate invariants of the economic mechanism." In this model, however, we include a lagged endogenous variable (i.e., *previous* year spending) essentially treating this metric as a strictly exogenous variable (e.g., see Greene 2000). In this case, previous year spending can affect reliability, but current year reliability cannot affect previous year spending. It is important to note that the inclusion of lagged endogenous variables as instruments can be "problematic" if serial correlation is not addressed (Angrist and Krueger 2001). Following the lead of Granger (1969) and Sims (1972), a number of related testing procedures have been proposed within the context of evaluating exogeneity.

the form outlined in Section 3) and conducted a series of robustness tests to evaluate them following procedures outlined in Hoen et al. (2009), which evaluated the impact of wind power projects on residential property values.[9] The procedures involve starting with a simplified model and then developing alternatives to it by adding grouping of related explanatory variables incrementally. Many econometric analyses have traditionally identified preferred models based on only one selection criteria: model performance ("fit"). This over-emphasis on one type of model diagnostic can lead to unpredictable and spurious interpretations. For this reason, we evaluate each alternative by reviewing statistical measures of the model based on: (1) performance (i.e., fit); (2) parsimony (i.e., smallest number of explanatory variables); and (3) coefficient stability.

We started with the final regression model developed in Eto et al. (2012), which we label Model A, and then sequentially incorporated groupings of new explanatory variables that were of interest, which we label Models B through G (see Table 5). This sequential modeling approach allowed us to evaluate incrementally the extent to which incorporation of abnormal weather, non-linear measures of weather severity, utility ownership type, percent of line miles underground, line miles per customer, T&D O&M spending, etc. improved the performance of the model, while not violating the preference of econometricians to use "simpler, more parsimonious statistical models" (Hoen et al. 2009, Newman 1956).

Model A, which is a close proxy to the Eto et al. (2012) configuration, includes the following

9 The technical appendix shows that the preferred models, which include the lagged endogenous spending variable, are stationary and that both serial correlation and heteroscedasticity has been addressed. The appendix also includes detailed results for the regressions and tests for both the presence of utility effects and whether a random effects model is preferred over a fixed effects model.

explanatory variables: electricity delivered, heating and cooling degree-days, year, the presence of outage management systems, and the length of time the OMS has been installed at each utility.[10] Model B extends Model A by replacing the basic temperature metrics with abnormal measures of temperature, precipitation, wind speed, and lightning. Model C adds to Model B by also including non-linear weather terms. Model D further adds to Model C by also including previous year T&D spending. Model E removes non-linear weather terms with the exception of wind speed and includes customers per line mile. Model F is similar to Model E but with the addition of share of underground T&D line miles. Model G includes all of the explanatory variables considered in any one of the prior six models—with the exception of absolute measures of HDDs and CDDs.

Table 5. Parameters included for base model and six alternatives

Model	**A (Eto et al. 2012)**	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	●	●	●	●	●	●	●
Electricity delivered (MWh per customer)	●	●	●	●	●	●	●
Heating degree-days (#)	●						
Cooling degree-days (#)	●						
Outage management system?	●	●	●	●	●	●	●
Years since outage management system installation	●	●	●	●	●	●	●
Year	●	●	●	●	●	●	●
Abnormally cold weather (% above average HDDs)		●	●	●	●	●	●

[10] There are some differences between Eto et al. (2012) and Model A in the manner the explanatory variables are expressed. In Model A, sales are normalized by number of customers and utility-specific annual heating/cooling degree-days are used. Eto et al. (2012) did not normalize sales by customers and incorporated state-level annual heating/cooling degree-days linked to a single state where the utility primarily operates.

Model	A (Eto et al. 2012)	B	C	D	E	F	G
Abnormally warm weather (% above average CDDs)		●	●	●	●	●	●
Abnormally high # of lightning strikes (% above average strikes)		●	●	●	●	●	●
Abnormally windy (% above average wind speed)		●	●	●	●	●	●
Abnormally wet (% above average total precipitation)		●	●	●	●	●	●
Abnormally dry (% below average total precipitation)		●	●	●	●	●	●
Abnormally cold weather squared			●	●			●
Abnormally warm weather squared			●	●			●
Abnormally windy squared			●	●	●	●	●
Abnormally wet squared			●	●			●
Abnormally dry squared			●	●			●
Lagged T&D O&M expenditures ($2012 per customer)				●	●	●	●
Number of customers per line mile					●	●	●
Share of underground T&D miles to total T&D miles						●	●

4.1 Selecting the preferred models

For the SAIDI regressions (both without and with major events), we found that Model F has slightly better performance—as measured by generalized r-squared or root mean squared error (RMSE)—when compared to Model E. However, it is important to note that the RMSE is the same for both Model F and Model G, but the Bayesian Information Criterion (BIC) is significantly lower for Model F—indicating that Model G is less parsimonious. Similarly, for the SAIFI regressions, both the RMSE and BIC are lower for Model F (and the adjusted R^2 is higher) when compared to Model E. The RMSE and BIC for Model G are both larger when compared to Model F. In summary, based on these statistical measures, Model F is superior to the other six models we considered.

However, we also observe that the number of utilities included in Model F is significantly less than those included in Model E. Larsen et al. (2015) shows that the number of utilities modeled drops by approximately 50% between Models E and F. We traced this drop to the fact that we did not have information on underground T&D lines for a relatively large number of utilities. This significantly impacted the final number of utilities used in both the Model F and G regressions.

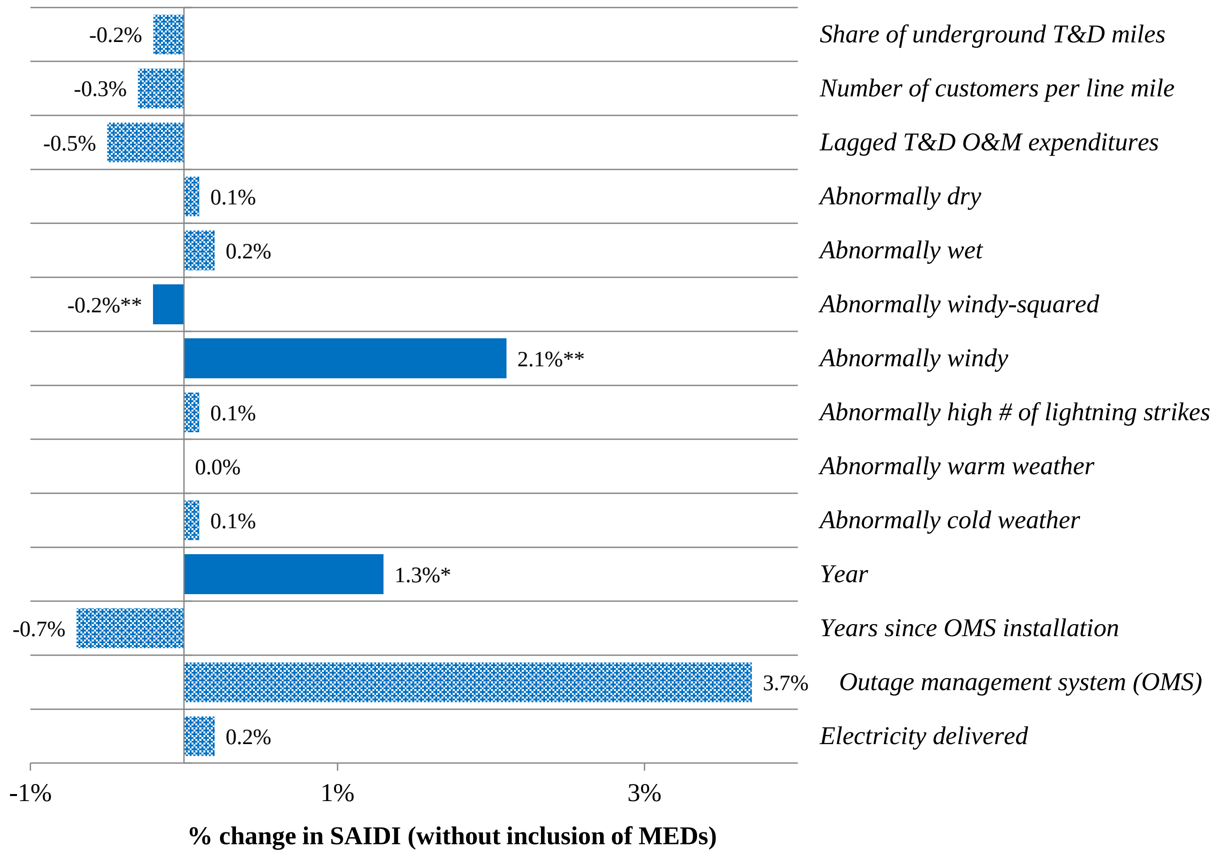
5. Principal findings

This section describes the principal findings from our analysis. Figure 5 through Figure 8 show results for the SAIDI and SAIFI regressions, both with and without major events included.

5.1 Factors correlated with the average number of minutes of power interruptions (SAIDI)

If major events are not included (see Figure 5), we find the following statistically significant relationships:

- A 5% increase in annual average wind speed—above the long-term (generally, 13-year) average— is correlated with a 5% increase in SAIDI; yet a 10% increase in annual average wind speed is correlated with a 2% decrease in SAIDI
- Independent of these factors, each successive year over the analysis period is correlated with a slightly greater than 1% increase in the SAIDI



Notes:
(1) *** represents coefficients that are significant at the 1% level.
(2) ** represents coefficients that are significant at the 5% level.
(3) * represents coefficients that are significant at the 10% level.

Figure 5. Percentage change in SAIDI (without major events) corresponding to a change in the explanatory variable

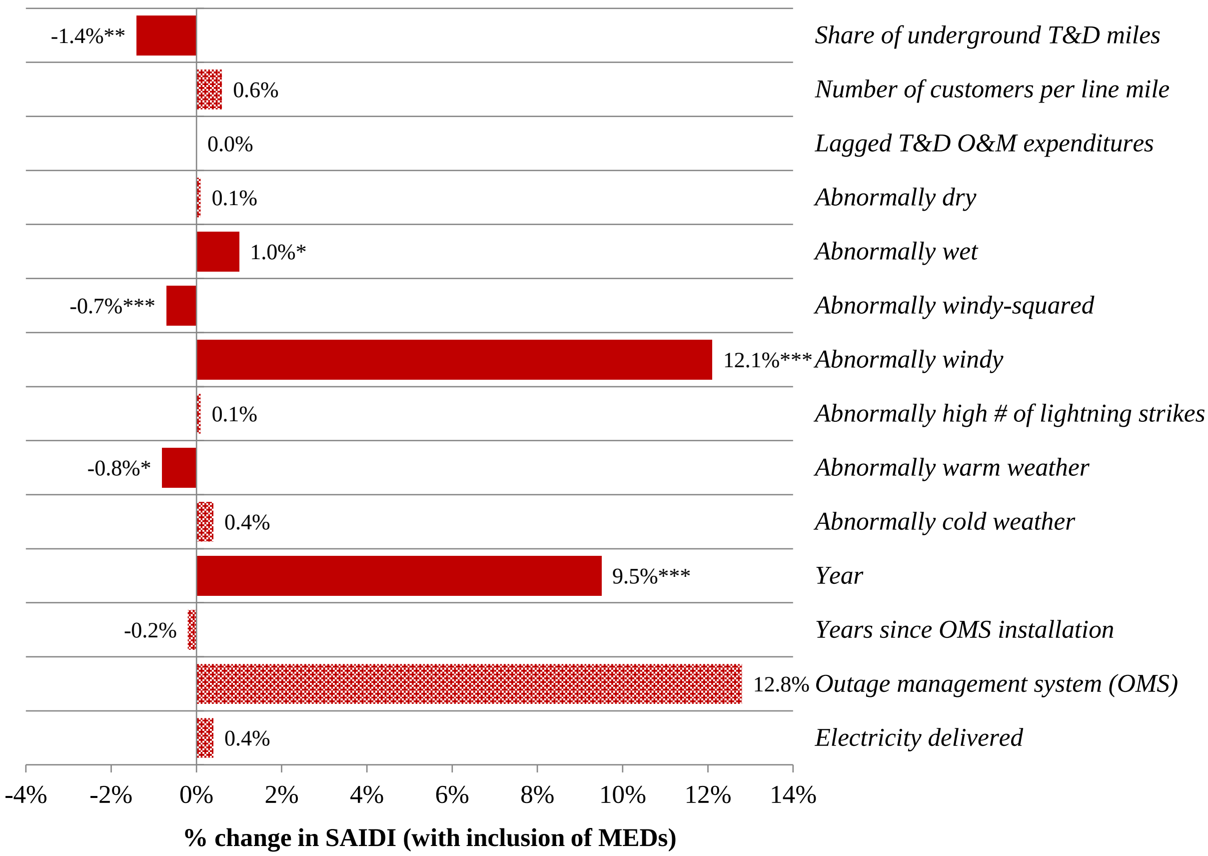
If major events are included (see Figure 6), we find the following statistically significant relationships:

- A 10% increase in annual precipitation—above the long-term (generally, 13-year) average—is correlated with a 10% increase in SAIDI
- A 10% increase in the number of cooling degree-days (i.e., warmer weather)—above the long-term (generally,13-year) average—is correlated with a 8% decrease in SAIDI

- A 5% increase in annual average wind speed—above the long-term (generally, 13-year) average— is correlated with a 56% increase SAIDI; a 10% increase in annual average wind speed is correlated with a 75% increase in SAIDI

- A 10% increase in the percentage share of underground line miles is correlated with a 14% decrease in SAIDI

Independent of the above factors, each successive year over the analysis period is also correlated with a nearly 10% decrease in SAIDI.



Notes:
(1) *** represents coefficients that are significant at the 1% level.
(2) ** represents coefficients that are significant at the 5% level.
(3) * represents coefficients that are significant at the 10% level.

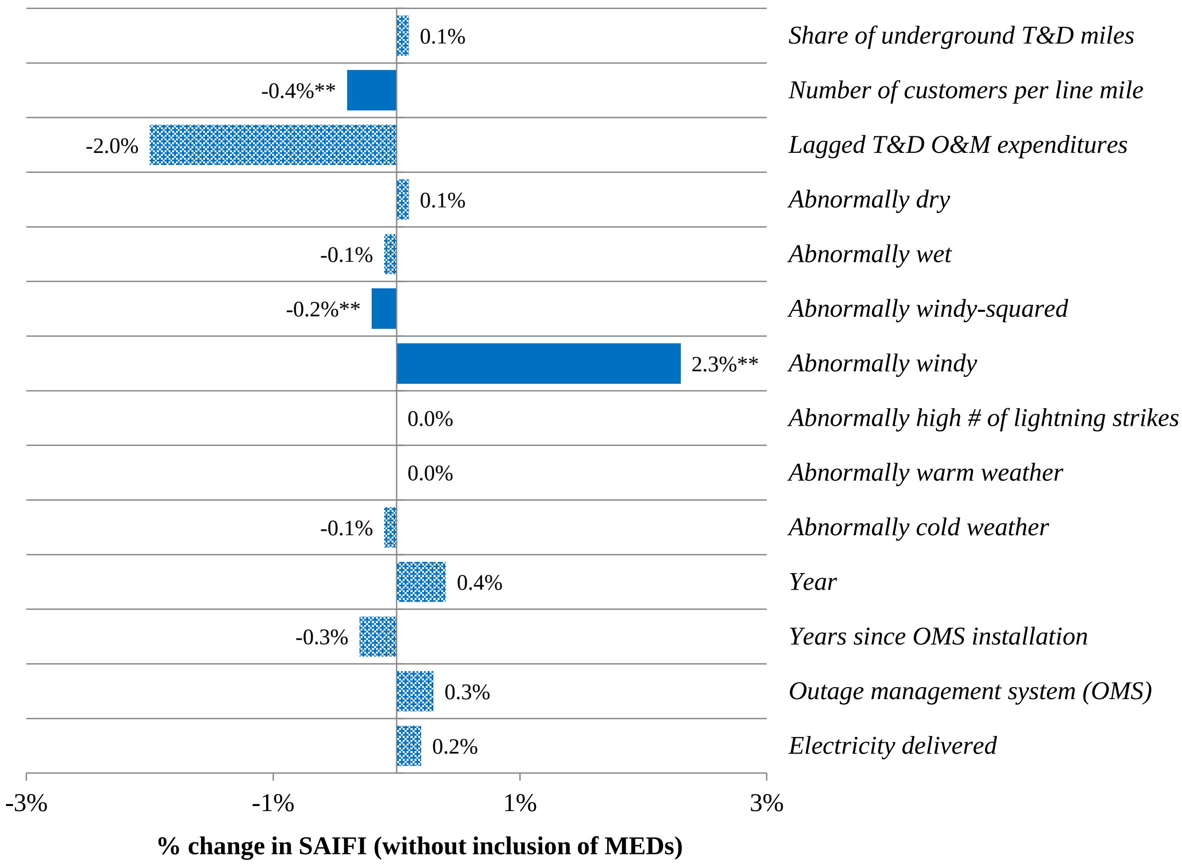
Figure 6. Percentage change in SAIDI (with major events) corresponding to a change in the explanatory variable

5.2 Factors correlated with the annual average frequency of power interruptions (SAIFI)

If major events are not included (see Figure 7), we find the following statistically significant relationships:

- A 10% increase in the number of customers per line mile is correlated with a 4% decrease in SAIFI
- A 5% increase in annual average wind speed—above the long-term (generally, 13-year) average— is correlated with a 6% increase in SAIFI; yet a 10% increase in annual average wind speed is correlated with only a 1% increase in SAIFI

Above average wind and population density are correlated with more frequent interruptions. In 2012, Eto et al. found that the installation of an OMS was correlated with more frequent interruptions, but that an OMS-related "learning effect" may have reduced the frequency of interruptions over time. In these results, we find that there was no statistically significant correlation between the installation of OMS (or years since the installation) and the frequency of interruptions.



Notes:
(1) *** represents coefficients that are significant at the 1% level.
(2) ** represents coefficients that are significant at the 5% level.
(3) * represents coefficients that are significant at the 10% level.

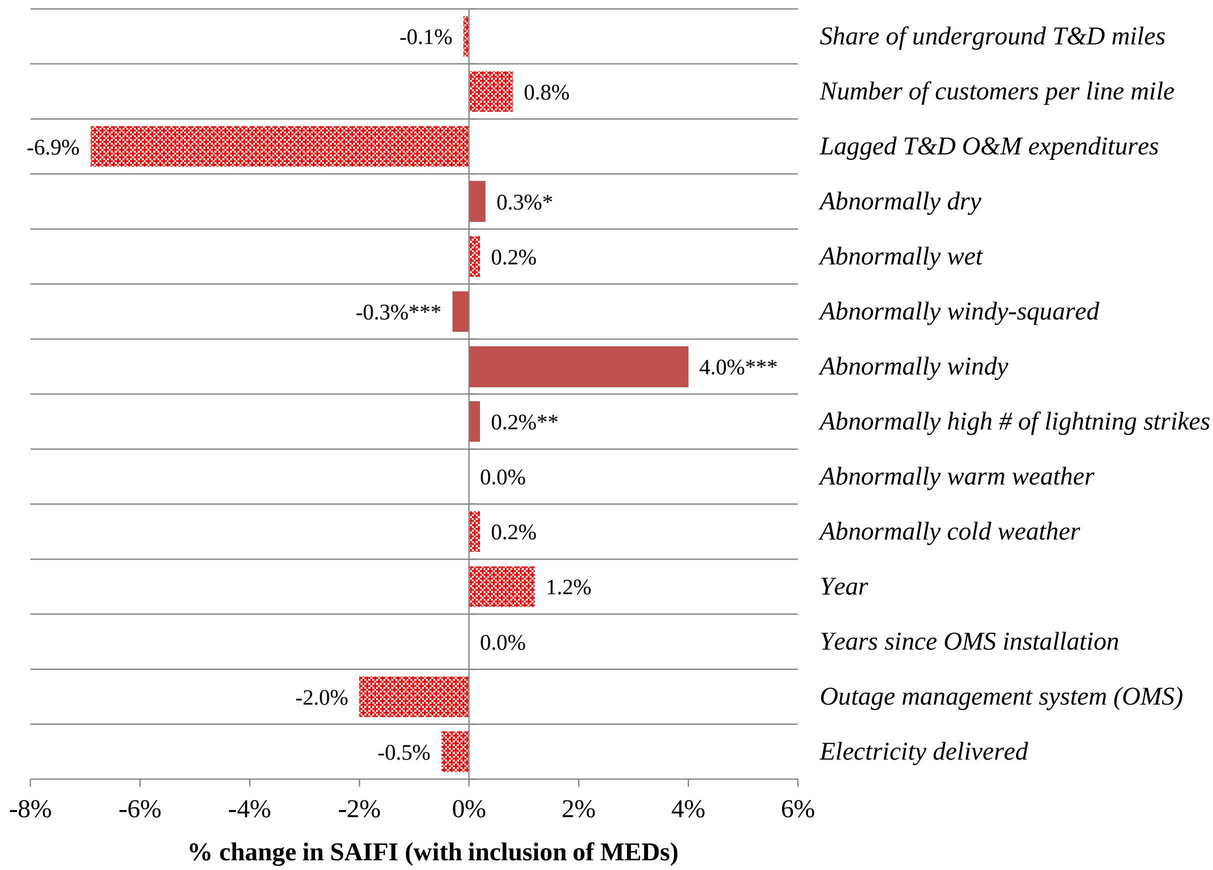
Figure 7. Percentage change in SAIFI (without major events) corresponding to a change in the explanatory variable

If major events are included (see Figure 8), we find the following statistically significant relationships:

- 10% increase in annual lightning strikes is correlated with a 2% increase in SAIFI
- 5% increase in annual average wind speed—above the long-term (generally, 13-year) average— is correlated with a 14% increase in SAIFI; 10% increase in annual average wind speed is correlated with a 15% increase in SAIFI

- 10% decrease in average total precipitation—below the long-term (generally, 13-year) average— is correlated with a 3% increase in SAIFI

Above average wind and lightning and below average precipitation is correlated with more frequent interruptions, but no other potential factors are statistically significant in this fixed effects model (when major events are included).



Notes:
(1) *** represents coefficients that are significant at the 1% level.
(2) ** represents coefficients that are significant at the 5% level.
(3) * represents coefficients that are significant at the 10% level.

Figure 8. Percentage change in SAIFI (with major events) corresponding to a change in the explanatory variable

6. Discussion

6.1 Major events are causing decreases in U.S. power system reliability over time

A key finding of this analysis is that there is an increasing trend in the annual average number of minutes of power interruptions over time. The trend is larger when major events are included, which means that increases in the severity of major events over time has been the principal contributor to the observed trend. Figure 9 and Figure 10 show the year coefficients for all seven SAIFI and SAIDI models, respectively, both without and with major events included. Figure 9 shows that both when major events are and are not included in SAIFI, the year coefficients are both modest and not highly statistically significant.

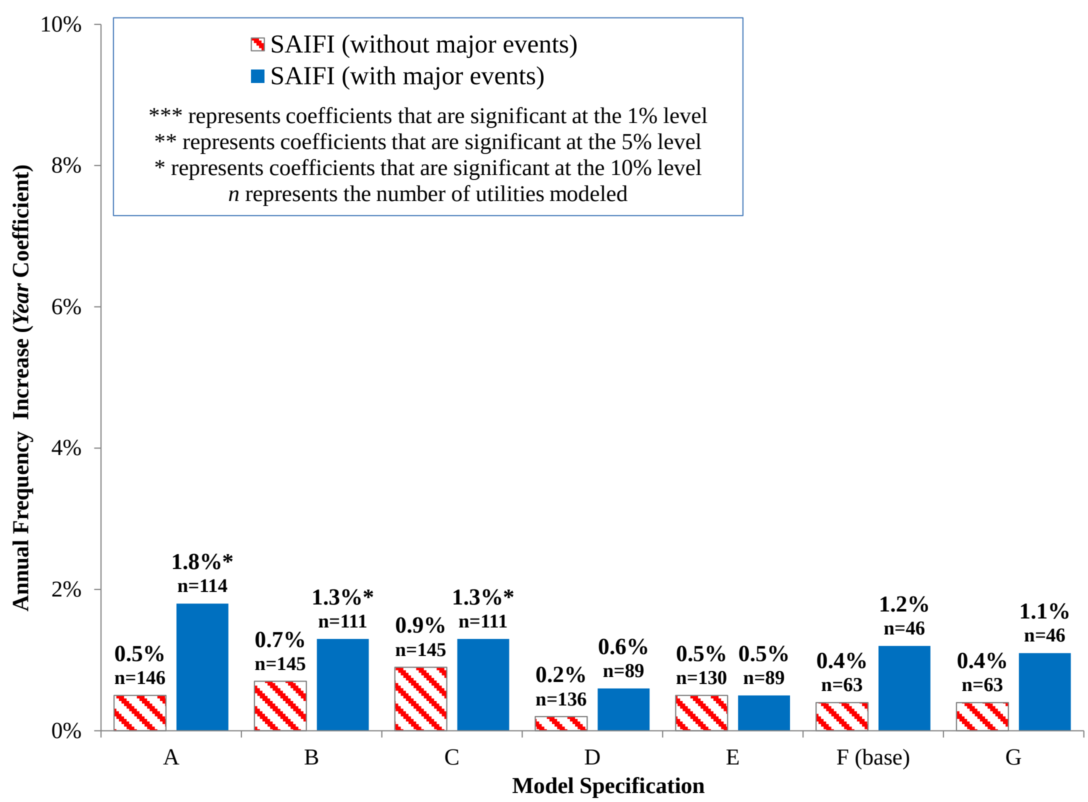


Figure 9. Annual increase in frequency of interruptions: all models considered

Figure 10 shows that when major events are included in SAIDI, the year coefficients are always both positive and highly statistically significant for all seven models. It also shows that when major events are not included in SAIDI that the year coefficients, while positive, are both smaller and less statistically significant.

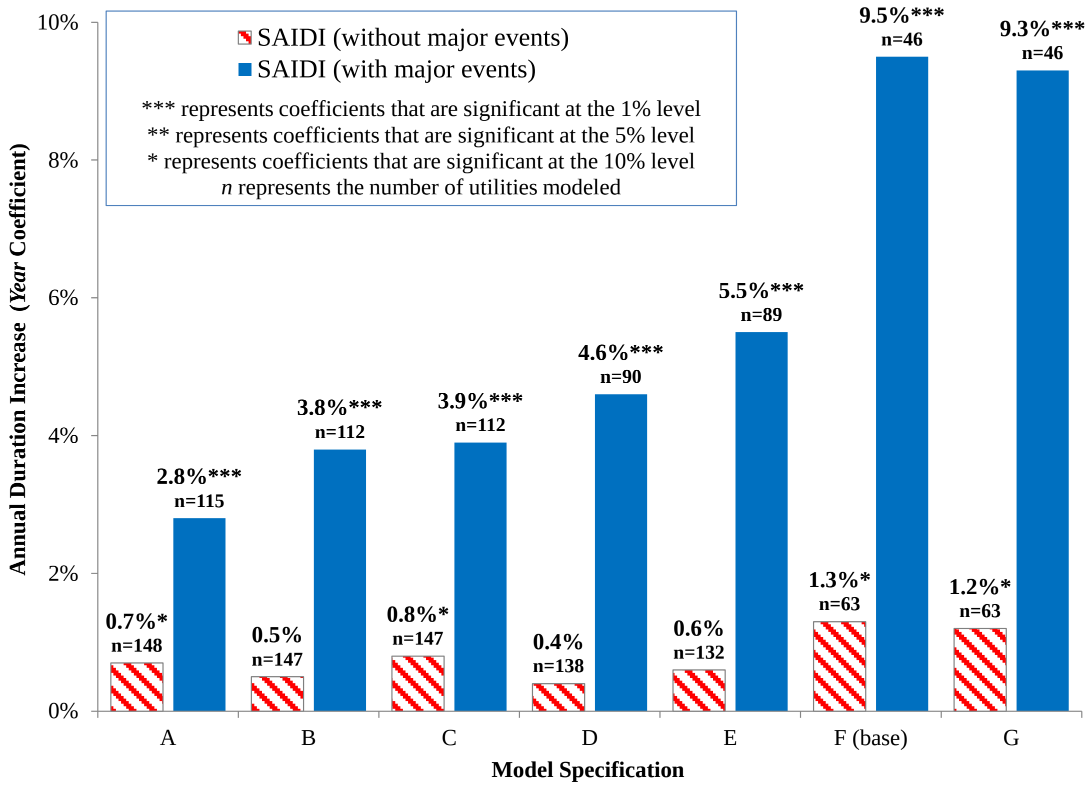


Figure 10. Annual increase in total minutes customers are without power: all models considered

6.2 Previous year O&M spending and subsequent year reliability

We were somewhat surprised to find that increased T&D O&M spending in the previous year was not consistently correlated in any statistically significant fashion with improvements in reliability in the following year. We suspect that reliability is affected differently depending on whether utilities spend relatively more on preventative O&M when compared to reactive O&M. For example, proactive utility T&D spending may anticipate future reliability problems and then justify investing a large amount of resources now to reduce the likelihood of a future interruption. In this case, the utility would have higher (lagged) T&D O&M spending and a relatively lower SAIDI and/or SAIFI. Alternatively, a reactive electric utility simply spends more on O&M as reliability problems arise. In this case, the utility would have higher (current year, not lagged) T&D O&M spending and a relatively higher SAIDI and/or SAIFI. The presence of "competing" effects within the utility O&M spending data may be influencing the results and leading to the counter-intuitive findings. And this analysis did not consider the reliability impacts from annual utility capital investments (e.g., incremental investments in electricity distribution infrastructure). Unfortunately, we did not have access to more detailed information on the constituents of utility O&M and capital spending in order to fully evaluate the role of annual T&D spending on reliability.

6.3 Important considerations when interpreting these findings

There are a number of caveats that should be considered when evaluating the results of this study. Specifically, there is the possibility of selection bias affecting this analysis (Heckman, 1979). Our sample of 195 utilities contains a disproportionate share of larger utilities—expressed in sales—compared to the population (17% for this study versus 14% for the entire population of utilities). Many of the largest utilities are required by regulators to report annual reliability metrics. However, many under-represented smaller utilities, which may include cooperatives and municipals not typically required to file reliability reports, could have fundamentally different reliability than the sample of 195 utilities evaluated in this study. It is important to note that the 195 utilities included in this study represent a significant portion of total electricity sales from all regions of the country except the East South Central census region. For these reasons, future research attempting to extrapolate these finding to a broader set of utilities within the U.S. or abroad should acknowledge this potential issue.

Second, we have found that the regression results differ significantly depending on whether major events are included in SAIFI and SAIDI. While there are industry standards for defining major events (IEEE, 2012), utilities sometimes use other criteria to define them (Eto et al., 2012 and Eto and LaCommare, 2008). Reliability reported with inconsistent major event definitions may bias the results. The effects models (random or fixed) which were used in this study were implemented to mitigate the effect of these types of utility-by-utility differences. However, we cannot state conclusively that these inconsistencies have been fully mitigated.

Third, although this econometric analysis is an improvement over the models originally specified in Eto et al. (2012) and Alvehag and Söder (2011), there are still areas for improvement. A number of the regressors used in this model are simple proxies for the inconsistently reported causes of reliability events. And we were unable to collect consistent data describing annual capital spending information for the utilities considered in this study.

7. Research implications and conclusion

The principal finding from this research—that reliability is getting worse over time due to severe-weather related increases in annual average power interruption frequency and number of minutes customers are without power—has important implications for planners, policymakers, and other industry stakeholders. At the highest level, this finding suggests that increased attention to preparation for and recovery from major events may be warranted. Utilities and regulators should consider planning for abnormal weather, because these deviations from long-term average weather conditions are clearly impacting the reliability of power systems across the United States. As part of these planning activities, our findings suggest that consideration of increases in future weather-related causes of power system interruptions (and total annual response times) is also prudent. The 2014 U.S. National Climate Assessment found that “some extreme weather and climate events have increased in recent decades…extreme weather events and water shortages are already interrupting energy supply and impacts are expected to increase in the future” (Melillo et al. 2014). National models of power system reliability, like the one described in this paper, could be used—both in the U.S. and abroad—to estimate power interruptions and total annual response times under a wide range of future climate scenarios and utility operating conditions.

Furthermore, findings from this study could be directly used to quantify associated benefits of strategies to improve grid resiliency to severe weather. For example, it was shown that the percentage share of utility miles that are underground is correlated with improved reliability. Larsen (2016) showed that undergrounding transmission and distribution lines can be a cost-effective strategy to improve reliability, but only if certain criteria are met before the decision to underground is made. The economic benefits of avoided outages—due to undergrounding—were a key determinant in the cost-benefit analysis constructed by Larsen (2016). It follows that the model coefficient on this specific explanatory variable could be used as an important assumption in studies that evaluate the benefits of this specific strategy to improve grid resiliency. In general, information that precisely details the factors that affect broad reliability trends can help justify additional resources—from both the private and public sector—to help respond to future environmental changes and associated impacts on power system reliability.

While we believe this analysis is the most comprehensive study of this topic that has ever been performed, there are a number of areas where we believe improvements should be considered in future analyses of U.S. electricity reliability.

It is important to collect information on annual capital spending and extend the analysis to evaluate the relationship between annual O&M *and* capital spending and changes in reliability. Also, the relationship between reliability and the long-run deployment of other "smart" technologies that enhance grid resiliency should be explored further as new information becomes available. Finally, 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).

The reliability of the electric power system is determined by how it is operated in the face of the reliability-threatening events to which it is subjected. Some of these factors can be managed, at least to a degree, by planning and preparing for routine events that the electric power system is expected to withstand. Other events are less manageable, including infrequent, yet catastrophic storms, which stress the electric power system beyond expectations. This study has sought to assess the relative contributions of planning and operations, on one hand, with the frequency and intensity of reliability-threatening events on the measured reliability performance of a large cross-section of U.S. electricity distribution companies over the past 13 years, on the other hand. In doing so, we hope that our findings will help to inform future public and private decisions that will influence the future reliability of electric power systems both in the U.S. and abroad.

Acknowledgment

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Technical Appendix A

This appendix contains detailed results for the four regressions and tests for the presence of utility effects and whether a random effects model is preferred over a fixed effects model.[11]

A.1 Cross-sectional and random effects

We carried out a two-step process to determine which type of regression effects model was best suited for analysis of each of the four datasets: (1) SAIDI without major events; (2) SAIDI with major events; (3) SAIFI without major events; and (4) SAIFI with major events. For the first step, we conducted an F-test to detect the presence of cross-sectional effects (i.e., utility-specific effects). For the second step, if the F-test fails to reject the null hypothesis of no utility effects (i.e., we confirm that there are utility-specific effects), we then used a Hausman (1978) test to determine whether a fixed effects or random effects regression model is more appropriate to use in developing models for each dataset. We illustrate application of this two-step method with intermediate results from the analysis conducted using Model F.

The results of the F-test for the first step for Model F (see Table A.1) indicates that the null hypothesis of no utility effects should be rejected for all four regressions (i.e., there are cross-sectional effects present in the data and that a pooled OLS is not the preferred model specification).

Table A.1 Test results for the presence of no utility effects (F-test)

	One-way fixed effect (utility)			
Reliability metric	***F-value***	***Degrees of freedom***	***Prob. >***	***Reject null of***

[11] Additional information about how serial correlation and heteroscedasticity were addressed simultaneously and tests for stationarity will be included in a subsequent manuscript. The authors can also provide these results upon request.

		(numerator/denominator)	F	no effects?
Log of SAIDI—without major events	16.8	62/461	< .0001	Yes
Log of SAIDI—with major events	3.3	45/290	< .0001	Yes
Log of SAIFI—without major events	18.8	62/460	< .0001	Yes
Log of SAIFI—with major events	10.3	45/292	< .0001	Yes

The results of the Hausman test for the second step for Model F (see Table A.2) indicates that the null hypothesis of random effects for three of the four regressions cannot be rejected, at $p \leq 0.15$.[12] In other words, the random effects model is the preferred choice for interpreting the results from three of the four sets of regressions and the fixed effects model is more appropriate for SAIFI (with major events).[13]

Table A.2 Test results for the presence of random effects (Hausman 1978)

	One-way random effect (utility)			
Reliability metric	***m-value***	***Degrees of freedom***	***Prob. > m***	***Reject null of random effects at p ≤ 0.15?***
LN SAIDI—without major events	8.3	7	0.30	No
LN SAIDI—with major events	5.7	9	0.77	No

[12] Technically speaking, a disadvantage of the fixed effects model estimator is that it does not allow the estimation of the coefficients of the time-invariant explanatory variables like, in this case, investor-owned utility designation (Baltagi et al. 2003). Accordingly, we conduct the Hausman (1978) test on model specifications that do not include the following time-invariant explanatory variable: investor-owned utility. A future improvement to this empirical analysis could entail implementing a Hausman and Taylor (1981) two-stage least squares procedure, which allows some of the explanatory variables to be correlated with the individual (utility) effects. We do not believe, however, that this technical enhancement would have a material impact on our findings.

[13] The random effects model is only valid if a very restrictive assumption holds: that the group effects are uncorrelated with the explanatory variables. If the composite error is correlated with the explanatory variables, then the random effects model is inconsistent and biased (Kennedy 2003). From a theoretical perspective, there is a valid argument to be made that a fixed effects model is preferred over a random effects model in this analysis, because weather varies significantly across large utility service territories. The modeling of weather within these sets of equations implies that utility effects would be correlated with the explanatory variables, which biases the random effects model. For this reason, we implemented two procedures to ensure that the findings were not biased: (1) we increased the Hausman (1978) hypothesis test rejection threshold from $p \leq 0.10$ to $p \leq 0.15$ (i.e. the null hypothesis of the Hausman test is that random effects is the preferred model); and (2) we report the findings from both the random and fixed effects models. Interestingly, the Hausman test failed to reject the null in three of the four regressions indicating that the random effects model is the preferred model for the majority of the regressions.

LN SAIFI—without major events	9.2	8	0.33	No
LN SAIFI—with major events	14.3	9	0.11	Yes

A.2 Candidate model performance

Table A.3 reports the statistical properties of each of the models. It shows that sequentially adding groupings of explanatory variables generally (but not always) improves model performance as measured by both increased adjusted/generalized r-squared and decreased root mean square error (RMSE). This is a well-understood artifact, which emphasizes the importance of also considering model parsimony. The Bayesian Information Criteria (BIC) (i.e., Schwarz Information Criterion) is often used to rank alternative models by their relative parsimony (Schwarz 1978, Hoen et al. 2009). A low BIC statistic indicates that a model is relatively more parsimonious than a model with a higher BIC statistic. As shown in Table A.3, the BIC statistic increases from Model A through Model C and then decreases as the previous year T&D spending, customers per line mile, and share of underground miles are incorporated into the model. Larsen et al. (2015) show that the coefficients remain stable—that is, the same explanatory variables generally remain significant at $p \leq 0.10$ and the signs on the coefficients do not switch from positive to negative (or vice versa).

Table A.3 Performance statistics for base model and six alternatives

Dependent variable and criteria		**A (Eto et al. 2012)**	**B**	**C**	**D**	**E**	**F (Preferred Model)**	**G**
SAIDI (without major events)	Adjusted R^2 (fixed) / Generalized R^2 (random)	0.78	0.79	0.04	0.80	0.80	0.05	0.08
	Root mean square error	0.31	0.31	0.31	0.29	0.28	0.26	0.26

Dependent variable and criteria		A (Eto et al. 2012)	B	C	D	E	F (Preferred Model)	G
	Bayesian Information Criteria (BIC)	1,186.5	1,168.8	1,523.3	1,029.3	784.5	447.7	501.0
	Utility effects:	Fixed	Fixed	Random	Fixed	Fixed	Random	Random
	Degrees of freedom	1,479	1,463	1,604	1,327	1,260	523	519
SAIDI (with major events)	Adjusted R^2 (fixed) / Generalized R^2 (random)	0.06	0.09	0.10	0.13	0.12	0.14	0.15
	Root mean square error	0.80	0.80	0.79	0.73	0.74	0.73	0.73
	Bayesian Information Criteria (BIC)	3,018.5	2,942.0	2,998.1	2,200.3	2,131.8	949.4	1,000.1
	Utility effects:	Random	Random	Random	Random	Random	Random	Random
	Degrees of freedom	1,124	1,091	1,086	820	813	335	331
SAIFI (without major events)	Adjusted R^2 (fixed) / Generalized R^2 (random)	0.01	0.01	0.02	0.02	0.02	0.03	0.03
	Root mean square error	0.38	0.38	0.38	0.34	0.33	0.24	0.25
	Bayesian Information Criteria (BIC)	1,926.8	1,923.5	2,000.4	1,531.1	1,355.5	335.5	404.9
	Utility effects:	Random	Random	Random	Random	Random	Random	Random
	Degrees of freedom	1,603	1,586	1,581	1,441	1,368	522	518
SAIFI (with major events)	Adjusted R^2 (fixed) / Generalized R^2 (random)	0.49	0.03	0.04	0.09	0.65	0.71	0.71
	Root mean square error	0.47	0.45	0.45	0.31	0.31	0.26	0.27
	Bayesian Information Criteria (BIC)	1,649.8	1,744.5	1,823.3	823.8	667.0	255.5	317.5
	Utility effects:	Fixed	Random	Random	Random	Fixed	Fixed	Fixed
	Degrees of freedom	1,009	1,091	1,086	820	727	292	288

A.3 Regression results and fit diagnostics

Table A.4 Results for SAIDI regressions

Explanatory variables:	**Log of SAIDI (without major events)**			**Log of SAIDI (with major events)**		
	Pooled	***Fixed Effects***	***Random Effects (preferred)***	***Pooled***	***Fixed Effects***	***Random Effects (preferred)***
Intercept	5.617 (15.84)	-14.062 (14.736)	-21.218 (13.53)	-169.108*** (40.624)	-165.597** (64.648)	-185.236*** (49.627)
Electricity delivered (MWh per customer)	-0.001* (0.001)	0.018* (0.01)	0.002 (0.002)	0.002 (0.008)	-0.019 (0.045)	0.004 (0.015)
Abnormally cold weather (% above average HDDs)	-0.001 (0.001)	0 (0.001)	0.001 (0.001)	0.004 (0.015)	0.008 (0.013)	0.004 (0.013)
Abnormally warm weather (% above average CDDs)	0.002 (0.002)	-0.001 (0.001)	0 (0.001)	-0.006 (0.005)	-0.007 (0.005)	-0.008* (0.004)
Abnormally high # of lightning strikes (% above average strikes)	0.001 (0.001)	0.001 (0.001)	0.001 (0)	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)
Abnormally windy (% above average wind speed)	0.015 (0.015)	0.019* (0.01)	0.021** (0.009)	0.11*** (0.034)	0.122*** (0.033)	0.121*** (0.031)
Abnormally windy squared	0 (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.005** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
Abnormally wet (% above average total precipitation)	-0.001 (0.003)	0.002 (0.002)	0.002 (0.002)	0.007 (0.006)	0.01** (0.005)	0.01* (0.005)
Abnormally dry (% below average total precipitation)	0.004* (0.002)	0.001 (0.002)	0.001 (0.002)	0.004 (0.005)	0 (0.006)	0.001 (0.005)
Outage management system?	-0.001 (0.066)	0.033 (0.05)	0.037 (0.049)	0.233* (0.137)	0.112 (0.15)	0.128 (0.136)
Years since outage management system installation	-0.004 (0.009)	0.002 (0.01)	-0.007 (0.009)	-0.034* (0.02)	-0.011 (0.036)	-0.02 (0.025)
Year	0 (0.008)	0.009 (0.007)	0.013* (0.007)	0.087*** (0.02)	0.085*** (0.032)	0.095*** (0.025)
Lagged T&D O&M expenditures ($2012 per customer)	-0.084** (0.035)	-0.017 (0.035)	-0.005 (0.026)	-0.05 (0.038)	-0.347 (0.538)	0 (0.07)
Number of customers per line mile	-0.009*** (0.001)	0.002 (0.004)	-0.003 (0.003)	-0.003 (0.004)	0.033* (0.017)	0.006 (0.007)
Share of underground T&D miles to total T&D miles	-0.005*** (0.002)	0.002 (0.005)	-0.002 (0.004)	-0.015*** (0.003)	-0.006 (0.012)	-0.014** (0.007)
Degrees of freedom:	523	461	523	335	290	335

Explanatory variables:	Log of SAIDI (without major events)			Log of SAIDI (with major events)		
	Pooled	***Fixed Effects***	***Random Effects (preferred)***	***Pooled***	***Fixed Effects***	***Random Effects (preferred)***
Number of utilities:	63	63	63	46	46	46
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.18	0.75	0.05	0.16	0.44	0.14
Root mean square error	0.46	0.27	0.27	0.86	0.75	0.73

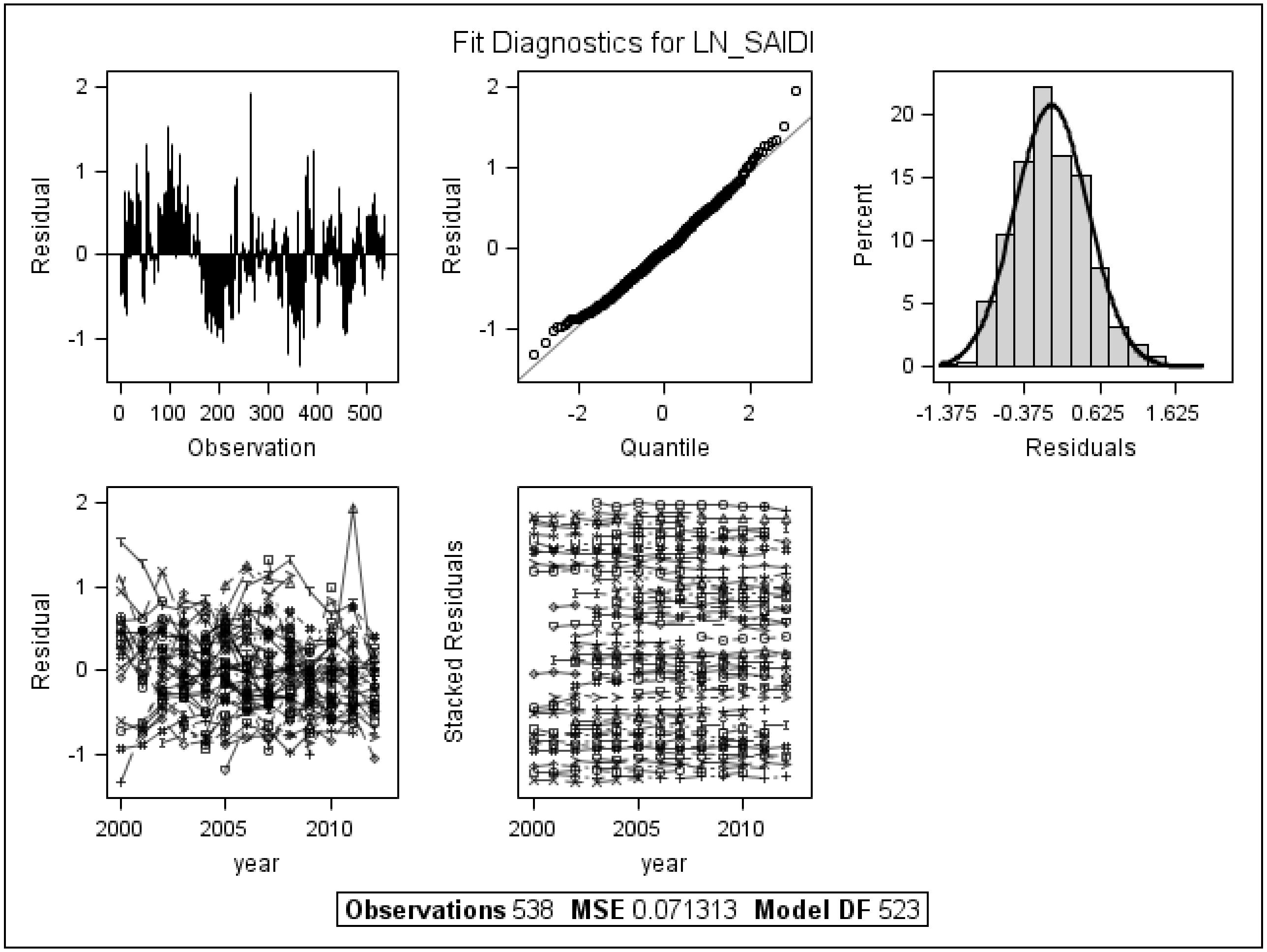

Figure A.1 SAIDI base model fit diagnostics (without major events included)

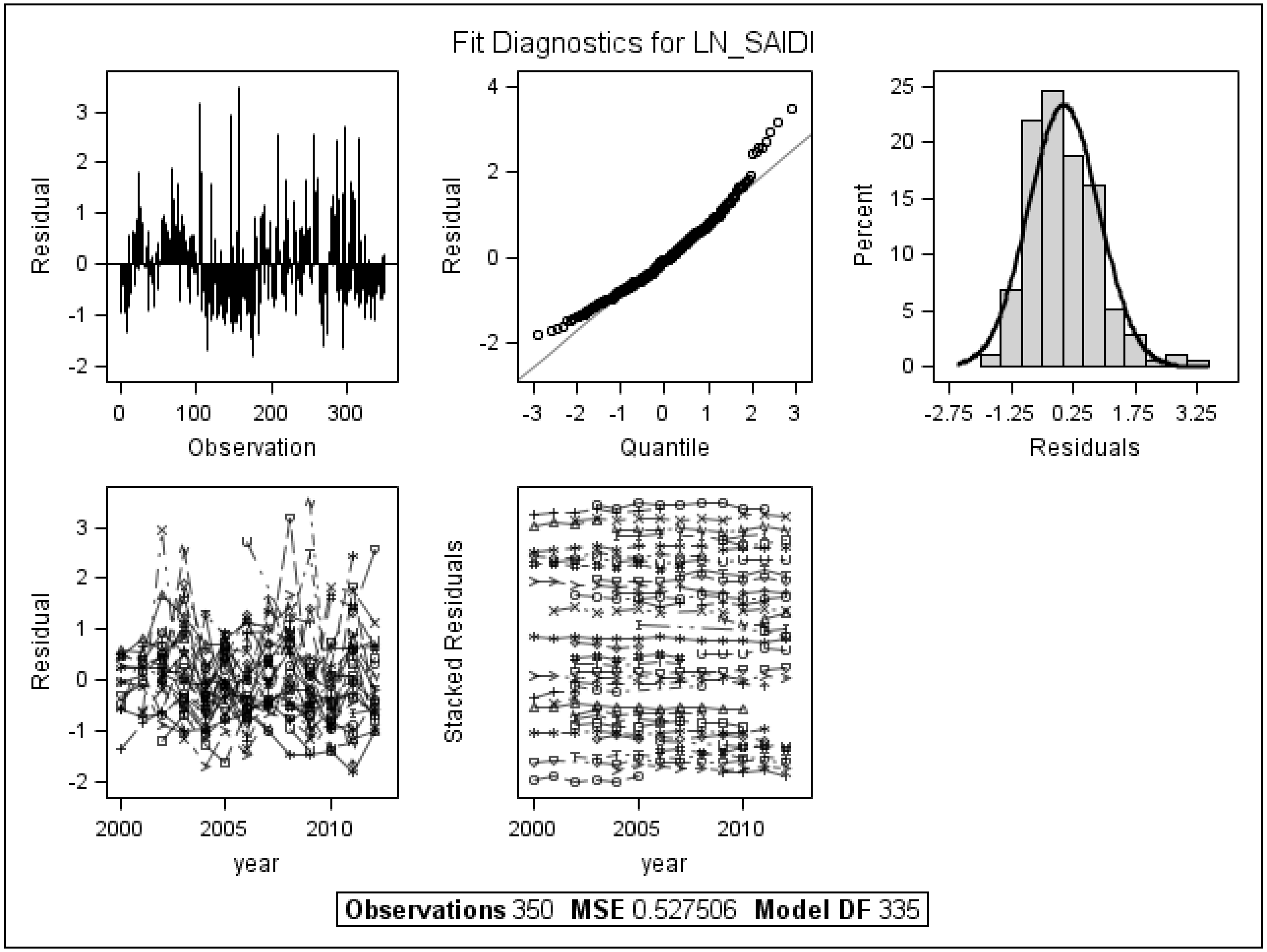

Figure A.2 SAIDI base model fit diagnostics (with major events included)

Table A.5 Results for SAIFI regressions

Explanatory variables:	Log of SAIFI (without major events)			Log of SAIFI (with major events)		
	Pooled	***Fixed Effects***	***Random Effects (preferred)***	***Pooled***	***Fixed Effects (preferred)***	***Random Effects***
Intercept	-4.635 (18.676)	0.509 (18.277)	-8.622 (15.225)	-57.398*** (16.256)	-23.488 (20.295)	-39.159** (16.705)
Electricity delivered (MWh per customer)	0.001* (0.001)	0.003 (0.007)	0.002 (0.002)	0 (0.002)	-0.005 (0.011)	0.002 (0.004)
Abnormally cold weather (% above average HDDs)	0.001 (0.002)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.007)	0.002 (0.005)	0.001 (0.005)
Abnormally warm weather (% above average CDDs)	-0.003 (0.002)	0 (0.001)	0 (0.001)	-0.002 (0.002)	0 (0.001)	0 (0.001)
Abnormally high # of lightning strikes (% above average strikes)	0 (0.001)	0 (0.001)	0 (0.001)	0.002** (0.001)	0.002** (0.001)	0.001** (0.001)
Abnormally windy (% above average wind speed)	0.012 (0.016)	0.023** (0.011)	0.023** (0.011)	0.025 (0.016)	0.04*** (0.012)	0.04*** (0.012)
Abnormally windy squared	-0.001 (0.001)	-0.002*** (0.001)	-0.002** (0.001)	0 (0.001)	-0.003*** (0.001)	-0.002*** (0.001)
Abnormally wet (% above average total precipitation)	-0.002 (0.002)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.002)	0.002 (0.001)	0.002 (0.001)
Abnormally dry (% below average total precipitation)	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)	0.003 (0.002)	0.003* (0.002)	0.003* (0.002)
Outage management system?	-0.072 (0.053)	0.011 (0.039)	0.003 (0.038)	0.017 (0.066)	-0.02 (0.051)	-0.028 (0.05)
Years since outage management system installation	-0.009 (0.007)	0.003 (0.008)	-0.003 (0.006)	-0.022** (0.009)	0 (0.012)	-0.006 (0.009)
Year	0.003 (0.009)	0 (0.009)	0.004 (0.008)	0.029*** (0.008)	0.012 (0.01)	0.02** (0.008)
Lagged T&D O&M expenditures ($2012 per customer)	-0.08*** (0.021)	0.027 (0.035)	-0.02 (0.021)	-0.06*** (0.022)	-0.069 (0.184)	-0.026 (0.049)
Number of customers per line mile	-0.007*** (0.001)	0.001 (0.003)	-0.004** (0.002)	-0.004** (0.002)	0.008 (0.005)	0 (0.004)
Share of underground T&D miles to total T&D miles	-0.002 (0.001)	0.005 (0.003)	0.001 (0.002)	-0.01*** (0.002)	-0.001 (0.004)	-0.006* (0.003)
Degrees of freedom:	522	460	522	337	292	337
Number of utilities:	63	63	63	46	46	46
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.15	0.76	0.03	0.25	0.71	0.11
Root mean square error	0.43	0.24	0.24	0.40	0.26	0.26

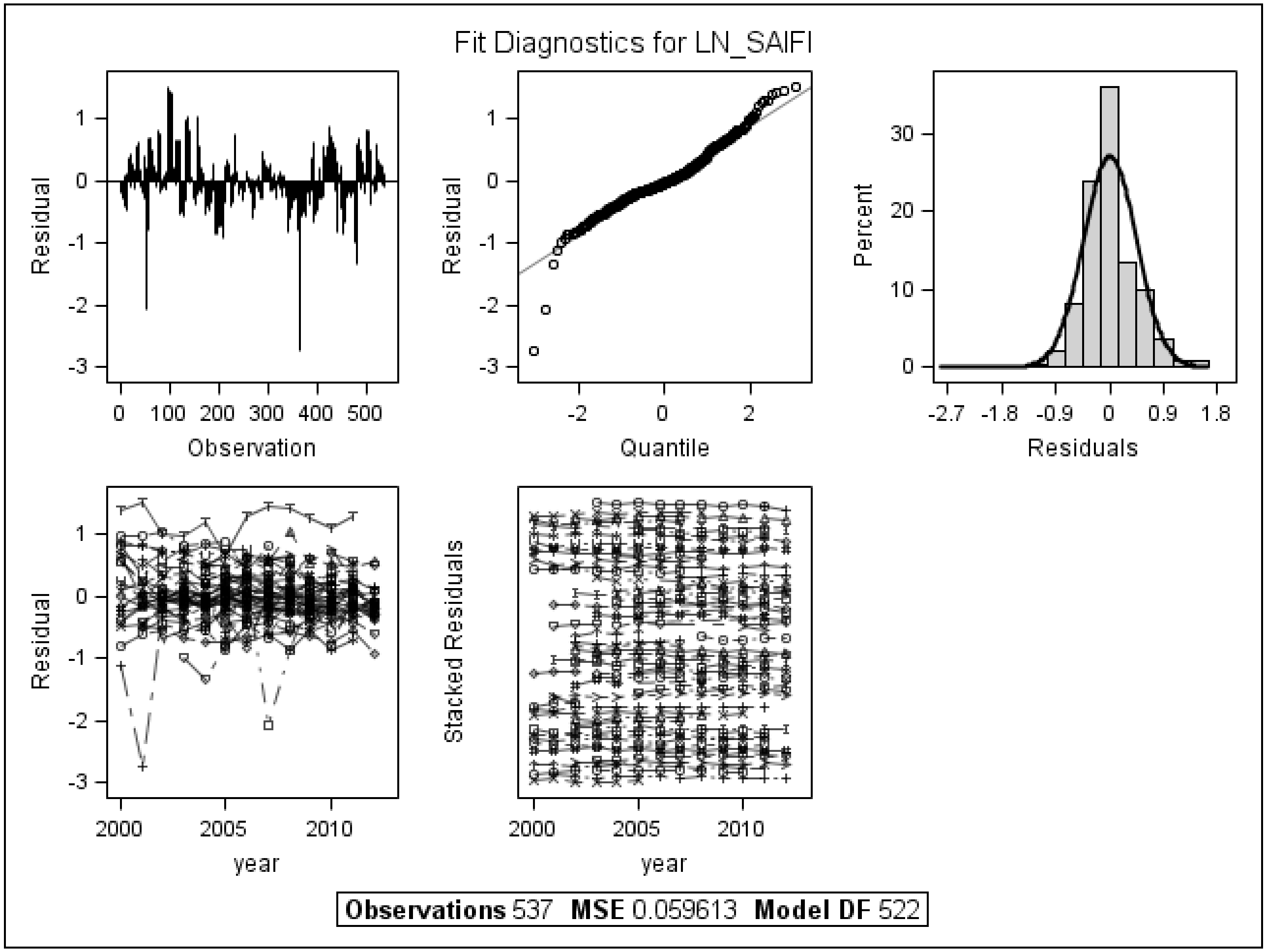

Figure A.3 SAIFI base model fit diagnostics (without major events included)

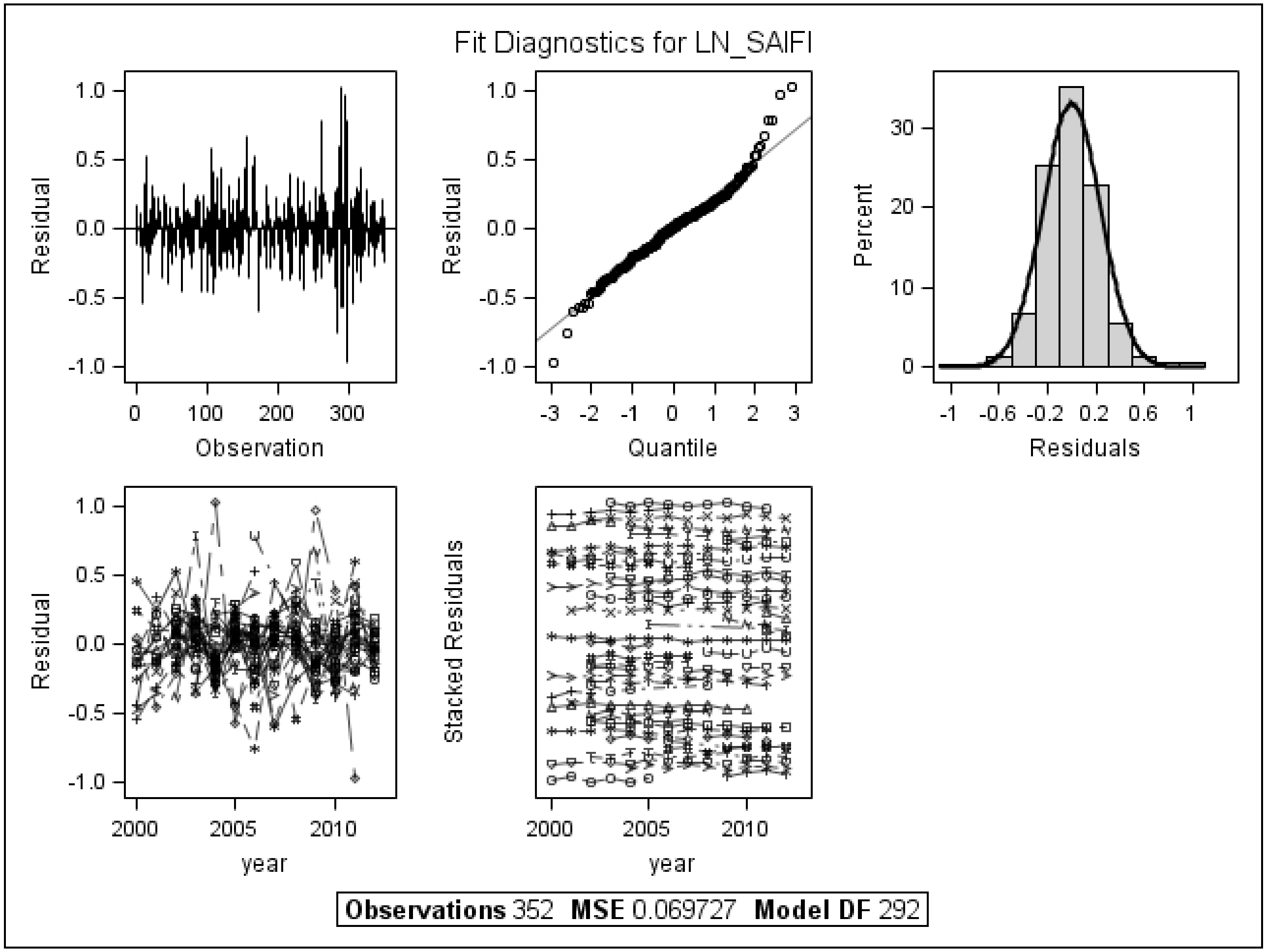

Figure A.4 SAIFI base model fit diagnostics (with major events included)