DTE Electric Company
One Energy Plaza, 1635 WCB
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September 12, 2024

Lisa Felice
Acting Executive Secretary
Michigan Public Service Commission
7109 West Saginaw Highway
Lansing, MI 48917

RE: In the matter of the Application of **DTE ELECTRIC COMPANY** for authority to increase its rates, amend its rate schedules and rules governing the distribution and supply of electric energy, and for miscellaneous accounting authority
MPSC Case No. U-21534

Dear Ms. Felice:

The following is attached for paperless electronic filing:

Official Exhibits of the DTE Electric Company admitted into the record on September 4-6, 2024 and September 9-10, 2024:

Exhibits A-41 thru A-45

If you have any questions or concerns with this filing, please contact me at the above referenced number.

Respectfully submitted,

Estella R. Branson

Digitally signed by Estella R. Branson
Date: 2024.09.12 12:48:36 -04'00'

Estella R. Branson
Senior Paralegal

Enclosure

MICHIGAN PUBLIC SERVICE COMMISSION
DTE Electric Company
Uncollectible Accounts Expense
Staff UCX Calculation
for the Projected Test-Period Ending December 31, 2025
(000's)

Case No.: U-21534
Exhibit: A-41
Schedule: FF1
Witness: J. E. Sparks
Page: 1 of 2

Staff Projection (Original Calculation)

	(a.)	(b.)	(c.)	(d.)	(e.)
Ln.	Description	Source	2023	2022	2021
1	Accounts Written-Off		$ 72,461	$ 65,303	$ 76,776
2	(less) Collection of Accounts Written-Off		$ (28,320)	$ (27,645)	$ (36,732)
3	Net Write-Offs		$ 44,141	$ 37,658	$ 40,044
4	Billed Revenue		$ 5,847,903	$ 5,614,043	$ 5,551,588
5	Net Write-Offs to Revenue Percentage		0.7548%	0.6708%	0.7213%
6	Charges to Direct Expense		$ 1,095	$ 2,744	$ (146)
7	Projected Billed Revenue 12 month's ending 12/31/25	A-16 F2, col. b., ln. 49			$ 5,561,302
8	3-Year Average Net Write-Offs to Revenue	avg(ln.5, col.c-e)			0.72%
9	Projected Net Write-Offs	(ln 7 x ln 8)			$ 39,799
10	Historical 3 Year Average Charges to Direct Expense (ln 7)	avg(ln.6, col.c-e)			$ 1,231
11	Projected Uncollectible Accounts Expense (ln 10+ ln 11)				$ 41,029

MICHIGAN PUBLIC SERVICE COMMISSION
DTE Electric Company
Uncollectible Accounts Expense
Staff UCX Calculation
for the Projected Test-Period Ending December 31, 2025
(000's)

Case No.: U-21534
Exhibit: A-41
Schedule: FF1
Witness: J. E. Sparks

Revised Staff Calculation with Projected Billed Revenue that includes PSCR Revenue

	(a.)	(b.)	(c.)	(d.)	(e.)
Ln.	Description	Source	2023	2022	2021
1	Accounts Written-Off		$ 72,461	$ 65,303	$ 76,776
2	(less) Collection of Accounts Written-Off		$ (28,320)	$ (27,645)	$ (36,732)
3	Net Write-Offs		$ 44,141	$ 37,658	$ 40,044
4	Billed Revenue		$ 5,847,903	$ 5,614,043	$ 5,551,588
5	Net Write-Offs to Revenue Percentage		0.7548%	0.6708%	0.7213%
6	Charges to Direct Expense		$ 1,095	$ 2,744	$ (146)
7	Projected Billed Revenue 12 month's ending 12/31/25	AGDE 1.27b, Exh. AG-41, line 5			$ 6,399,006
8	3-Year Average Net Write-Offs to Revenue	avg(ln.5, col.c-e)			0.72%
9	Projected Net Write-Offs	(ln 7 x ln 8)			$ 45,793
10	Historical 3 Year Average Charges to Direct Expense (ln 7)	avg(ln.6, col.c-e)			$ 1,231
11	Projected Uncollectible Accounts Expense (ln 10+ ln 11)				$ 47,024
12	**Change vs. original calculation**				**$ 5,995**

MPSC Case No: U-21534	
Requester: AG	
Question No.: AGDE-1.27b	
Respondent: J. Sparks	
Page: 1 of 1	

Question: 27. Refer to the Uncollectible Accounts expense shown on Exhibit A-13, Schedule C5.8. Please:

b. Regarding Projected Billed Revenue on line 8, provide a reconciliation of this revenue amount to the proposed revenues on Exhibit A-16, Schedule F2, line 49, column (b).

Answer: Assuming that the request is referencing column (c) and not (b) the response would be as follows: See below exhibit citation for projected billed revenue. Due to the uncollectible estimate being required prior to finalization of other forecast inputs and the calculation of overall projected revenue deficiency, the total revenue varies from Exhibit A-13 C5.8

Line Item	Exhibit	Amount
Total Revenue	Exhibit A-16, schedule F2, column c, row 49	$6,017,737
PSCR Factor Revenue	Not included in total revenue in exhibit A-16, schedule F2	$381,269
Total revenue		$6,399,006

Attachment: None

Michigan Public Service Commission
DTE Electric Company
Emergent Capital Savings Calculation

Case No.: U-21534
Exhibit: A-42
Schedule: GG1
Witness: R.C.Steudle
Page: 1 of 2

Line	Cost Category or Caption (a)	2024 Test Yr. Costs (b)	2022 Hist. Yr. Costs (c)	Savings from Lower 2024 Costs vs. 2022 (d)	Ex. A-22, Sch. L1 (e)
1	Tree Trim Reactive*	$ 2.1	$ 2.9	$ 0.8	Line 24
2	Tree Trim Storm*	12.8	17.2	$ 4.4	Line 25
3	Other DO-Service Operations Storm and Trouble*	52.0	69.6	$ 17.6	Line 26
4	Total Costs	66.9	89.7	22.8	
5	Less Company Savings Reflected in filed Capital Exhibit**			20.8	
6	**Additional Capital Reduction**			**$ 2.0**	

Michigan Public Service Commission
DTE Electric Company
Emergent Capital Savings Calculation

Line	Cost Category or Caption (a)	2025 Test Yr. Costs (b)	2022 Hist. Yr. Costs (c)	Savings from Lower 2025 Costs vs. 2022 (d)	Ex. A-22, Sch. L1 (e)
1	Tree Trim Reactive*	$ 1.9	$ 2.9	$ 1.0	Line 24
2	Tree Trim Storm*	11.4	17.2	$ 5.8	Line 25
3	Other DO-Service Operations Storm and Trouble*	46.3	69.6	$ 23.3	Line 26
4	Total Costs	59.6	89.7	30.1	
5	Less Campany Savings Reflected in filed Capital Exhibit**			21.4	
6	**Additional Capital Reduction**			**$ 8.7**	

Michigan Public Service Commission
DTE Electric Company
Projected Value of Tree Trim Risk Prioritization Model

Case No.: U-21534
Exhibit: A-42
Schedule: GG2
Witness: R.C.Steudle
Page: 1 of 2

Michigan Public Service Commission
DTE Electric Company
Projected Value of Tree Trim Risk Prioritization Model

Case No.: U-21297
Exhibit: A-22
Schedule: L2
Witness: S.M.Hartwick
Page: 1 of 2

Line No.	(a) Description	(b) 2022	(c) 2023	(d) 2024	(e) 2025	(f) 2026	(g) 2027	(h) 2028	(i) 2029	(j) 2030
1	**Tree Trim Program Spend**									
2	Total Program Spend (A-22 Schedule L1 Line 5)	$197.1	$200.9	$159.1	$166.0	$126.1	$129.8	$133.4	$137.3	$139.6
3	Maintenance Trimming Cost	$141.8	$148.4	$123.2	$139.4	$100.7	$103.4	$106.1	$109.1	$110.8
4	**NPV Analysis for Veg Analystics Model**									
5	Expected Risk-based Cycle Savings (5% of Trimming cost, Line 3)					$5.0	$5.2	$5.3	$5.5	$5.5
6	Tree Trim Risk Prioritization Model Capital costs (Exhibit A-12 Schedule B5.4 Page 12 Line 8)	($4.9)	($1.4)							
7	Tree Trim Risk Prioritization Model O&M Costs	($0.7)	($0.9)							
8	Digital Infrastructure and Services Capital costs (Exhibit A-12 B5.7.7 Line 25)	($8.3)	($0.3)							
9	Digital Infrastructure and Services O&M costs	($3.8)								
10	Re-occuring costs			($0.3)	($0.3)	($0.3)	($0.3)	($0.3)	($0.3)	($0.3)
11	Net Savings	($17.7)	($2.5)	($0.3)	($0.3)	$4.7	$4.9	$5.0	$5.2	$5.2
12	NPV	$11.2								
13	Rate of return	6.80%								

Michigan Public Service Commission
DTE Electric Company
Projected Value of Tree Trim Risk Prioritization Model

Case No.: U-21534
Exhibit: A-42
Schedule: GG2
Witness: R.C.Steudle
Page: 2 of 2

Michigan Public Service Commission
DTE Electric Company
Projected Value of Tree Trim Risk Prioritization Model

Case No.: U-21297
Exhibit: A-22
Schedule: L2
Witness: S.M.Hartwick
Page: 2 of 2

Line No.	(a) Description	(c) 2031	(d) 2032	(e) 2033	(f) 2034	(g) 2035	(h) 2036
1	**Tree Trim Program Spend**						
2	Total Program Spend (A-22 Schedule L1 Line 5)	$139.7	$143.8	$147.6	$151.8	$154.6	$154.6
3	Maintenance Trimming Cost	$110.3	$113.5	$116.4	$119.8	$121.7	$121.0
4	**NPV Analysis for Veg Analystics Model**						
5	Expected Risk-based Cycle Savings (5% of Trimming cost, Line 3)	$5.5	$5.7	$5.8	$6.0	$6.1	$6.1
6	Tree Trim Risk Prioritization Model Capital costs (Exhibit A-12 Schedule B5.4 Page 12 Line 8)						
7	Tree Trim Risk Prioritization Model O&M Costs						
8	Digital Infrastructure and Services Capital costs (Exhibit A-12 B5.7.7 Line 25)						
9	Digital Infrastructure and Services O&M costs						
10	Re-occuring costs	($0.3)	($0.3)	($0.3)	($0.3)	($0.3)	($0.3)
11	Net Savings	$5.2	$5.4	$5.5	$5.7	$5.8	$5.8

MPSC Case No: U-21534	
Requester: AG	
Question No.: AGDE-4.167 (S1)	
Respondent: R. Steudle	
Page: 1 of 1	

Question: 167. Refer to the request and response to AGDE-4.120 in Case No. U-21297. Please provide the same information for 2024 and 2025.

Answer: This discovery question from the AG was also requested in Case No. U-21297 and in Case No. U-20836.

The previous response used the numbers referred to in Exhibit A-22, Schedule L1, line numbers 4, 9, and 10. Those costs were the projected costs under the Surge scenario – not the relative cost savings produced as a result of doing the Surge. The attached file shows the correct line numbers and values that should have been used.

It is important to note the purpose of Exhibit A-22 is to compare the value of executing the Surge compared to the status quo alternative.

The cost savings demonstrated in Exhibit A-22 are based on the Tree Trim Surge Model. The model was developed when the Surge was first proposed in July of 2018 in Case No. U-20162. The information reflected in Exhibit A-22 is based on when the model was last updated in late 2021 for Case No. U-20836. The savings are calculated by comparing a scenario in which the Company continues the Surge (Surge Program) to a scenario in which the Surge funding does not continue (Status Quo). In U-20836 the Company used the model to demonstrate the benefit from continuing the Surge for the years 2022 through 2025, as opposed to stopping it in 2021.

The Company has already realized the modeled savings from 2022-2024 since the Surge has continued. DTE Electric included the U-20836 version of Exhibit A-22 to demonstrate the positive NPV and justification for the Surge program overall, however, the Company did not update this model for the final years of the Surge since majority of savings have already been realized.

Attachment: U-21534_AGDE-4.167 (S) - Exhibit A-22 Schedule L1 Savings

U-21534 - Previously Submitted

Estimated Tree-related Annual Cost savings ($ millions)				
Cost Category		Exhbit A-22, Schedule L1 Line No.	2024	2025
Tree-Related O&M	Tree Trim Reactive	4	8.9	7.4
	Tree Trim Storm	9	11.2	10.0
	Other DO – Service Operations Storm and Trouble	10	8.5	7.5
Tree-Related Capital	Tree Trim Reactive	24	2.1	1.9
	Tree Trim Storm	25	12.8	11.4
	Other DO – Service Operations Storm and Trouble	26	52.0	46.3

U-21534 - Corrected

Estimated Tree-related Annual Cost savings ($ millions)				
Cost Category		Exhbit A-22, Schedule L1 Line No.	2024	2025
Tree-Related O&M	Tree Trim Reactive	Line 16 minus Line 4	7.2	9.3
	Tree Trim Storm	Line 19 minus Line 9	5.0	7.1
	Other DO – Service Operations Storm and Trouble	Line 20 minus Line 10	3.8	5.4
Tree-Related Capital	Tree Trim Reactive	Line 29 minus Line 24	1.0	1.4
	Tree Trim Storm	Line 30 minus Line 25	5.8	8.1
	Other DO – Service Operations Storm and Trouble	Line 31 minus Line 26	23.3	33.0

MPSC Case No: U-21534	
Requester: AG	
Question No.: AGDE-4.160a.	
Respondent: R. Steudle	
Page: 1 of 1	

Question: 160. Refer to the table in Q41 on page 17 of Ms. Steudle's direct testimony on the tree trimming surge program cost escalation. Please: a. Provide the calculations and details in Excel showing how you determined each cost item.

Answer: See attached.

Attachment: *U-21534 AGDE-4 160a Details of Incremental Cost*

Drivers	$ Millions	
Higher On-Cycle Costs	$	133.6
Increased Outsource Premium	$	69.7
Programmatic Additions	$	30.5
Inflation	$	17.4
Total	$	251.2

Michigan Public Service Commission
DTE Electric Company
AGDE-4.160a

	2019	2020	2021	2022	2023	2024 & 2025
Subtrans $/Mile	$ 9,237.11	$ 12,334.21	$ 6,448.34	$ 13,228.62	$ 12,613.34	$ 11,153.72
Distribution Reclaim $/Mile	$ 29,402.95	$ 29,374.79	$ 28,506.95	$ 43,695.34	$ 35,086.42	$ 33,831.73
Distribution On-Cycle $/Mile			$ 17,318.98	$ 18,036.98	$ 25,496.43	$ 30,031.45

	2019	2020	2021	2022	2023	2024 & 2025
Subtransmission	1006	1006	726	723	711	1,707
DC-Reclaim	3,022	4,316	3,149	2,742	1,768	4,960
DC-Second-Cycle			1,545	2,726	2,582	7,436

U-20162 Forecast Cost per Mile *Actual Miles	$ 85,157,367.69	$ 136,738,230.97	$ 132,323,738.66	$ 144,135,082.62	$ 113,806,639.68	$ 338,308,546.14	
Actutals/U-21534 Forecast	$ 98,154,866.46	$ 139,190,650.79	$ 121,216,649.63	$ 178,523,259.70	$ 136,832,670.51	$ 410,162,552.06	
Delta	*$ 12,997,498.77*	*$ 2,452,419.82*	*$ (11,107,089.03)*	*$ 34,388,177.08*	*$ 23,026,030.84*	*$ 71,854,005.92*	*$ 133,611,043.40*

	2019-2022 Actuals	2023-2025 Forecast*	**Total**
U-20162	$38.89	$6.56	**$45.46**
Actuals/Forecast	$64.63	$50.53	**$115.16**
Net Impact			**$69.70**

*2023 forecast based on 8+4 forecast, 2024-2025 based on the estimated workforce needed to complete the Surge

	2019	2020	2021	2022	2023	2024	2025	**Total**
Spot Trimming	$ 5,000,000.00	$ 5,024,744.00	$ 5,300,000.00	$ 5,300,000.00	$ 5,000,000.00	$ 500,000.00	$ -	**$ 26,124,744.00**
Tree Trim Academy	$ -	$ 157,918	$ 1,000,690	$ 1,076,097	$ 696,980	$ 696,980	$ 696,980	**$ 4,325,644**
Total								**$ 30,450,388**

Michigan Public Service Commission
DTE Electric Company
AGDE-4.160a

Change in overall inflation rates

Program Funding		2019	2020	2021	2022	2023	2024	2025
	Base O&M	$ 94	$ 97	$ 100	$ 103	$ 106	$ 109	$ 112
	Reg Asset	$ 43	$ 74	$ 71	$ 58	$ 67	$ 53	$ 44
	Total	**$ 137**	**$ 171**	**$ 170**	**$ 161**	**$ 173**	**$ 162**	**$ 156**

Inflation Assumtions		2019	2020	2021	2022	2023	2024	2025
	Annual Infl	3%	3%	3%	3%	3%	3%	3%
U-20162	Compounc	1.00	1.03	1.06	1.09	1.13	1.16	1.19
LCTT Contract Labor	Annual Infl	3.0%	4.0%	4.0%	4.0%	5.7%	4.0%	4.2%
Increase	Compounc	1.00	1.04	1.08	1.12	1.19	1.24	1.29
	Difference		*1.0%*	*1.0%*	*1.0%*	*2.7%*	*1.0%*	*1.2%*

Relative Impact to Funding		2020	2021	2022	2023	2024	2025
	2020	$ 1.71	$ 1.73	$ 1.75	$ 1.79	$ 1.81	$ 1.83
	2021		$ 1.70	$ 1.72	$ 1.77	$ 1.79	$ 1.81
	2022			$ 1.61	$ 1.65	$ 1.67	$ 1.69
	2023				$ 4.67	$ 4.72	$ 4.78
	2024					$ 1.62	$ 1.64
	2025						$ 1.87
Total							**$ 13.62**

Impact of Delayed Rate Case Fillings to Increase Base O&M Annually

	2021	2022	
Projected (U-20561) ($M)	99.1	101.5	
Actual ($M)	97.9	98.9	
Net Impact	-1.2	-2.6	-3.8

Michigan Public Service Commission
DTE Electric Company
DEAG-2

MPSC Case No.	**U-21534**
Responding Party:	Attorney General
Respondent:	Sebastian Coppola
Requestor:	DTE Electric
Question No.:	**DEAG-2**

DEAG-2

In Case No. U-21534, please refer to S. Coppola's Direct testimony, page 67, line 7. Please provide the data source(s) and calculations used to derive the $496M of capitalized tree trimming. This request is continuing in nature and the Company requests supplementation for any and all changes or modifications to direct testimony, rebuttal testimony, and exhibits.

Response:

Refer to Case No. U-20162, line 25 of page 1 of Exhibit A-22, Schedule L1, for 2019 and 2020 for the Company's forecasted capitalized three trimming amounts and Case No. U-21534 (20836), line 27 on page 1 of Exhibit A-22, Schedule L1, for 2021 to 2025 amounts, as shown below to arrive at the $496 million amount included in Mr. Coppola's direct testimony.

($millions)		Capitalized Tree Trimming Surge Program Costs
U-20162, Exhibit A-11, Schedule L1	2019	$ 55.80
U-20162, Exhibit A-11, Schedule L1	2020	55.7
U-21534, Exhibit A-11, Schedule L1	2021	89.5
U-21534, Exhibit A-11, Schedule L1	2022	89.7
U-21534, Exhibit A-11, Schedule L1	2023	78.8
U-21534, Exhibit A-11, Schedule L1	2024	67.0
U-21534, Exhibit A-11, Schedule L1	2025	59.6
		$ 496.1

If Case U-20162 costs for 2019 and 2020 are replaced with the amounts shown in Case U-20561, line 25 of Exhibit A-22, Schedule L1, the total amount from 2019 to 2025 is $511.1 million.

Date: 8/5/24

MPSC Case No: U-21534	
Requester: MNSC	
Question No.: MNSCDE-15.23a	
Respondent: M. Elliott Andahazy	
Page: 1 of 1	

Question: 23. Refer to Ms. Elliot Andahazy's testimony at MEA-30:7 which states " Useful life is a standard industry term that does not represent the actual life of an asset, but rather the age at which an installed asset is expected to experience increasing failure rates and deliver reduced performance, such that it is often more prudent to replace than to continue to repair and maintain."

a. Confirm that the Company uses the terms "useful life" and "depreciation period" interchangeably. If this cannot be confirmed, please explain.

Answer: Not confirmed. The Company uses the term depreciation *rates* when describing how depreciation expense is calculated. Depreciation rates incorporate various factors including useful lives, average remaining lives, salvage, cost of removal and current depreciation reserves.

Attachment: N/A

Co-respondent: T. Uzenski

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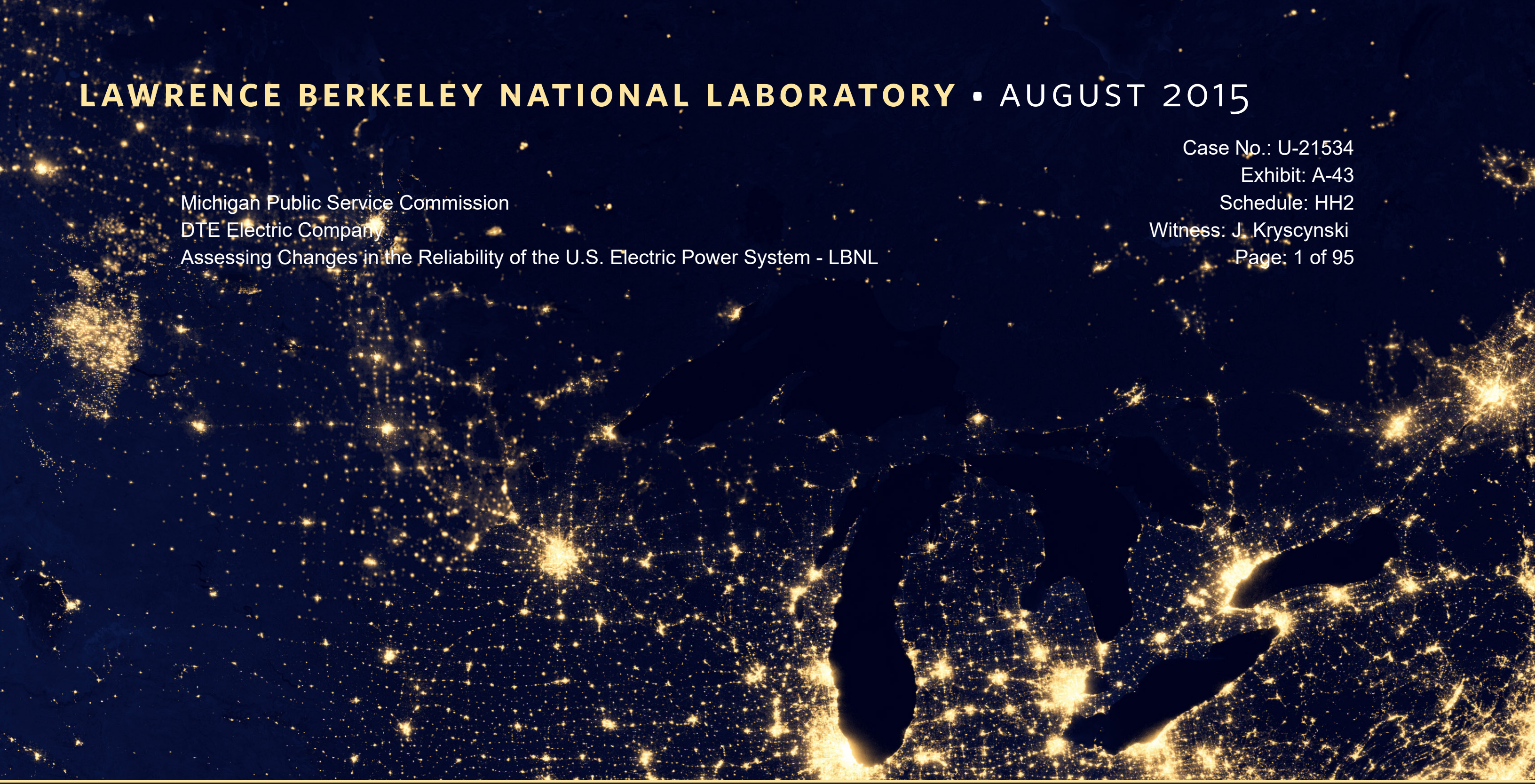

Assessing Changes in the Reliability of the U.S. Electric Power System

Peter H. Larsen
Kristina H. LaCommare
Joseph H. Eto
James L. Sweeney

BERKELEY LAB

LBNL-188741

Assessing Changes in the Reliability of the U.S. Electric Power System

Prepared for the
Office of Electricity Delivery and Energy Reliability
National Electricity Delivery Division
U.S. Department of Energy

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Lawrence Berkeley National Laboratory and Stanford University

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August 2015

The work described in this study was funded by the National Electricity Delivery Division of the U.S. Department of Energy's Office of Electricity Delivery and Energy Reliability under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

Disclaimer

Abstract

Recent catastrophic weather events, existing and prospective federal and state policies, and growing investments in smart grid technologies have drawn renewed attention to the reliability of the U.S. electric power system. Whether electricity reliability is getting better or worse as a result of these or other factors has become a material issue for public and private decisions affecting the U.S. electric power system.

This study examines the statistical 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 various measures of weather and utility characteristics.

We find statistically significant correlations between the average number of power interruptions experienced annually by a customer and a number of explanatory variables including wind speed, precipitation, lightning strikes, and the number of customers per line mile. We also find statistically significant correlations between the average total duration of power interruptions experienced annually by a customer and wind speed, precipitation, cooling degree-days, the percentage share of underground transmission and distribution lines. In addition, we find a statistically significant trend in the duration of power interruptions over time—especially when major events are included. This finding suggests that increased severity of major events over time has been the principal contributor to the observed trend.

Acknowledgments

The work described in this report was funded by the Office of Electricity Delivery and Energy Reliability, National Electricity Delivery Division of the U.S. Department of Energy (DOE) under Contract No. DE-AC02-05CH11231. The authors are grateful to David Meyer for his support of this research.

We gratefully acknowledge a number of individuals who provided technical assistance, constructive advice, and/or encouragement at various points during this project: Amber Armentrout (Ventyx), William Morrow, Peter Cappers, Annika Todd, Liesel Hans, and Anna Spurlock (Lawrence Berkeley National Laboratory), Alex Hofmann, Mike Hyland (APPA), Marek Samotyj (EPRI), Bernard Neenan (Neenan Associates), Caitlin Callaghan, Rakesh Batra, and David Ortiz (DOE), Seth Blumsack (Pennsylvania State University), James Bouford (Quanta-Technology), Brett Efaw (Idaho Power), Larry Conrad (Conrad Technical Services), and John Weyant (Stanford University). We thank Dana Robson and Danielle Callaghan for their assistance with formatting the final version of the report and disseminating the results to interested stakeholders.

Peter would like to thank the LBNL Tuition Assistance Program for indirectly supporting this research project. Finally, we are indebted to staff at the electric utilities and public utility commissions who shared reliability performance metrics and other insightful information with us in the early stages of this project. Without this assistance, this study would not have been possible.

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Acronyms and Abbreviations

AIC	Akaike Information Criterion
APPA	American Public Power Association
BIC	Bayesian Information Criterion
CDD	cooling degree-day
DOE	U.S. Department of Energy
EIA	Energy Information Administration
FERC	Federal Energy Regulatory Commission
HDD	heating degree-day
IEEE	Institute of Electrical and Electronics Engineers
IOU	investor-owned utility
LBNL	Lawrence Berkeley National Laboratory
MED	major event day
NCDC	National Climatic Data Center
NLDN	National Lightning Detection Network
NOAA	National Oceanic and Atmospheric Administration
OLS	ordinary least squares
OMS	outage management system
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
T&D	transmission and distribution

Executive Summary

Recent catastrophic weather events, existing and prospective federal and state energy and environmental policies, and growing investments in smart grid technologies have drawn renewed attention to the reliability of the U.S. electric power system. Whether electricity reliability is getting better or worse as a result of these or other factors has become a material issue for public and private decisions affecting the U.S. electric power system.

Over the past 15 years, the most well-publicized efforts to assess trends in U.S. electric power system reliability have focused only on a subset of all power interruption events (see, for example, Amin 2008 and Campbell 2012)—namely, only the very largest events, which trigger immediate emergency reporting to federal agencies and industry regulators. Anecdotally, these events are thought by many 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 on these data as reliable sources for assessing trends, even with the reliability events they report (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 et al. 2006). 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.

Accordingly, we assembled up to 13 years of information on the annual duration and frequency of power interruptions for a large cross-section of U.S. electricity distribution utilities. These utilities, taken together, represent 70% of both U.S. electricity sales and total U.S. electricity customers. We then performed an econometric analysis to correlate annual changes in reliability reported by these utilities with a broad set of explanatory variables, including annual information on lightning strikes, average wind speeds, temperatures, numbers of customers per line mile of distribution, percentage of the distribution system underground, installation or upgrade of an automated outage management system, and transmission and distribution (T&D) spending.

The measures of electricity reliability used in this study are the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI). SAIDI can be thought of as the total amount of time that a utility's customers, on average, are without power over the course of a year. SAIFI can be thought of as the total number of times that a utility's customers, on average, have experienced power interruptions over the course of a year.

We conducted separate analyses of SAIDI and SAIFI both without and with inclusion of what utilities term "major events." In order to facilitate year-on-year comparisons of utility reliability performance, utilities report SAIDI and SAIFI both without and with inclusion of major events. Major events refer to 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 including them has a disproportionate effect on year-to-year trends in reported reliability.

Findings related to the annual average duration of power interruptions (SAIDI)

If major events are not included (see Figure ES - 1), we find the following statistically significant relationships:

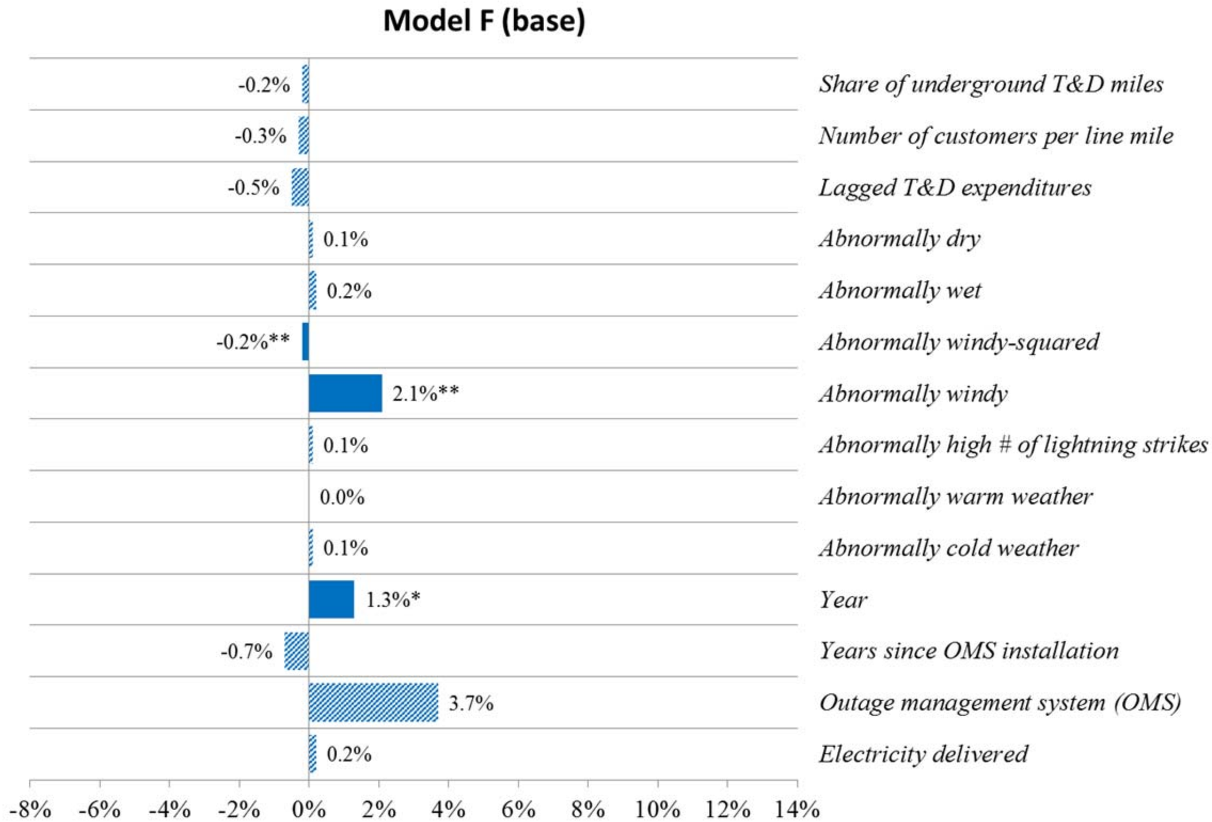
- A 5% increase in annual average wind speed—above the long-term (generally, 13-year) average— is correlated with a 5% increase in SAIDI; yet a 10% increase in annual average wind speed is correlated with a 2% decrease in SAIDI[1]
- Independent of these factors, each successive year over the analysis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

If major events are included (see Figure ES - 2), 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

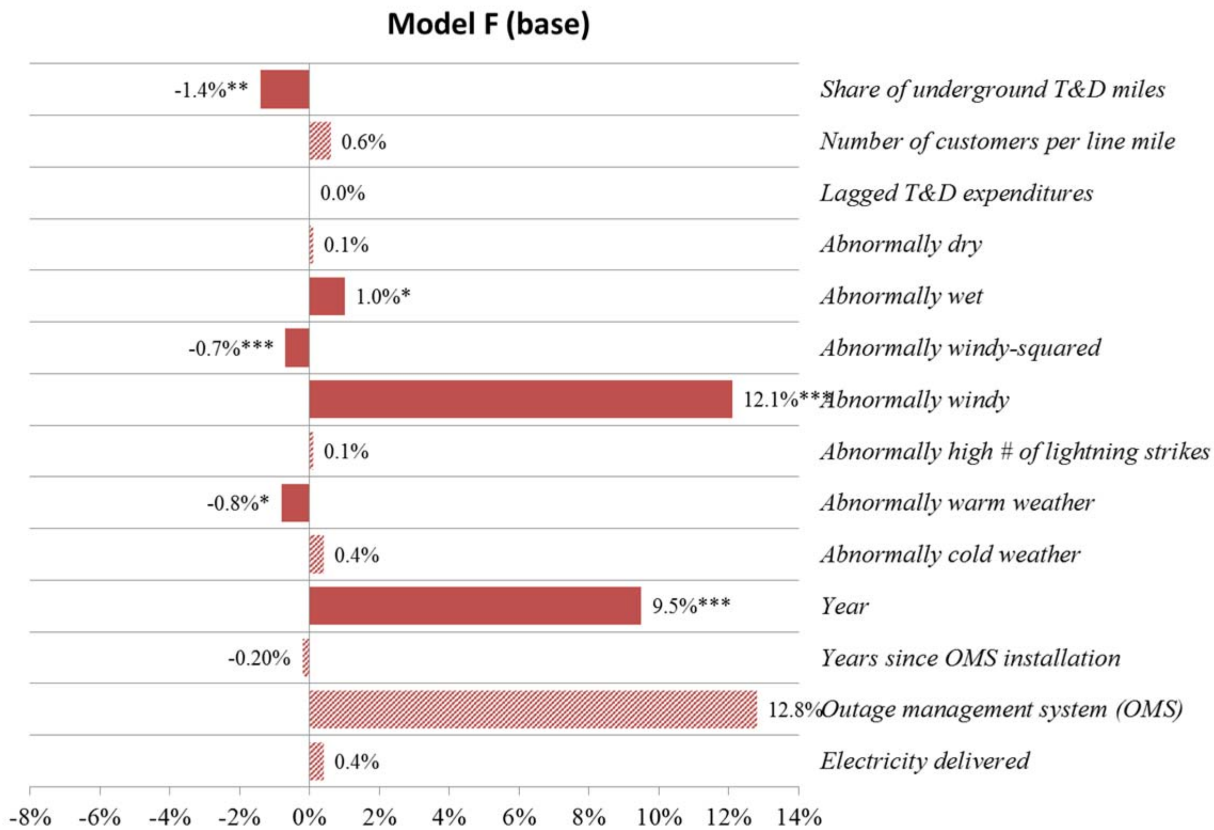
Independent of the above factors, each successive year over the analysis period is also correlated with a nearly 10% increase in SAIDI.

[1] We believe that this apparently counterintuitive result is explained by recognizing that utilities categorize higher average wind speed events (i.e., major storms) into the dataset that includes major events.



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.
(4) See exact interpretation for these covariates earlier in this executive summary or in section four.

Figure ES - 1: Percentage change in SAIDI (without major events) corresponding to a change in the explanatory variable



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.
(4) See exact interpretation for these covariates earlier in this executive summary or in section four.

Figure ES - 2: Percentage change in SAIDI (with major events) corresponding to a change in the explanatory variable

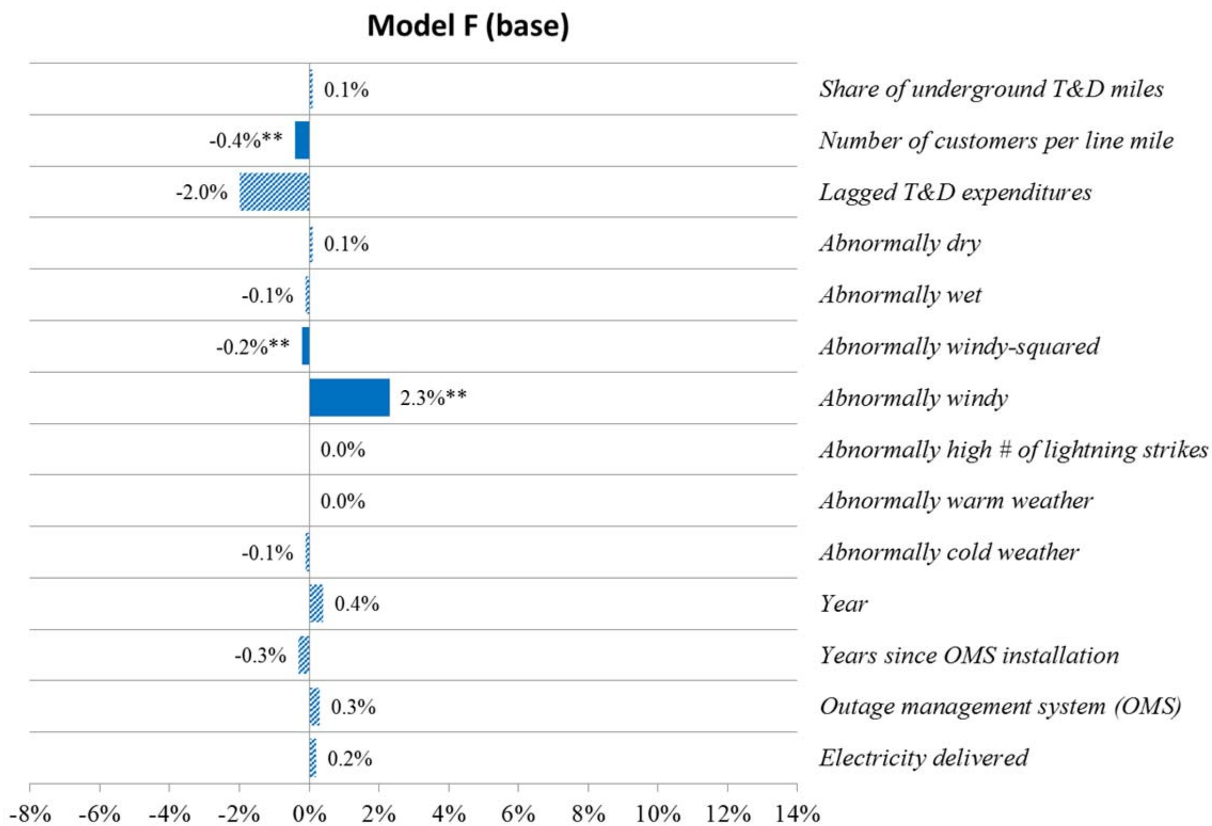
Findings related to the annual average frequency of power interruptions (SAIFI)

If major events are not included (see Figure ES - 3), 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

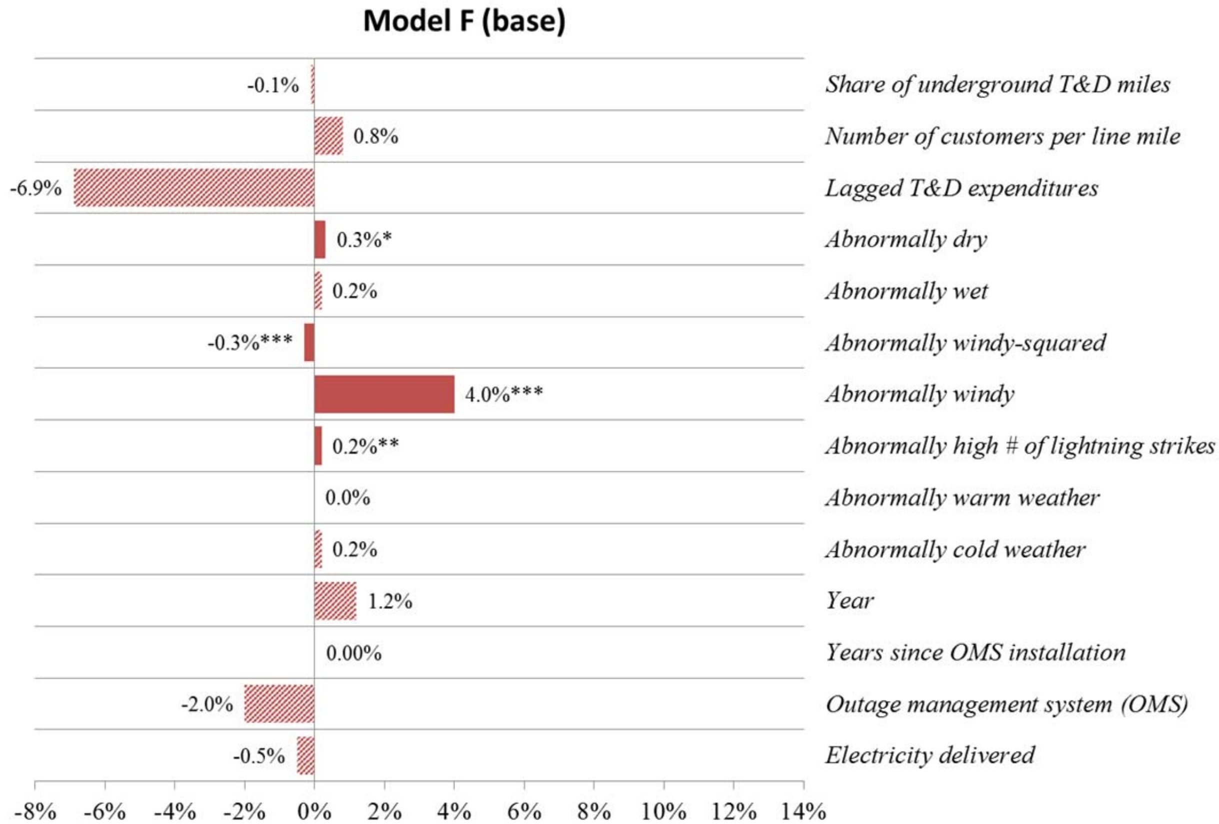
If major events are included (see Figure ES - 4), we find the following statistically significant relationships:

- A 10% increase in annual lightning strikes is correlated with a 2% increase in SAIFI
- A 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
- A 10% decrease in average total precipitation—below the long-term (generally, 13-year) average— is correlated with a 3% increase in SAIFI



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.
(4) See exact interpretation for these covariates earlier in this executive summary or in section four.

Figure ES - 3: Percentage change in SAIFI (without major events) corresponding to a change in the explanatory variable



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.
(4) See exact interpretation for these covariates earlier in this executive summary or in section four.

Figure ES - 4: Percentage change in SAIFI (with major events) corresponding to a change in the explanatory variable

Discussion of Findings

We find a statistically significant trend in increasing annual average duration of power interruptions over time. The trend is larger when major events are included, which suggests that increases in the severity of major events over time has been the principal contributor to the observed trend.

We were also surprised to find that increased T&D spending in the previous year was not 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 maintenance when compared to reactive maintenance. The presence of "competing" effects within the utility spending data may be influencing the results and leading to the counter-intuitive findings. Unfortunately, we did not have access to more detailed information on the constituents of annual utility T&D spending in order to explore these possibilities.

Strictly speaking, these findings apply only to the utilities whose data we included in our analysis. Specifically, the 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. More precisely, our findings cannot be assumed to apply to the 25%, 99%, and 97% of investor-owned, municipally-owned, and cooperative utilities, respectively, that were not included in our study.

Hence, while we believe this analysis is the most comprehensive study of this topic that has been performed to date, there are a number of areas where we believe improvements should be considered in future analyses of U.S. electric power system.

First, there may be more appropriate annual weather parameters available to better capture the factors underlying major events (e.g., number of days per year with peak wind speeds greater than 35 mph, significant drought years followed by abnormally wet years).

Second, as noted, it is important to continue to explore the relationship between reactive and proactive T&D spending and reliability. Related to this, we also believe that the relationship between reliability and the long-run deployment of other “smart” technologies should be explored further.

We hope that our findings will help to inform future public and private decisions that will influence the future reliability of the U.S. electric power system.

1. Introduction

Recent catastrophic weather events, current and prospective federal and state energy and environmental policies, and recent federal investments in smart grid technologies have drawn renewed attention to the reliability of the U.S. electric power system. Whether electricity reliability is getting better or worse as a result of these or other factors has become a material issue for public and private decisions affecting the U.S. electric power system.

Over the past 15 years, the most well-publicized efforts to assess trends in U.S. electric power system reliability have focused on only a subset of all power interruption events (Amin 2008 and Campbell 2012)—namely, only the very largest events, which trigger immediate emergency reporting to federal agencies and industry regulators. Anecdotally, these events are thought by many 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 reliable sources for assessing trends, even on 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 (see, for example, 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 et al. 2006). 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.

The Eto et al. (2012) study applied econometric methods to account for utility-specific differences among electricity reliability reports and found that average annual duration and frequency of power interruptions had been increasing annually per year from 2000 to 2009. In other words, reported reliability was getting worse. But, the Eto et al. (2012) paper was not able to identify statistically significant factors, such as which aspects of weather 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.

This paper seeks to extend the Eto et al. (2012) analysis along exactly these lines. We first assemble up to 13 years of information on the annual duration and frequency of 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 then attempt to correlate reliability reported by these utilities with a broad set of explanatory variables, including annual information on lightning strikes, wind speeds, temperatures, numbers of customers per line mile of distribution, percentage of the distribution system underground, installation or upgrade of an automated outage management system, and transmission and distribution (T&D) spending.[2]

Electricity Reliability Metrics: SAIDI, SAIFI, and Major Events

The measures of electricity reliability used in this study are System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI). The Institute of Electrical and Electronics Engineers (IEEE), Distribution Reliability Working Group has developed a standard that defines both terms, as well as a related concept called Major Event Days (MEDs) (see Appendix A).

The IEEE Standard 1366 defines SAIDI and SAIFI as follows:

$$\text{SAIDI} = \frac{\sum \text{Customer interruption durations}}{\text{Total number of customers served}} \quad \text{minutes of interruption per year}$$

$$\text{SAIFI} = \frac{\sum \text{Total number of customers interrupted}}{\text{Total number of customers served}} \quad \text{number of interruptions per year}$$

SAIDI can be thought of as the total amount of time that a utility's customers, on average, are without power over the course of a year. SAIFI can be thought of as the total number of times that a utility's customers, on average, have experienced power interruptions over the course of a year.

Major events refer to 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-on-year comparisons of utility reliability performance, SAIDI and SAIFI are often reported without inclusion of the interruptions associated with major events. A discussion of the method developed by IEEE to identify major events is provided in Appendix A.

This report examines and compares trends in SAIDI and SAIFI both with and without major events included.

With this improved set of information, we seek to answer the following questions:

- Are warmer/cooler, wetter/drier, and/or windier than average years correlated with changes in the duration and/or frequency of power interruptions? What is the mathematical form of any such relationship; e.g., is it linear or non-linear?
- 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 duration and/or frequency of power interruptions? Is previous year T&D spending correlated with changes in the duration and/or frequency of power interruptions in subsequent years?
- Are there trends in the duration and/or frequency of power interruptions over time, which we cannot explain by considering the above factors?

[2] The present analysis differs from that in Eto et al. (2012) by including: (1) more utilities: 195 compared to 155, which represented 50% of U.S. electricity sales and less than 60% of U.S. electricity customers; and (2) a more comprehensive and granular set of explanatory variables.

This report consists of five additional sections and five technical appendices following this introduction. Section 2 describes types, source, and summary information of the data we collected for the analysis. Section 3 describes technical aspects of the approaches we used to analyze the data. Section 4 presents the principal results from the final regression models we developed to explain, separately, SAIDI and SAIFI without major events, and SAIDI and SAIFI with major events included. Section 5 presents supporting analysis we conducted to explore selected aspects of the principal findings. Section 6 summarizes our findings and outlines next steps that we recommend should be considered in future analyses of U.S. electricity reliability.

2. Data Collection and Review

This section reviews the information we collected for use in the analysis, including information on utility reliability as well as on the utilities whose data we analyzed (Section 2.1). We also present a range of possible utility-specific (Section 2.2) and weather-related factors (Section 2.3), which we explored as possible statistically significant correlates to changes in the utilities' reliability data.

2.1. Distribution utility reliability performance data

As described in the previous section, the measures of reliability used in this paper are SAIDI and SAIFI. The collected information represents SAIDI and SAIFI with or without major events included (although sometimes both were reported). Major events refer to times during the year when the utility is subjected to significant, yet generally infrequent stresses, often due to severe weather (see text box in Section 1 as well as Appendix A).

Our analysis considered each of these 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 commissions 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. (see Eto et al. (2006) for a review of state utility commission reporting practices). 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 and reports posted by the utility.

Ultimately, we collected reliability data for 195 different utilities located across the U.S. Of these, 152 of the utilities are investor-owned utilities and 43 are either municipals or electricity cooperatives. In the following subsections, we review the geographic coverage, completeness, and summarize trends in SAIDI and SAIFI information we collected.

2.1.1. Geographic coverage

Figure 1 illustrates the geographic distribution of the utilities by U.S. census division. This figure denotes the number of utilities in each region along with the share of total regional electricity sales they represent.

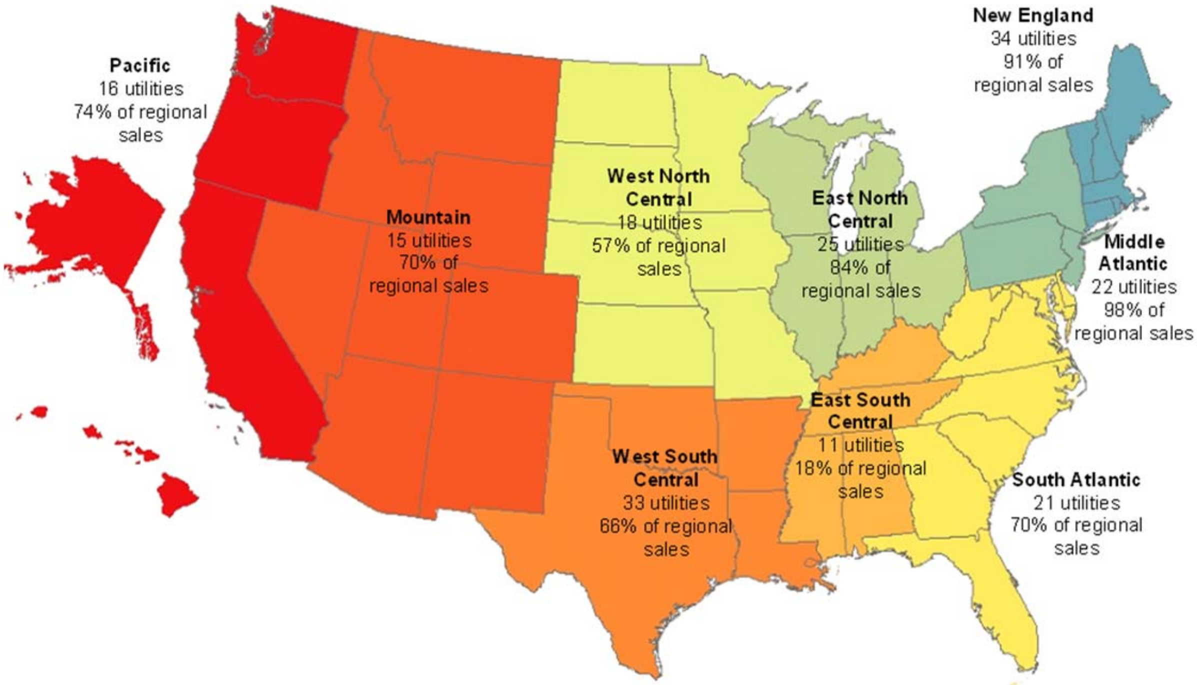


Figure 1: Geographic coverage of utilities included in this study

Table 1 presents the share of retail electricity sales represented by each census division as well as relative to total U.S. sales. In general, the information we collected represents a large proportion (nearly two-thirds or more) of total electricity sales for every region of the United States except the East South Central region. We sought, but were unable to obtain, information from utilities in this region either because (a) they are not required to report reliability performance data to their state utility commission, or their state utility commission does not make these data publicly available, or (b) because we did not readily find information from the utilities directly in this region. Consequently, our findings are not well represented in this region compared to regions for which we obtained more information on reliability performance. See Section 5.4 for a more detailed assessment of the representativeness of our sample to the total population of U.S. utilities.

Overall, the 195 utilities account for approximately 70% of total U.S. electricity retails sales (and 71% of U.S. electricity customers).

Table 1: Utility sales (2012) and coverage by U.S. Census Division

Census division	Total electricity sold (2012; Million TWh)	Total electricity sold by utilities for which data were collected (Million TWh)	Percentage of region (Eto et al. 2012)	Percentage of region (current analysis)	Percentage of sales to U.S. total
New England	120.5	109.2	86%	91%	3%
Middle Atlantic	362.9	353.9	74%	98%	10%
East North Central	574.8	484.2	68%	84%	13%
West North Central	293.7	168.7	46%	57%	5%
South Atlantic	769.5	537.7	46%	70%	15%
East South Central	320.0	57.1	1%	18%	2%
West South Central	556.0	366.9	26%	66%	10%
Mountain	271.4	190.9	51%	70%	5%
Pacific	398.6	294.3	71%	74%	8%
TOTAL	**3,694.6**	**2,562.8**	**50%**	**70%**	**70%**

2.1.2. Completeness of reported reliability data by utility and over time

We sought to collect a complete time series of reliability data for each utility, spanning the years 2000–2012, for all four types of reliability metrics: SAIDI and SAIFI, both with and without major events included. However, we were only able to obtain a complete record of this information for some of the utilities. Figure 2 shows the number of utilities by year and type of reliability data. This chart shows that utilities in our sample more often reported reliability information without major events than with major events. In addition, there is a marked increase in the total number of utilities between years 2000 and 2006 and a very slight decrease in the last four years.

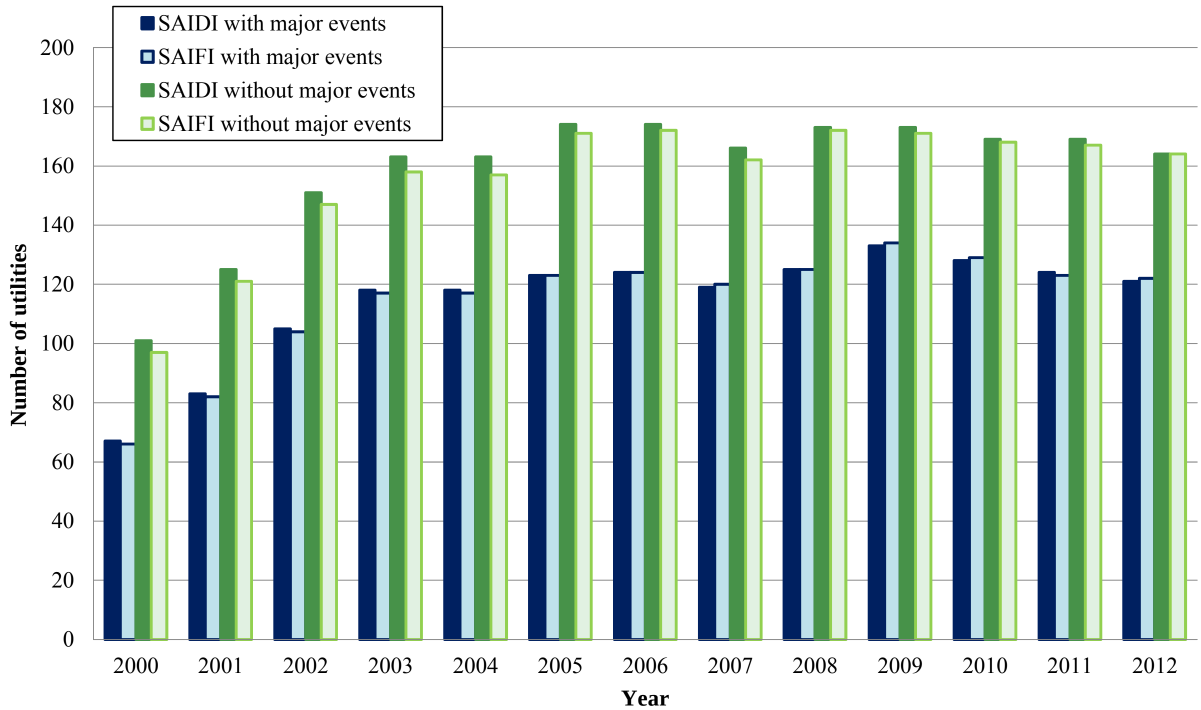


Figure 2: Number of utilities with SAIDI and SAIFI data

Figure 3 shows the number of utilities in our sample according the number of years of reliability data we collected for that utility. This chart shows that we were able to collect a complete dataset (for all years 2000–2012) 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. Overall, we were able to collect at least nine years of reliability performance information for over 80% of the utilities used in our analysis.

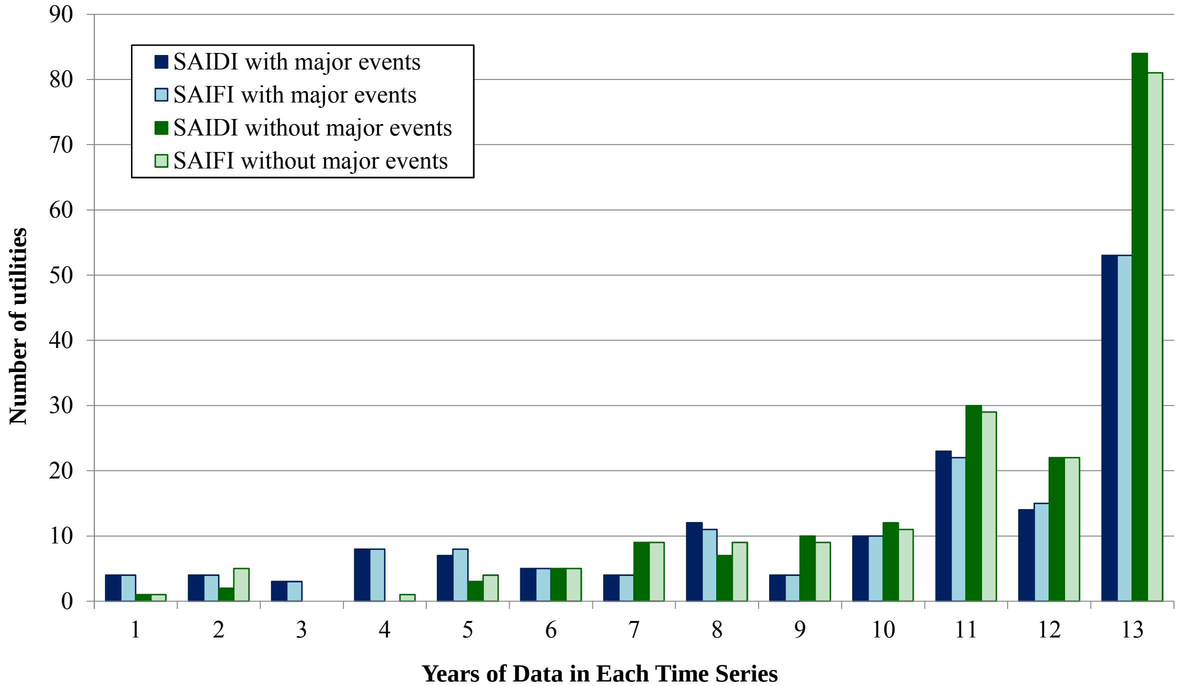


Figure 3: Completeness of time series

2.1.3. Distribution of reported SAIDI and SAIFI over time

Figure 4 and Figure 5 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.

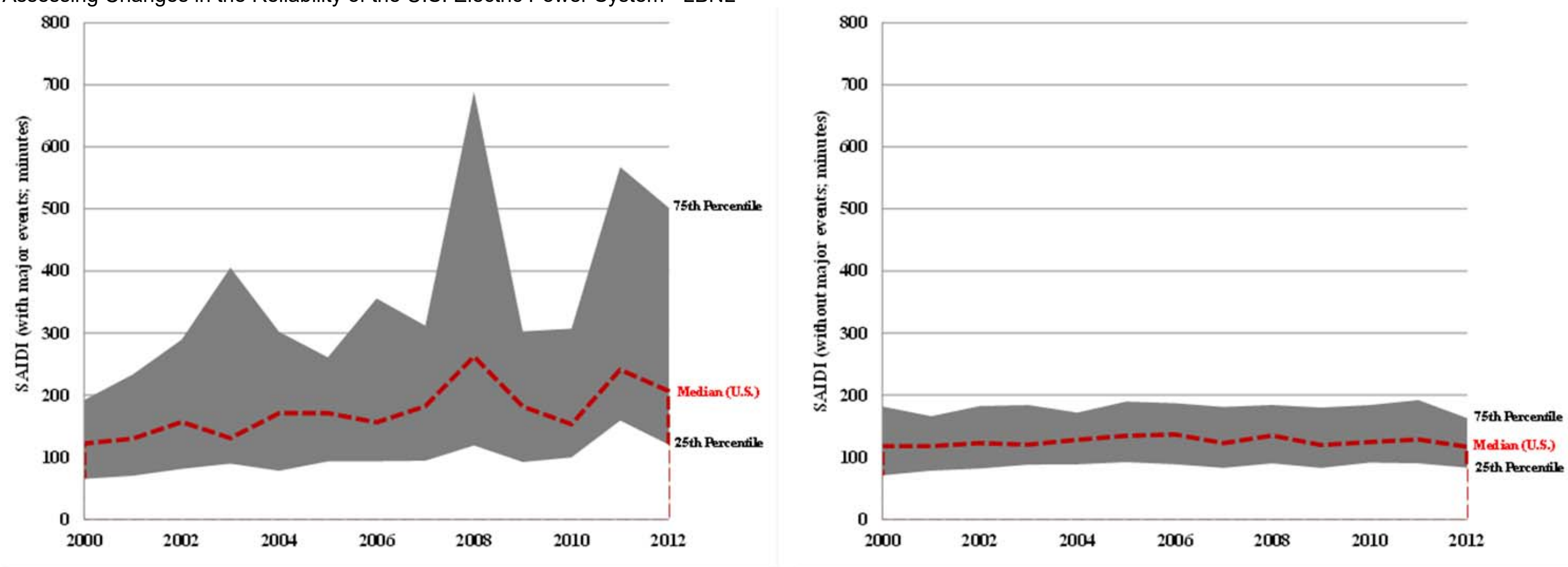


Figure 4: SAIDI with (left) and without (right) major events included in the current study

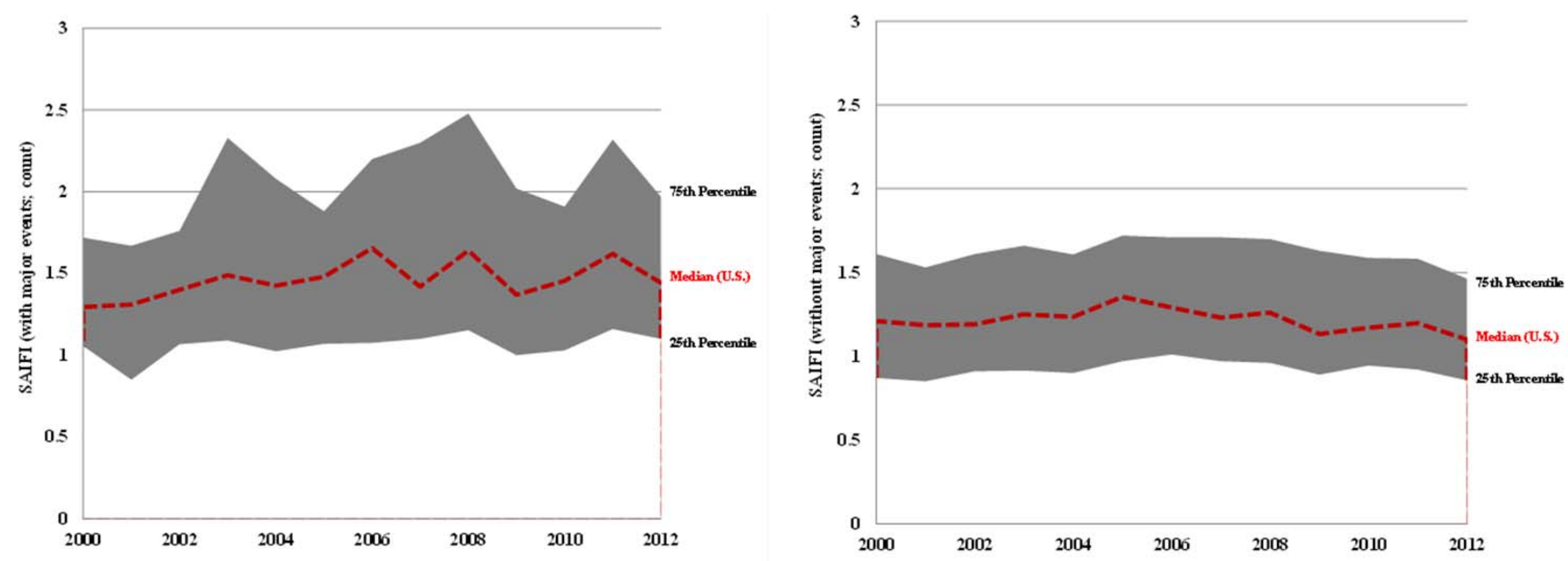


Figure 5: SAIFI with (left) and without (right) major events included in the current study

2.2. Utility Data

In addition to collecting reliability information for each utility, we also collected information on aspects of the utility itself, including its physical characteristics. The information included:

- year when the utility installed or upgraded its automated outage management systems (OMS)
- number of miles of T&D lines
- annual expenditures on T&D
- share of the utility lines that are underground versus overhead
- annual retail electricity sales

The following subsections describe and present summary information on each of these. Section 3 describes transformations we made to these data for use in the analysis.

2.2.1. Outage management systems (OMS)

An OMS is an automated means for collecting information on utility reliability. It replaces manual methods for recording the number of customers who are without power and for how long. Eto et al. (2012) found that installation or updates to these systems were correlated with a decrease in reported reliability in the following year. They attributed this to a change in the accuracy of reliability reporting not to a change in reliability experienced by customers.

Table 2 summarizes, by U.S. census division, the number of utilities that installed or upgraded their OMS by the end of 2012. We found that 146 utilities (nearly 75%) of the 195 utilities in this study had installed or upgraded their OMS by 2012.

Table 2: Utilities reporting the installation or upgrade of OMS by 2012 by U.S. census division

Census division	Number of utilities considered in this study	Number of utilities reporting the use of OMS
New England	34	15
Middle Atlantic	22	22
East North Central	25	23
West North Central	18	14
South Atlantic	21	19
East South Central	11	10
West South Central	33	18
Mountain	15	12
Pacific	16	13
TOTAL:	**195**	**146**

Figure 6 shows the cumulative percentage of the 195 utilities in our study that installed or upgraded their OMS.

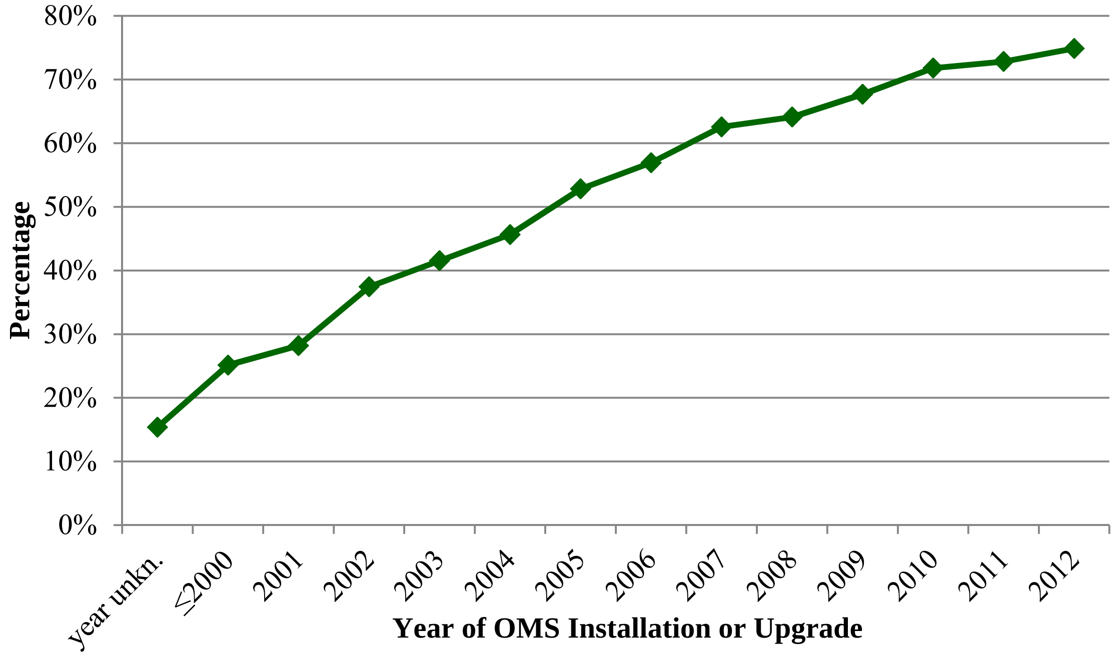


Figure 6: Cumulative percentage of the number of utilities that have installed or upgraded their OMS over time relative to total number of utilities in this study

2.2.2. Retail electricity sales

We obtained retail electricity sales for each utility for the years 2000 to 2012 from information collected by the U.S. Energy Information Administration (EIA) via Form 861 (EIA 2013). We also collected information on total customers served by each utility over time from the same EIA source. Total customers include all customers served by a utility, including residential, commercial, and industrial customers.

Figure 7 shows median electricity sales per customer by year and by census region for the utilities examined in our study. Figure 8 shows geographically the median across these years of annual sales per customer.

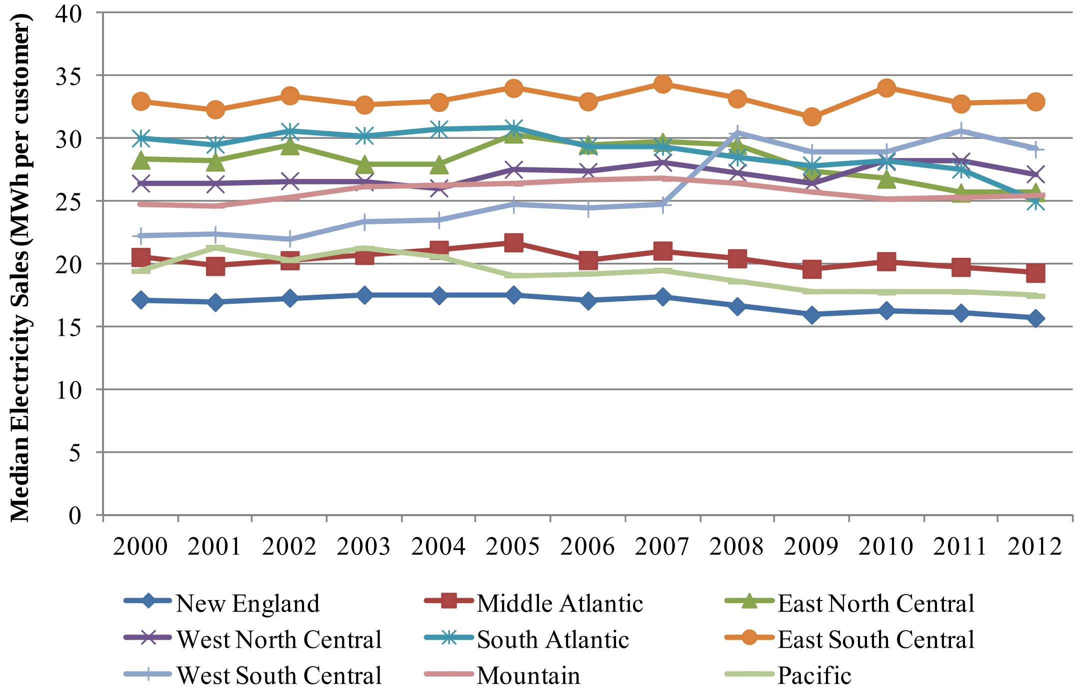


Figure 7: Median electricity sales per customer by census division and year

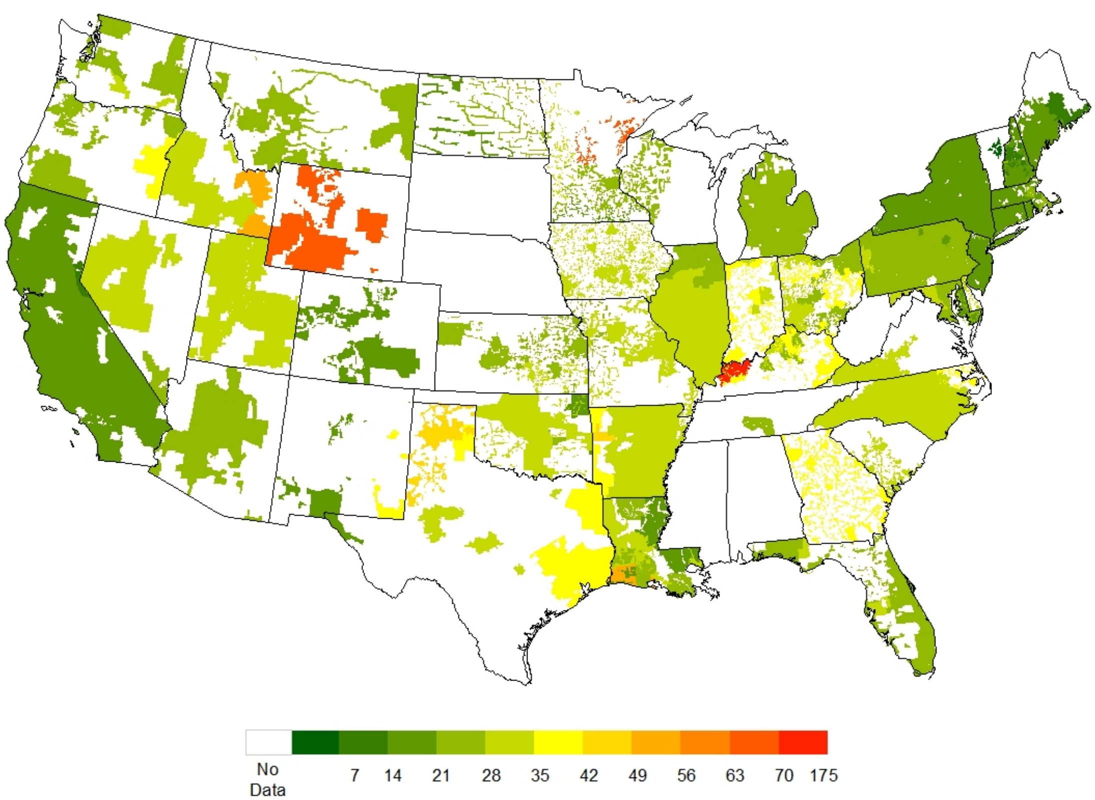


Figure 8: U.S. map of median annual electricity delivered per customer

2.2.3. Transmission and distribution spending

Information on total annual T&D spending for each of the years 2000 through 2012 was obtained by using the Ventyx Velocity Suite system, which assembles the data from information collected by FERC (using Form 1) and makes them publicly available for a fee (FERC 2014). Total T&D spending includes both fixed and variable expenses. We converted all spending data to real 2012 dollars using the Handy-Whitman index of T&D construction costs (Whitman, Requardt, and Associates 2013).

Figure 9 shows median distribution spending per electricity customer by census region and year. In general, some regions appear to show a modest decline in spending over the last decade, while others report relatively constant levels of spending. Note, however, some aspects of these trends are likely due to different numbers of utilities in the sample each year (see Figure 2), as well as missing data. For example, the sharp declines in the West South Central region in years 2005 and 2012 are due to missing values for a few utilities in those years.

Figure 10 shows the regional mapping of the median T&D spending per customer for all years. This map indicates that the median for the utilities in our study in the West and West North Central regions spent relatively more per customer, which is consistent with Figure 9.

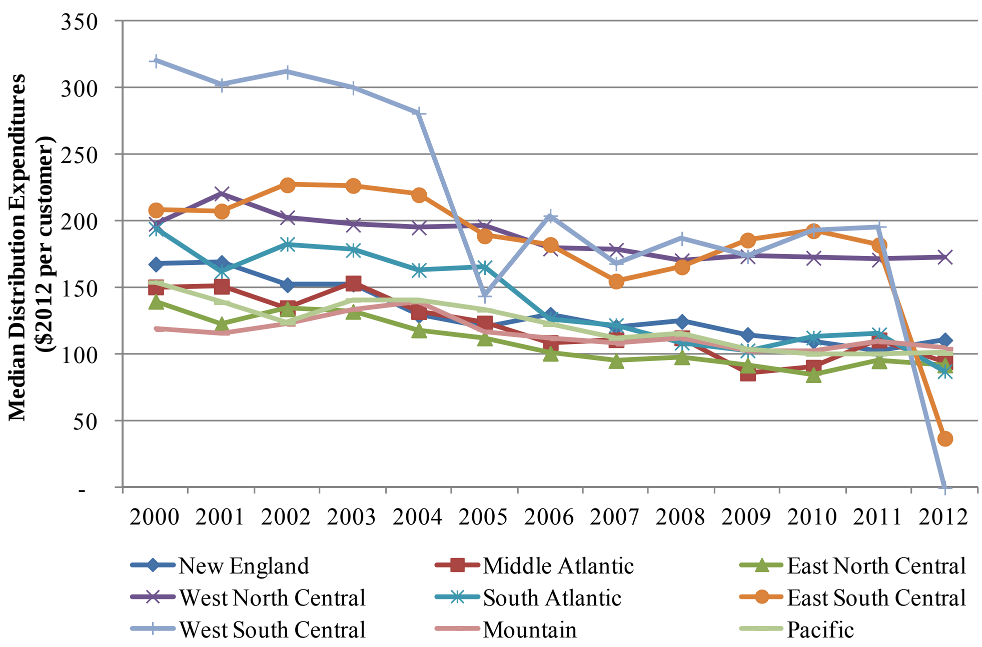


Figure 9: Median Distribution spending per customer ($2012) by census division and year[3]

[3] It should be noted that nominal expenditures—for utilities in our sample—are generally increasing over time. However, the Handy-Whitman T&D construction price index is increasing at a higher rate relative to the observed increase in nominal expenditures. Furthermore, the number of utility customers is also increasing over time. The combined effect of the increasing number of customers and the relatively higher construction price index results in decreasing *real* expenditures per customer.

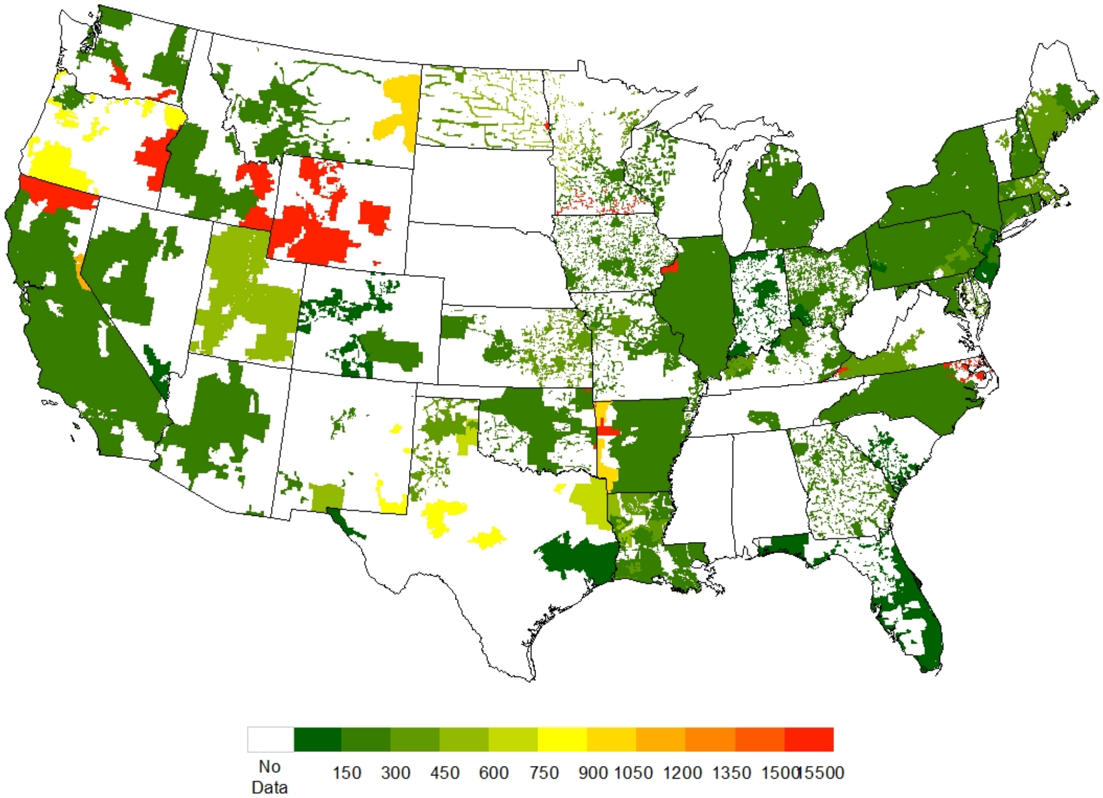


Figure 10: U.S. map of median T&D line expenditures per customer ($2012)

2.2.4. Transmission and distribution line miles

We also obtained T&D line miles, which are also reported on FERC Form 1, from the Ventyx Velocity Suite. Figure 11 shows the median number of customers per T&D line mile by census region and year for the utilities for which we obtained data. The New England region shows a noticeably higher concentration of customers per line mile due to the relatively higher population density for much of this region coupled with some years with missing data that result in the drop in value, as seen in years 2005 and 2012. The Pacific Northwest, some parts of Texas, Nevada and Southeastern areas (e.g., Georgia, Florida Panhandle) also reflect higher concentrations of customers per line mile. Figure 12 shows geographically the median number of customers per T&D line mile.

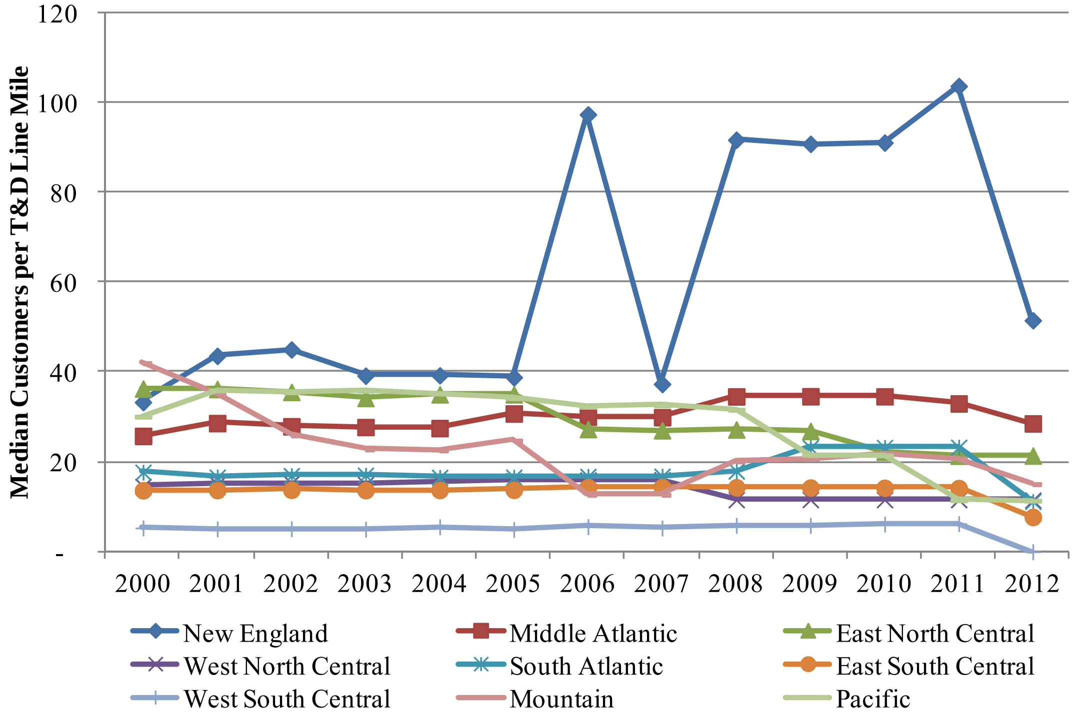


Figure 11: Median number of customers per line mile by census division and year

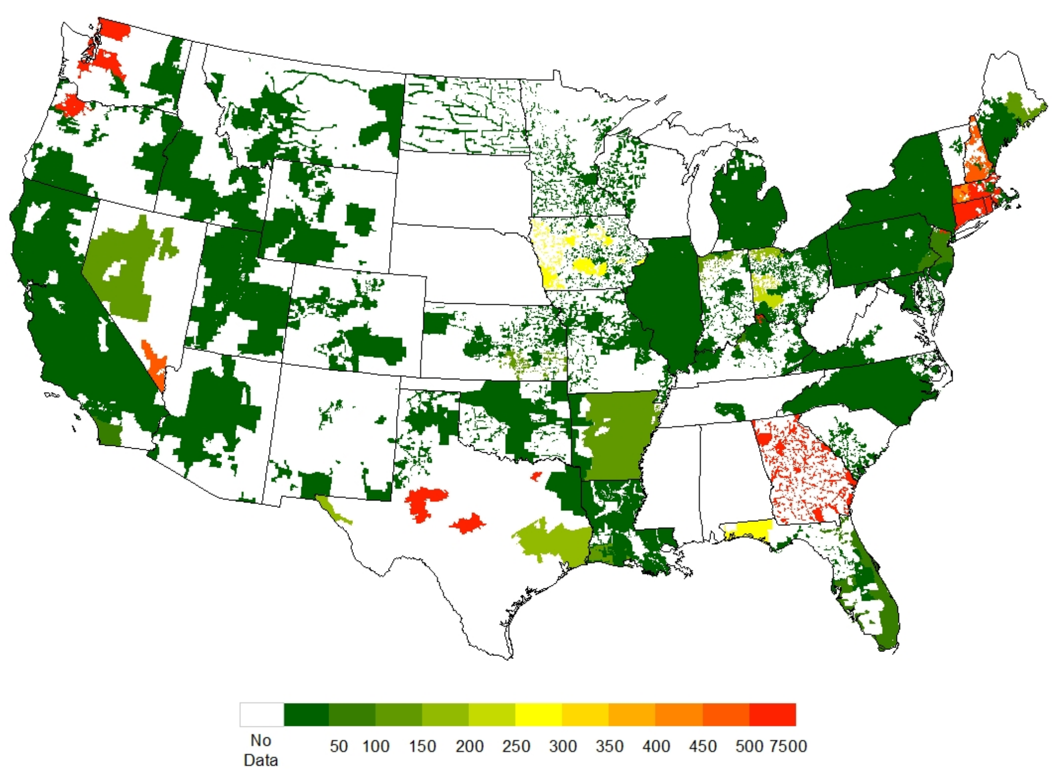


Figure 12: U.S. map of the median number of customers per T&D line mile

2.3. Weather Data

Weather is a well-recognized cause of power interruptions. Due to the exploratory nature of our analysis, we sought to develop information on a wide variety of weather variability measures. Specifically, we assembled annual weather information for each utility including:

- lightning strikes
- precipitation
- wind speeds
- heating degree-days (HDD)
- cooling degree-days (CDD)

2.3.1. Lightning data

Information on lightning strikes was collected from the Vaisala National Lightning Detection Network (NLDN) (NLDN/LBNL 2013). According to the NLDN documentation, NLDN provides flash detection efficiency of 95% and thunderstorm detection efficiency greater than 99%.

We used the latitude and longitude of each strike and the utility service territory boundaries available in the Ventyx Velocity Suite database system to map each recorded lightning strike to each utility in our dataset. Utility lightning strikes were then aggregated to an annual total.

Figure 13 shows the median number of annual lightning strikes per customer by census division. With the exception of the West South Central region, the trends are flat over time. In the West South Central region, lightning—for the utilities in our analysis—appears to be more prevalent than in other parts of the United States. The large changes in the medians over time reflect the fact that there are a different numbers of utilities in the distributions from which these medians are drawn.

Figure 14 shows the U.S. mapping of the median number of lightning strikes per customer, again illustrating the elevated frequency in Texas and Louisiana consistent with the West South Central line in Figure 13.

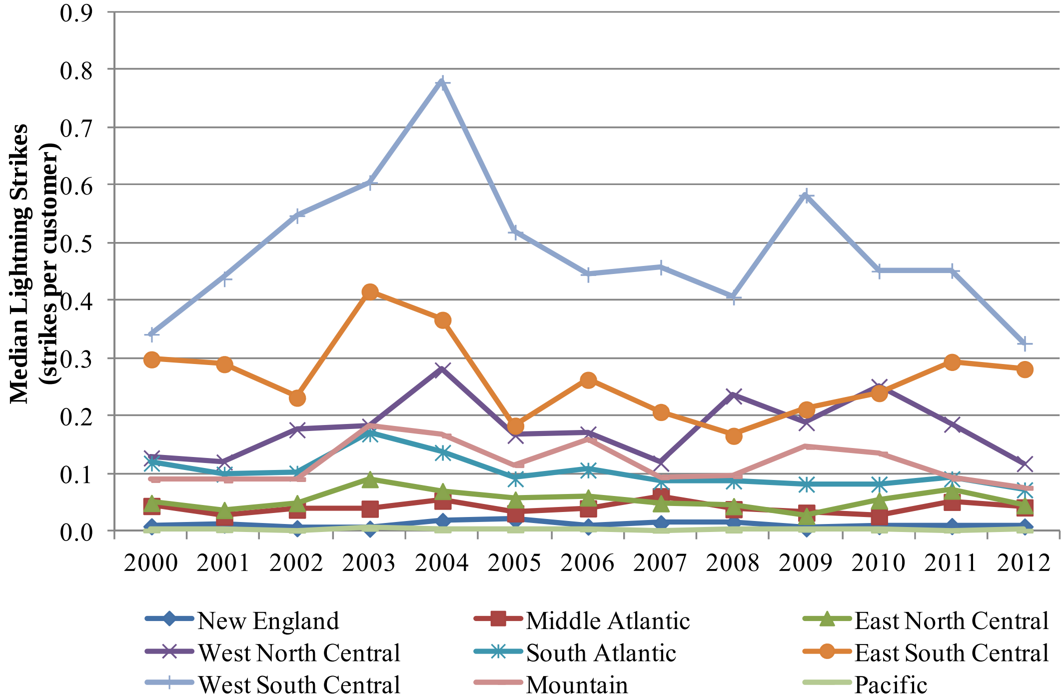


Figure 13: Median number of lightning strikes per customer by census division and year

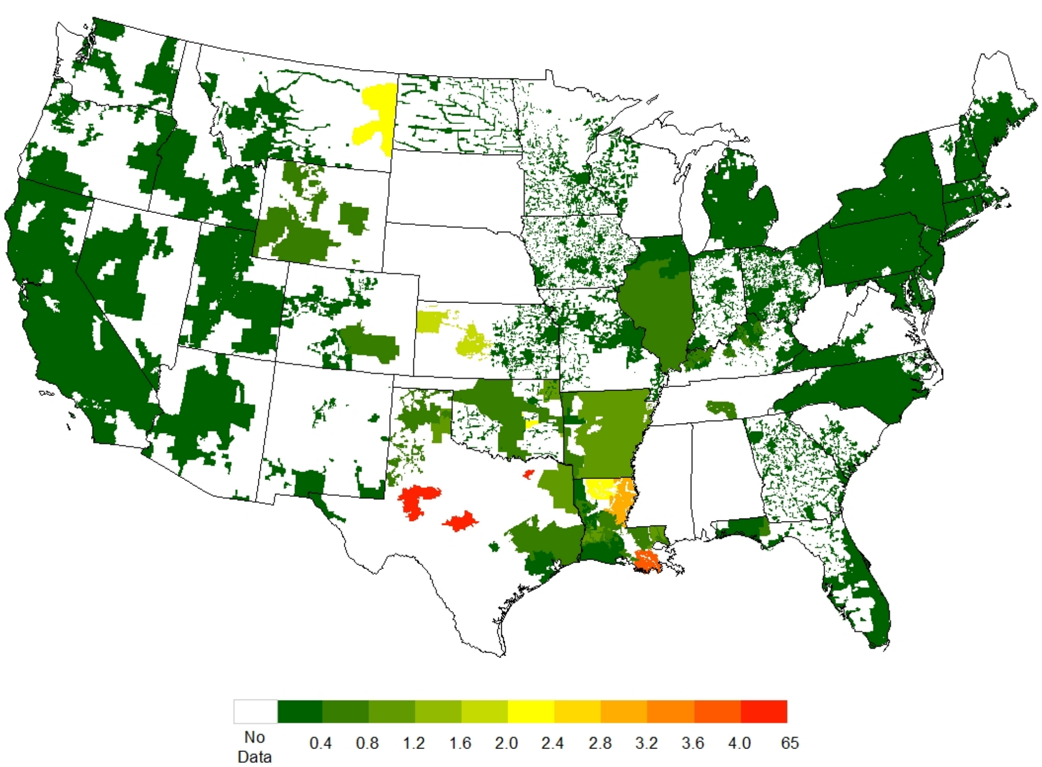


Figure 14: U.S. map of the median number of lightning strikes per customer

2.3.2. Precipitation data

The Ventyx Velocity Suite was also used to obtain annual precipitation data that is collected by the National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) (NCDC/Ventyx 2014). Ventyx compiled the daily precipitation data (in inches) for each weather station in each utility service territory for each year. To estimate precipitation at the annual level, Ventyx sums up daily precipitation in a given year and then finally calculates an average across all stations to estimate an annual total precipitation value per utility.

Figure 15 shows the median annual precipitation (in inches) by region over time. Figure 16 shows the medians over time for each utility geographically. Both show generally higher rainfall for the utilities in our sample in the Eastern United States compared to those in the West.

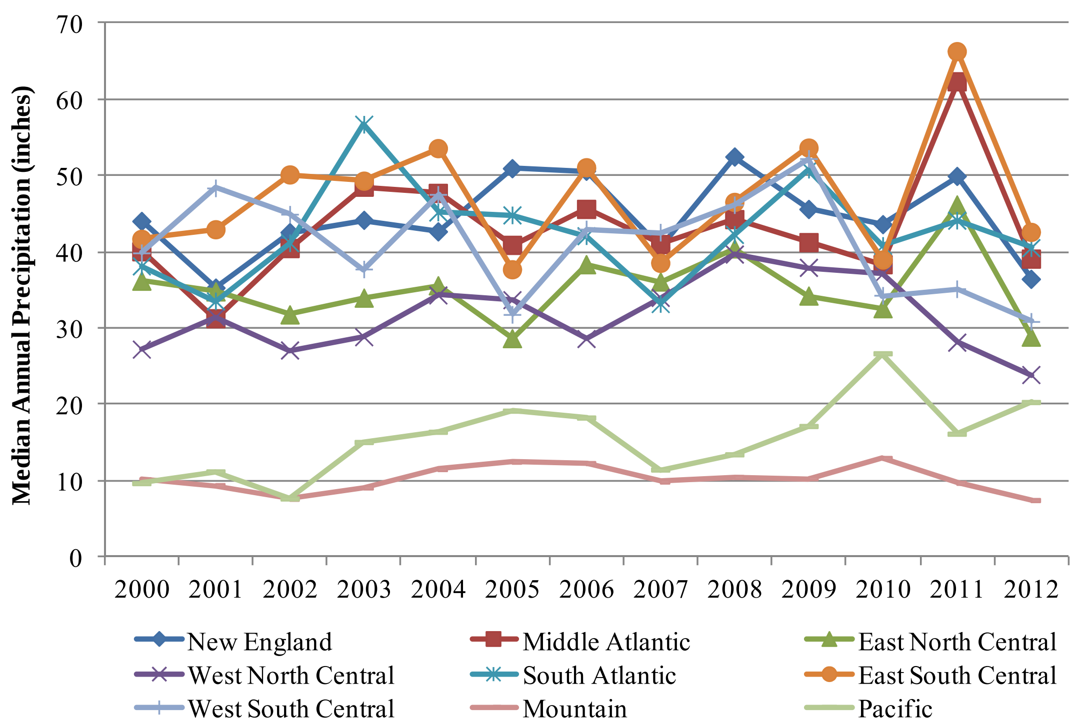


Figure 15: Median annual precipitation by census division and year

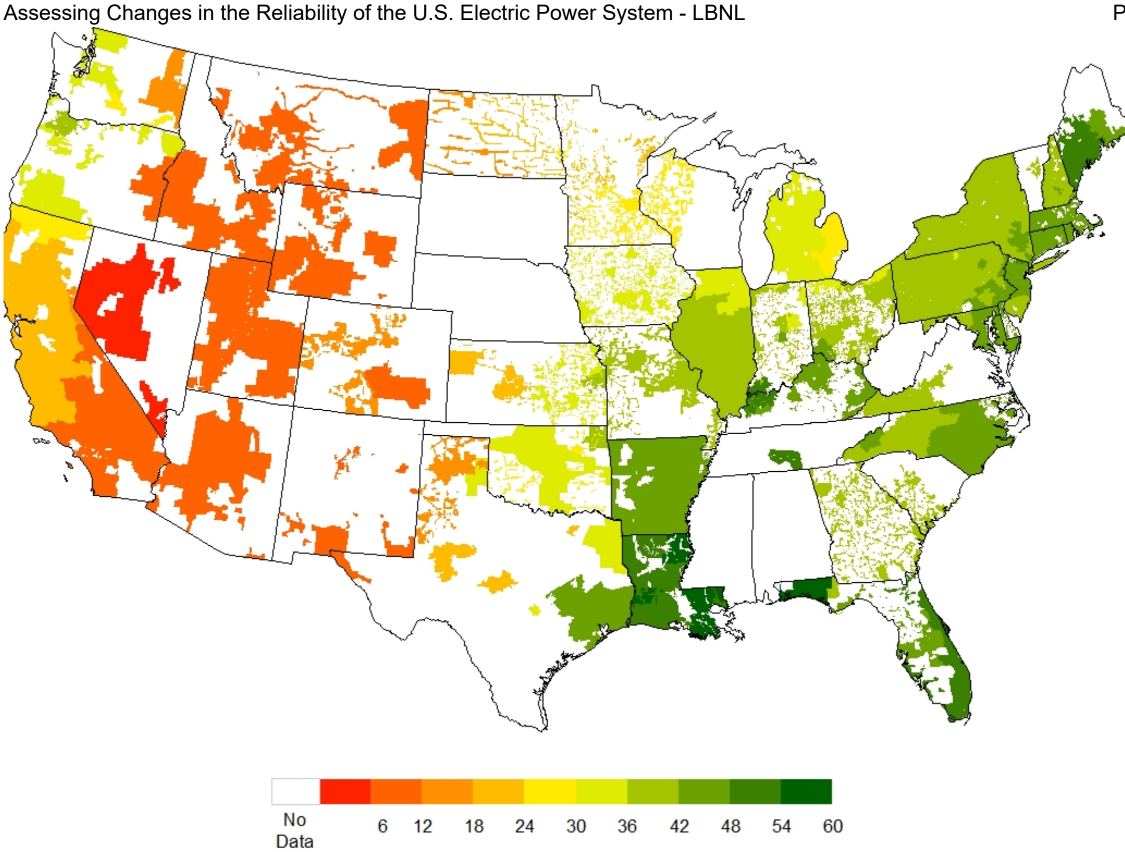


Figure 16: U.S. map of median annual precipitation

2.3.3. Wind Data

The Ventyx Velocity Suite was used to obtain NCDC data for wind speed across all weather stations assigned to a utility in the contiguous United States. (NCDC/Ventyx 2014). Similar to precipitation, these data were summed and averaged for each year.

Figure 17 shows the median wind speed at utilities located within each census division. This plot shows a slight decline in median annual wind speeds over time. Figure 18 is a map of the United States showing that the highest median wind speeds were experienced by utilities in the Great Plains.

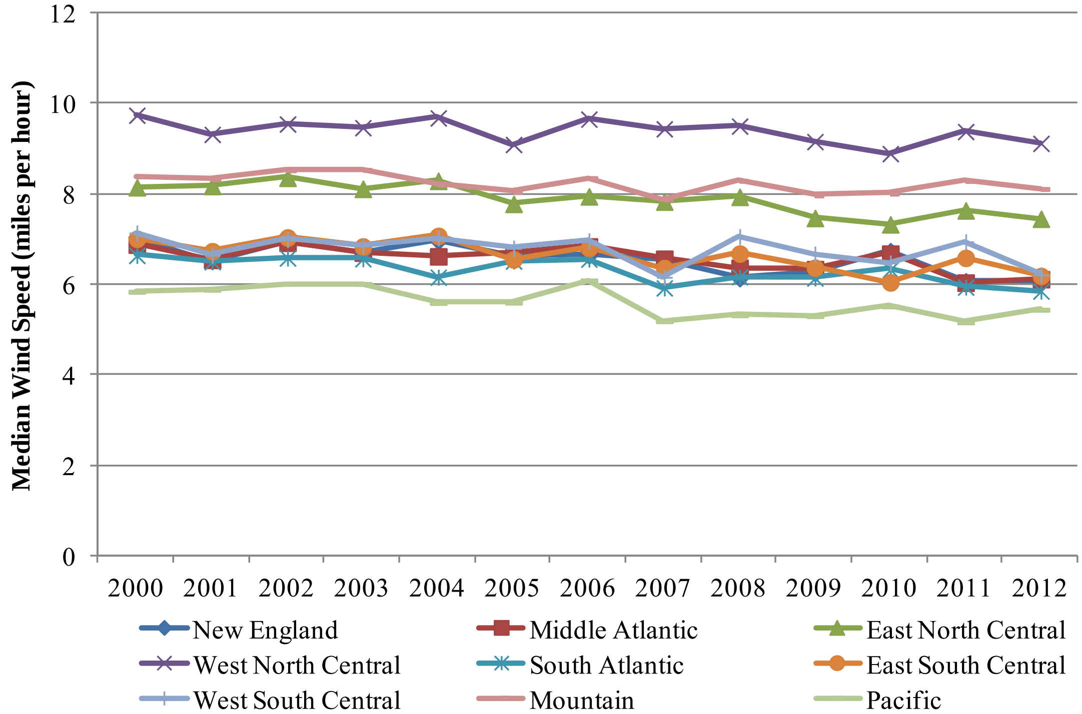


Figure 17: Median annual wind speed by census division

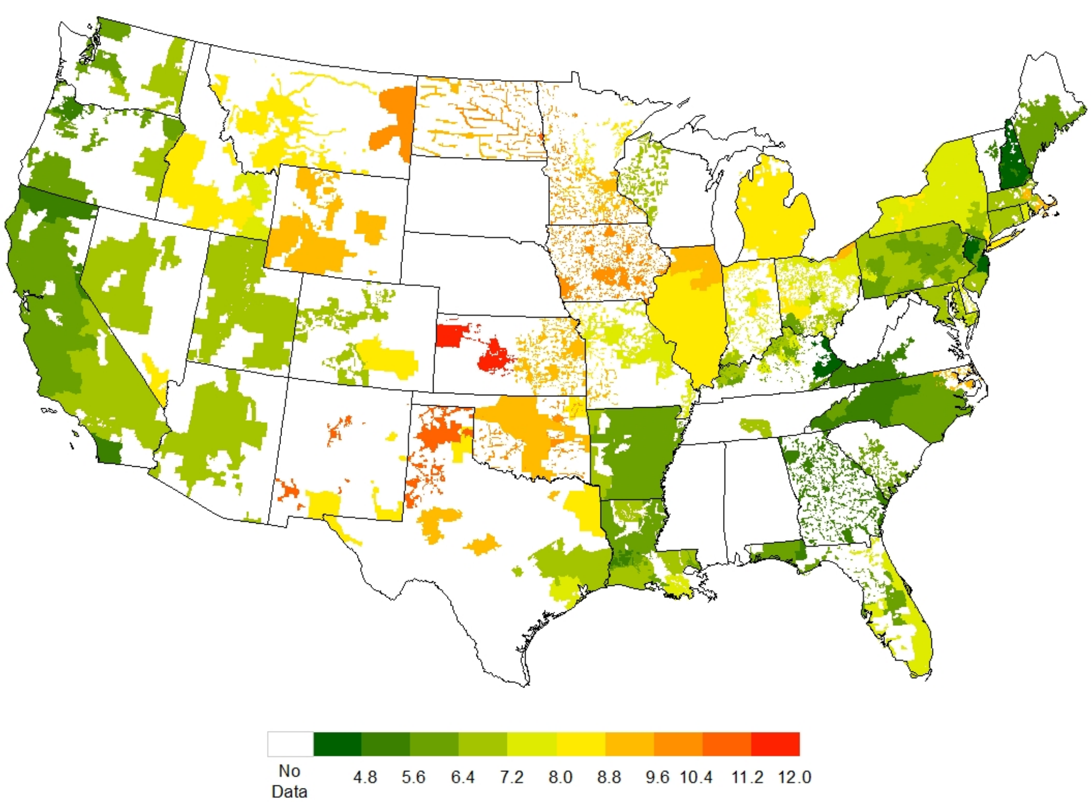


Figure 18: U.S. map of median annual wind speed

2.3.4. Heating and cooling degree-days (temperature)

Annual heating and cooling degree-days (HDD and CDD, respectively) were used to examine the relationship between temperature and electricity reliability.[4] Using the Ventyx Velocity Suite, we obtained temperature data from the National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC/Ventyx 2013). Ventyx was able to provide us with HDD and CDD data at the utility service territory level within each state. Figures 19–22 show the median by census division.

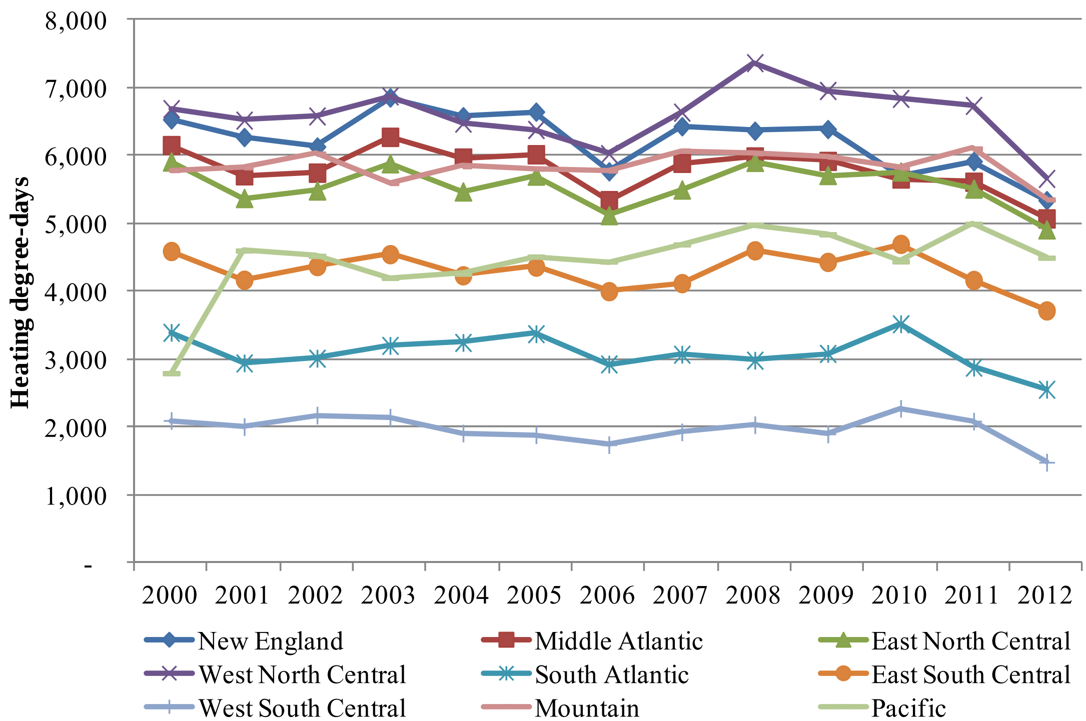


Figure 19: Median number of annual heating degree-days by census division

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[4] HDD and CDD were originally developed to assess heating or cooling requirements for building. They are calculated by subtracting the average between the daily high and low temperature from a reference value. The reference value is intended to represent the temperature below or above which heating or cooling is required, respectively.

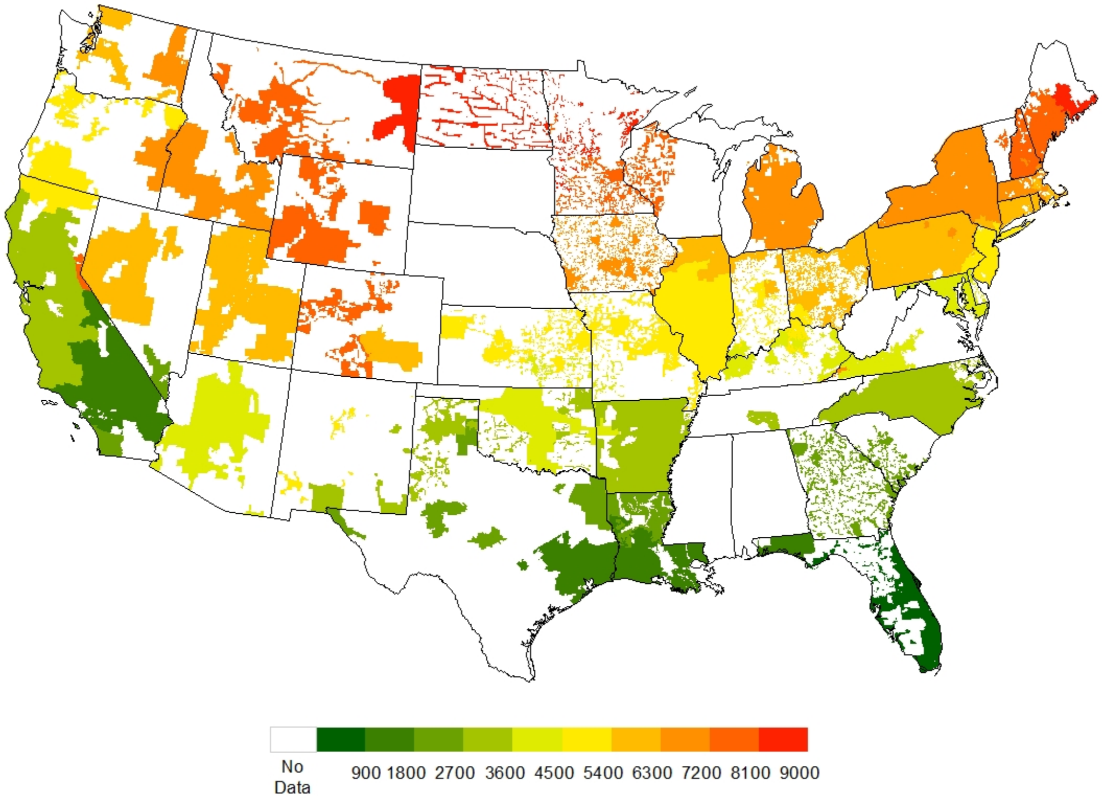

Figure 20: U.S. map of median annual heating degree-days

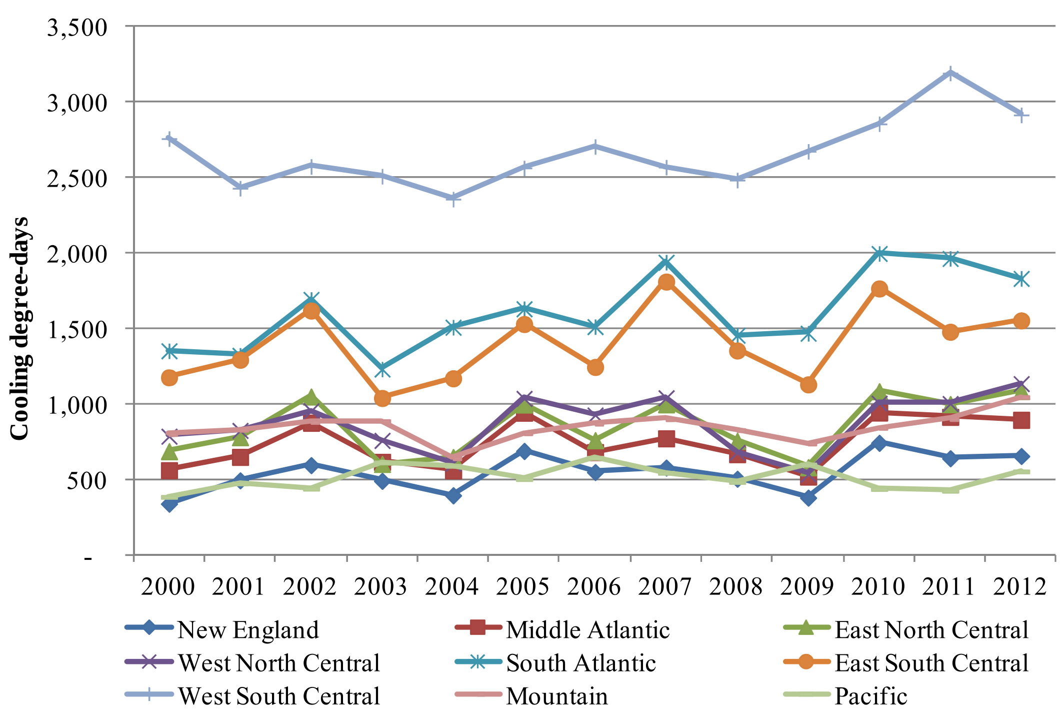

Figure 21: Median number of annual cooling degree-days by census division

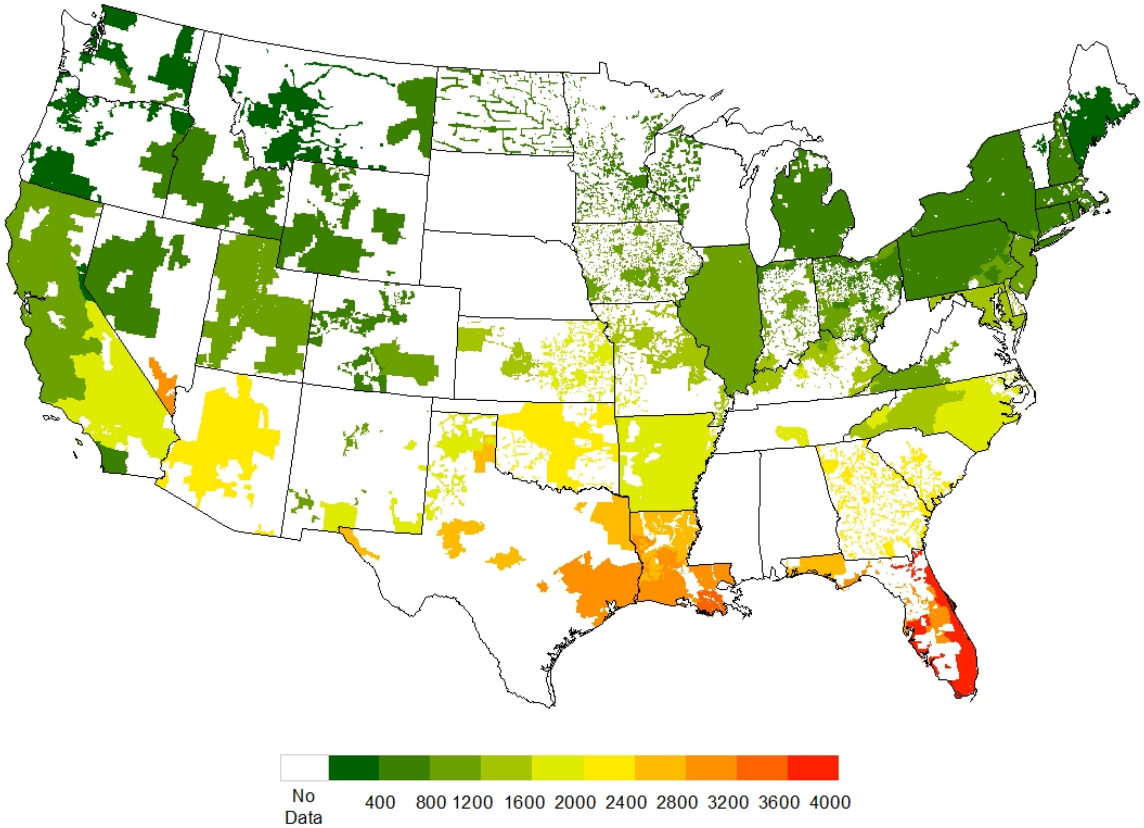

Figure 22: U.S. map of median annual cooling degree-days

3. Analysis Method and Model Development

This section describes the approaches we used to analyze the data. We first introduce the overall analysis method known as multivariate regression (Section 3.1). We next summarize, in aggregate, the data described in section 2 and discuss how we prepared the data for analysis by removing missing values and extreme outliers. We also describe transformations we made to some of these data in order to examine specific possible correlations in our analysis (Section 3.2). We then present intermediate results for preliminary statistical tests we performed in order to determine the appropriate regression analysis technique to apply to the data (Section 3.3). Then, we describe the sequence of alternate model specifications we developed and report on their statistical properties (Section 3.4). Finally, we describe the considerations that guide how we use the results from these analyses to develop the findings that are presented in Section 4.

3.1. Statistical analysis method

We employ a statistical analysis technique known as multivariate regression to develop quantitative estimates of the correlation between a dependent variable (in this case, SAIDI or SAIFI) and a set of independent, or explanatory, variables. 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:

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

The general model specification described in equation (1) above follows the general form used in earlier energy-related multivariate panel regressions (e.g., see Erdogdu 2011; 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 spending and variables in Z might include non-observable factors that vary across 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 2 describes the reduced form empirical model used in this analysis.

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

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.

3.2. 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. The tables show that, 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 12 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. That is, referring to Figure 2, the dataset of utility SAIDI without major events included contains different utilities than the dataset of utility SAIDI with major events included.

Table 3: 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	143.1	125.6	1,015.1	86.9
SAIFI (# of events)	2,026	0	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
T&D lines (customers per line mile)	2,024	0	172.2	23.3	8,942.6	672.8
Share of underground (%)	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 spending ($2012 per customer)	2,084	$4.4	$883.0	$239.8	$52,261.0	$2,328.4

Table 4: 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	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 (%)	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 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 from the analysis.

It is important to note that a utility has to have at least three years of continuous and balanced panel data in order for the regression program to find a solution. The regression software will fail to find a solution if a utility within the panel dataset contains: (1) less than three years of data; or (2) three or more years of data that are spread out into less than three year blocks throughout the time-series (e.g., 2001, 2002, 2006, 2011); or (3) the covariates and dependents contain at least three years of continuous data, but the blocks of reported data are misaligned over the full time series. For example, in this special case, a utility could have five years of continuous SAIDI data (e.g., 2000-2005) and four years of continuous covariates (e.g., 2007-2011), but this misalignment would lead to the utility being excluded from the econometric analysis.

In addition, 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.

For the above reasons, a number of utilities were either automatically (using regression software) or manually (by the authors) excluded from the datasets prior to conducting the econometric analyses. For example, prior to running Model A, the regression software automatically removed the following number of utilities due to insufficient data coverage: 28 (SAIDI without major events), 27 (SAIDI with major events), 31 (SAIFI without major events), and 28 (SAIFI with major events). In order to get all of the regressions to solve, we also manually excluded seven more utilities, which although they each had covariates and dependents containing at least three years of continuous data, the individual groupings of covariates (or dependents) were not aligned with one another in time. Finally, we excluded two additional utilities prior to conducting the first econometric analysis, because these utilities (1) failed the outlier screen and (2) we were able to independently confirm that their reported reliability performance metrics were inaccurate.

We also transformed some of the explanatory variables in order to examine statistically different ways that they might be related to changes in reliability. First, we transformed the weather-related variables to capture the extent to which they deviated from the sample (e.g., 13-year) average. Second, we transformed some of these same variables to emphasize how much they deviated annually from the sample average. Finally, we transformed T&D spending data by lagging it in order to examine how spending in previous years might be correlated with reliability performance in subsequent years.

Data transformation to capture "abnormal" weather

In order to explore the possibility that warmer/cooler, wetter/drier, windier/less windy etc. than average years were correlated with changes in the duration and/or frequency of power interruptions, we develop a metric to capture "abnormal" atmospheric conditions. We transformed the weather variables ($\overrightarrow{\boldsymbol{W}}$) into pairs of positive (see equation 3) and negative (see equation 4) deviations from the 13-year average.

$$\overset{+}{\Delta}\vec{W}_{it}\begin{cases}\dfrac{\left(W_{it-}\overline{W}_i\right)}{\overline{W}_i}\times 100: & \dfrac{\left(W_{it-}\overline{W}_i\right)}{\overline{W}_i}\times 100>0\\ 0: & \dfrac{\left(W_{it-}\overline{W}_i\right)}{\overline{W}_i}\times 100\le 0\end{cases} \tag{3}$$

$$\overset{-}{\Delta}\vec{W}_{it}\begin{cases}0: & \dfrac{\left(W_{it-}\overline{W}_i\right)}{\overline{W}_i}\times 100\ge 0\\ \dfrac{\left(W_{it-}\overline{W}_i\right)}{\overline{W}_i}\times 100: & \dfrac{\left(W_{it-}\overline{W}_i\right)}{\overline{W}_i}\times 100<0\end{cases} \tag{4}$$

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.

Data transformation to capture non-linear relationships involving weather

We also transformed the weather variables to explore the possibility that the relationship between weather, including temperature, precipitation, and wind—and the 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. (2008) 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.

Data transformation to capture effects of prior year T&D spending

Finally, we lagged T&D spending variables by one year to test the hypothesis that spending in a given year would not have an effect on reliability performance metrics until the following year (see equation 5).

$$\text{Expenditures}_{\text{it-1}} = \left(\frac{\text{TFC}_{\text{it-1}} + \text{TVC}_{\text{it-1}} + \text{DFC}_{\text{it-1}} + \text{DVC}_{\text{it-1}}}{\text{Customers}_{\text{it}}} \right) \times \left(\frac{\text{HW}_{2012}}{\text{HW}_{\text{t-1}}} \right) \tag{5}$$

3.3. Testing for the presence of 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, which will be described in greater detail in Section 3.4.

The results of the F-test for the first step for Model F (see Table 5) 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 5: Test results for the presence of no utility effects (F-test)

	One-way fixed effect (utility)			
Reliability metric	***F-value***	***Degrees of freedom (numerator/denominator)***	***Prob. > F***	***Reject null of 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 6) indicates that the null hypothesis of random effects for three of the four regressions cannot be rejected, at $p \leq 0.15$.[5] 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).[6]

Table 6: 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
LN SAIFI—without major events	9.2	8	0.33	No
LN SAIFI—with major events	14.3	9	0.11	Yes

3.4. Model development

We developed a sequence of model specifications (each a distinct regression equation following the form outlined in Section 3.1) 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. The procedures involve starting with a simplified model and then developing alternatives to it by adding new explanatory variables incrementally. 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. This sequential modeling approach allowed us to evaluate incrementally the

5 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.

6 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 in the technical appendix 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.

extent to which incorporation of abnormal weather, non-linear measures of weather severity, utility ownership type, percent underground, line miles per customer, T&D 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).

Table 7 lists the explanatory variables included in all seven models (Models A through G).

Table 7: Parameters for base model and six alternatives

Model	A	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)		●	●	●	●	●	●
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 expenditures ($2012 per customer)				●	●	●	●
Number of customers per line mile					●	●	●
Share of underground T&D miles to total T&D miles						●	●

Model A, which is a close proxy to the Eto et al. (2012) configuration, includes the following 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.[7] 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.

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 7, 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. Technical Appendix B contains full regression results for all seven models for each of the four reliability metrics. Appendix B shows 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).

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 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 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 R2 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.

Table 8 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.

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[7] 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.

However, we also observe that the number of utilities included in Model F is significantly less than those included in Model E. Technical Appendix B shows that the number of utilities modeled drops by approximately 50% between Models E and F. We traced 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.

In view of these results, we will structure the presentation of findings as follows: first, in Section 4, we will present detailed findings on the impacts of well-understood factors, such as weather and utility characteristics, on reliability based on Model F. Second, in examining aspects of our main findings in greater detail, in Section 5, we will present findings based on all of the models we developed.

Table 8: Performance statistics for base model and six alternatives

Dependent variable and criteria		A	B	C	D	E	F	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
	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

4. Principal Findings

This section describes the principal findings from our analysis. Figure 23 and Figure 24 show results for the SAIDI and SAIFI regressions, both with and without major events included for Model F.[8] Our findings will refer to the coefficients for the statistically significant explanatory variables listed in the following figures and in the tables in Technical Appendices B and C.

4.1. What factors are correlated with the annual average *duration* of power interruptions (SAIDI)?

If major events are not included (see Figure 23 and Figure 25), 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[9]
- Independent of these factors, each successive year over the analysis period is correlated with a slightly greater than 1% increase in the SAIDI

If major events are included (see Figure 24 and Figure 25), we find the following statistically significant relationships:

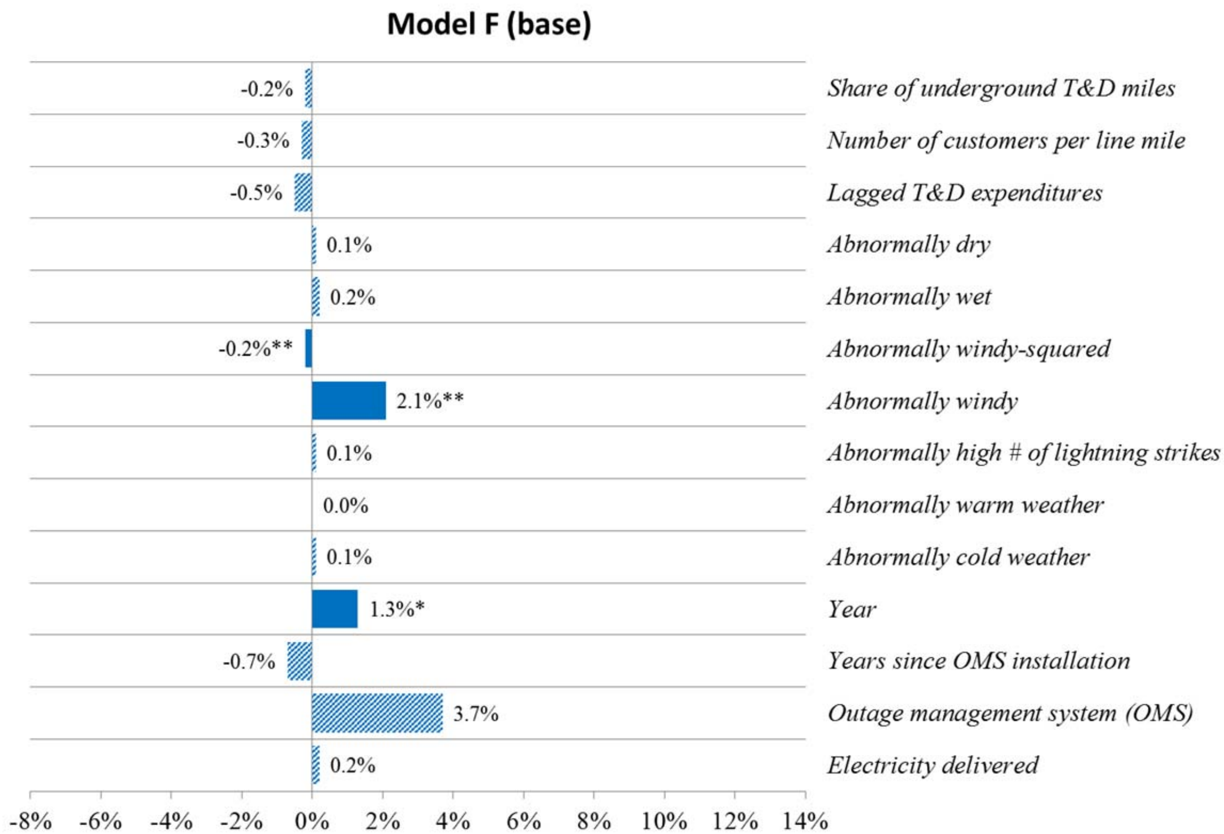
- A 10% increase in annual precipitation—above the long-term (generally, 13-year) average—is correlated with a 10% increase in SAIDI
- A 10% increase in the number of cooling degree-days (i.e., warmer weather)—above the long-term (generally,13-year) average—is correlated with a 8% decrease in SAIDI
-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

Above average precipitation and wind speed are correlated with longer duration interruptions and warmer than average temperatures and increased line miles undergrounded are correlated with shorter duration interruptions, but no other potential factors, except for the time trend, are statistically

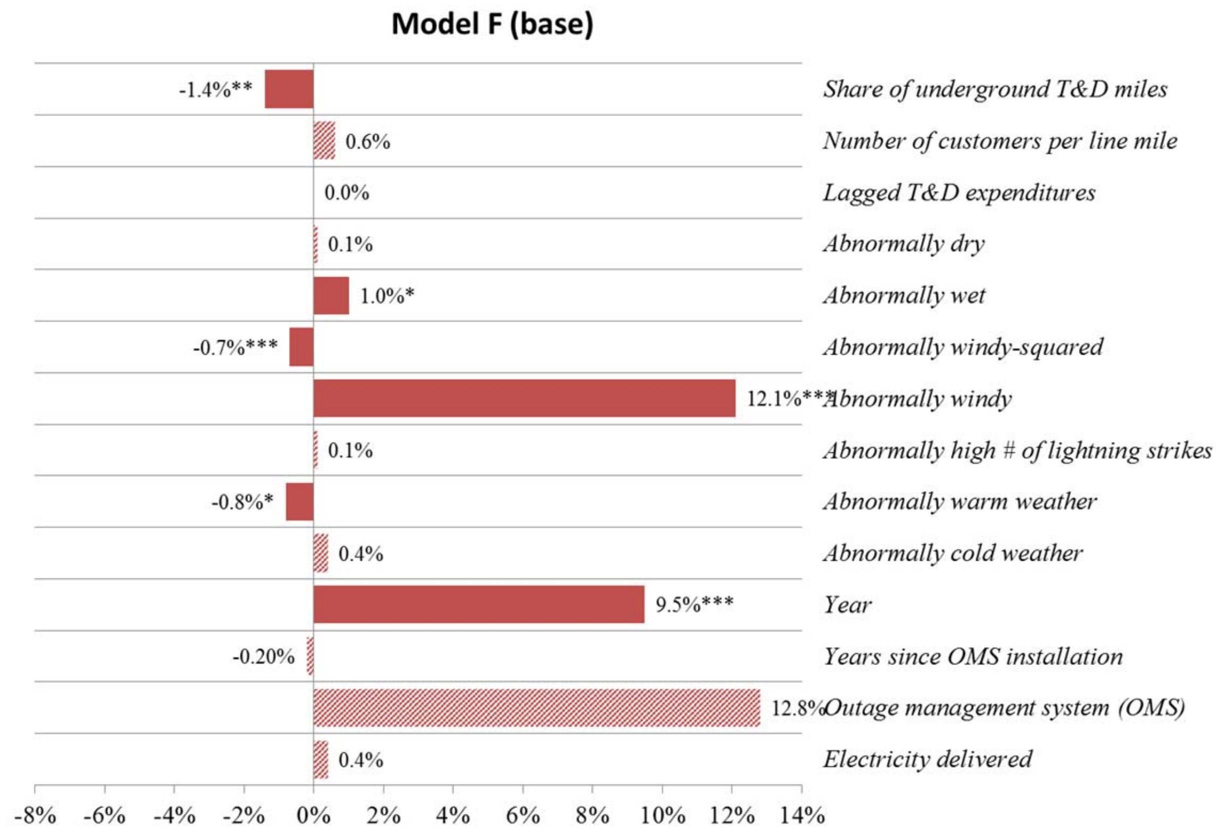
[8] Comparable and more detailed results for all seven model specifications (pooled OLS, fixed, random) and reliability metrics (SAIDI and SAIFI—both without and with major events included) are presented in Technical Appendices B and C.
[9] We believe that this apparently counterintuitive result is explained by recognizing that utilities categorize higher average wind speed events (i.e., major storms) into the dataset that includes major events.

significant in Model F (when major events are included). In view of its potential significance, we will explore further our finding regarding the time trend in SAIDI with major events included in Section 5.



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.
(4) See exact interpretation for these covariates earlier in this section.

Figure 23: Percentage change in SAIDI (without major events) corresponding to a change in the explanatory variable



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.
(4) See exact interpretation for these covariates earlier in this section.

Figure 24: Percentage change in SAIDI (with major events) corresponding to a change in the explanatory variable

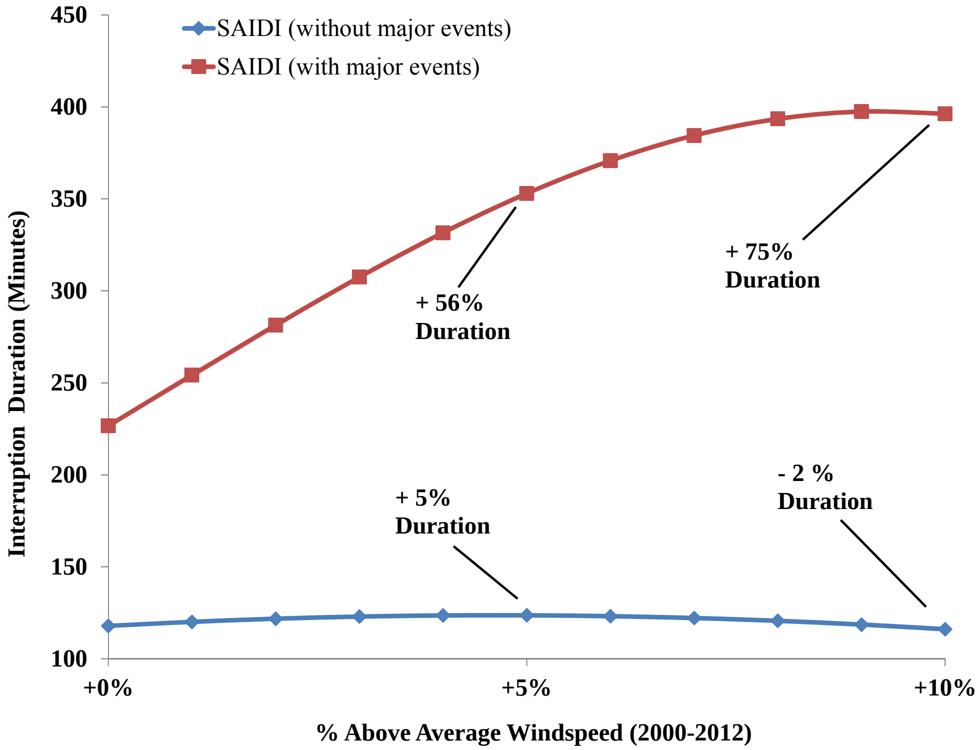


Figure 25: Above-average wind speed and duration of interruptions (SAIDI)

4.2. What factors are correlated with the annual average *frequency* of power interruptions (SAIFI)?

If major events are not included (see Figure 26 and Figure 28), 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

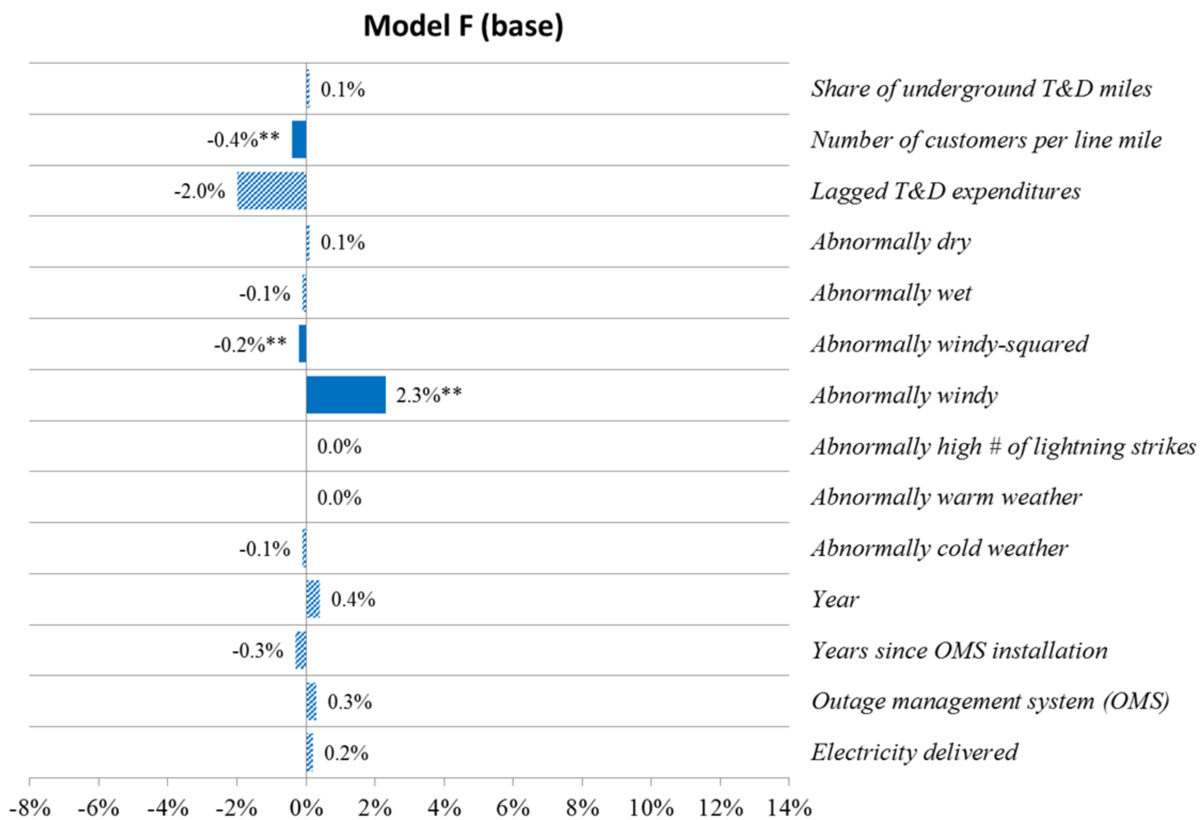
Above average wind and population density are correlated with more frequent interruptions. Eto et al. (2012) found that the installation of an OMS was correlated with more frequent interruptions, but that an OMS-related "learning effect" may have reduced the frequency of interruptions over time. In these 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.

If major events are included (see Figure 27 and Figure 28), we find the following statistically significant relationships:

- 10% increase in annual lightning strikes is correlated with a 2% increase in SAIFI

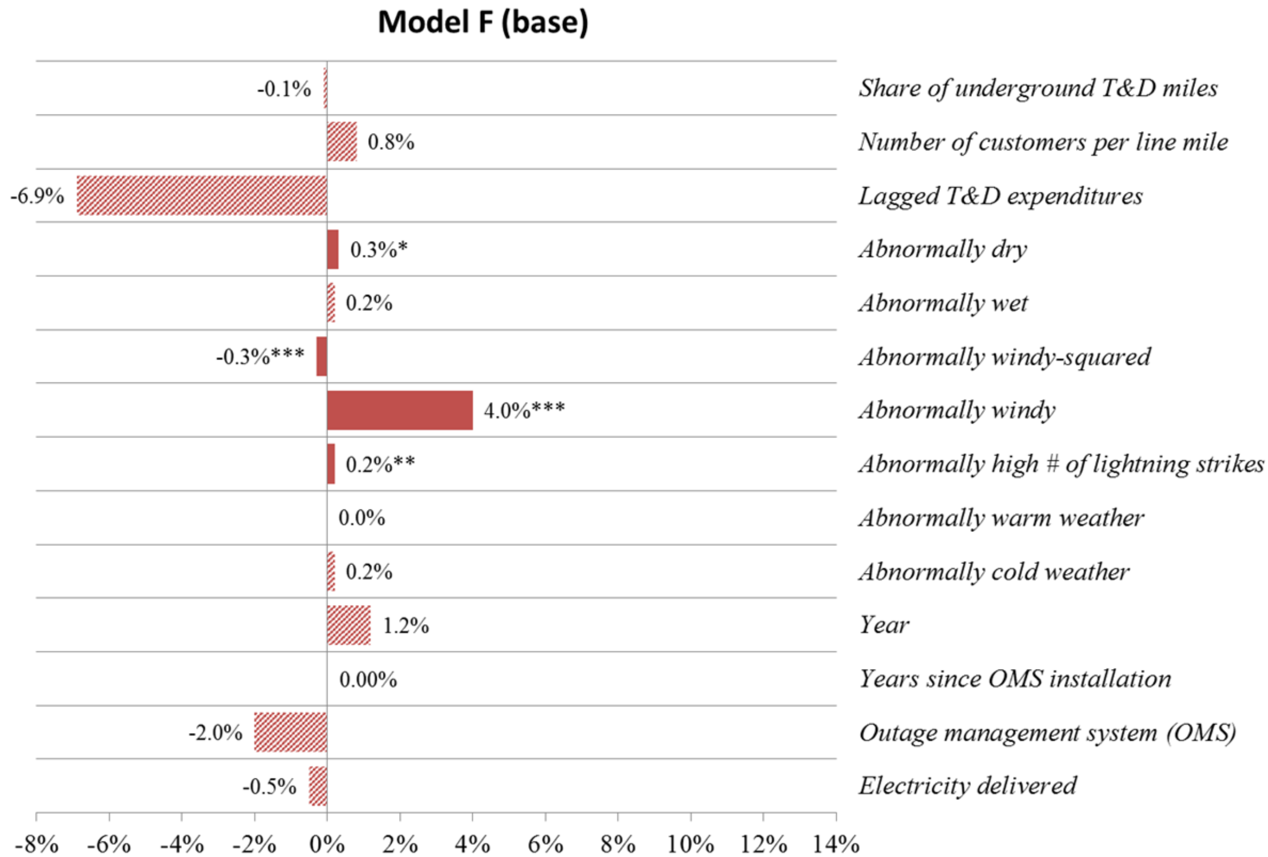
- 5% increase in annual average wind speed—above the long-term (generally, 13-year) average—is correlated with a 14% increase in SAIFI; 10% increase in annual average wind speed is correlated with a 15% increase in SAIFI
- 10% decrease in average total precipitation—below the long-term (generally, 13-year) 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.
(4) See exact interpretation for these covariates earlier in this section.

Figure 26: Percentage change in SAIFI (without major events) corresponding to a change in the explanatory variable



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.
(4) See exact interpretation for these covariates earlier in this section.

Figure 27: Percentage change in SAIFI (with major events) corresponding to a change in the explanatory variable

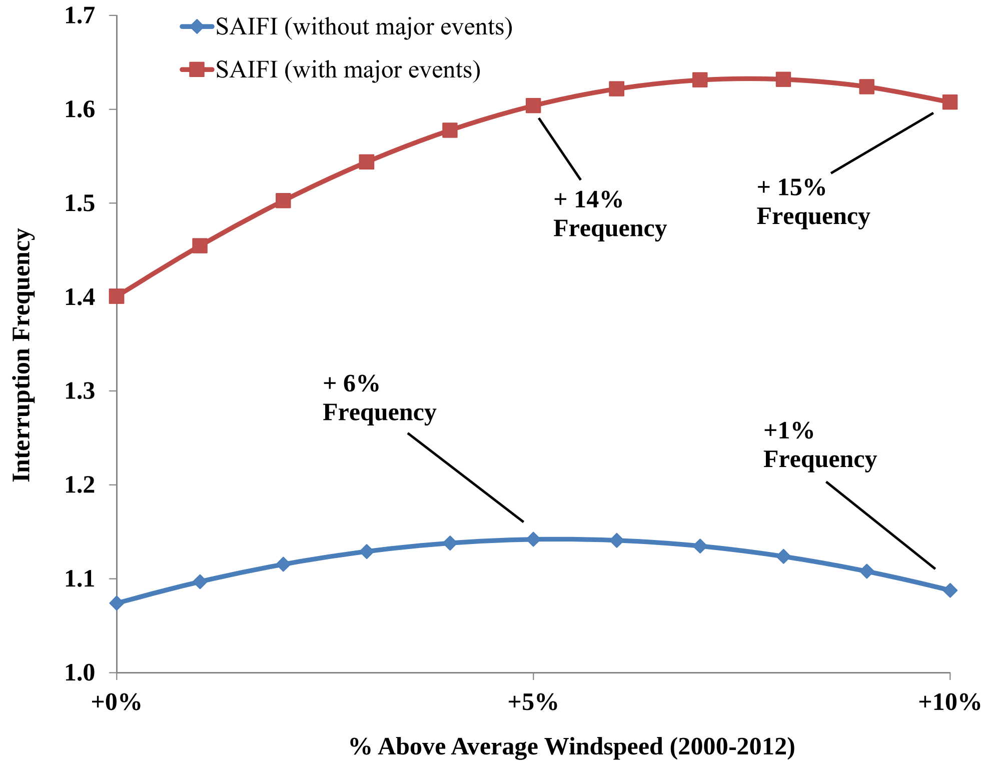


Figure 28: Above-average wind speed and frequency of interruptions (SAIFI)

5. Assessment, Discussion, and Caveats

This section discusses factors that should be considered when interpreting our findings. First, we review the composition of the dataset as compared to the population of U.S. electric utilities so that we can comment on the segments of the industry represented (and not represented) in our analysis. Second, we examine in greater detail our findings regarding a time trend in reliability that is not explained by other factors we considered. Third, we comment on our findings regarding the absence of a statistically significant correlation between prior year T&D expenditures and reliability. Fourth, we compare our findings to those developed earlier in Eto et al. (2012). Fifth, we conclude by reviewing caveats and other considerations affecting interpretation of findings from the current study.

5.1. Discussion of utilities included in this study versus population of utilities

Strictly speaking, our findings apply only to the utilities whose data we included in our analysis. As discussed earlier, we collected information from nearly 200 utilities, which taken together represent approximately 70% of total U.S. electricity sales. A key question is how the utilities that are included in our study compare to the utilities that are not included in our study. As noted in Section 2.2, geographically speaking, the utilities included in our study represent a significant portion of total electricity sales from all regions of the country except the East South Central census region. In this subsection, we extend this review by examining differences in both the ownership and size of the utilities included and not included in our analysis.

Figure 29 shows the number of utilities by ownership type that are included in this study. Nearly three-fourths of the utilities are IOUs with the remainder comprised of a mix of municipals, cooperatives or other types.[10] EIA reports that there are 192 investor-owned, 2,009 municipally owned and 877 cooperative utilities in the United States (EIA 2013). Accordingly, the 145 investor-owned utilities, 30 municipal utilities, and 16 cooperatives included in our study represent 75%, <1%, and 3%, respectively, of these totals. In other words, our findings cannot be assumed to apply to the 25%, 99%, and 97% of investor-owned, municipally-owned, and cooperative utilities, respectively, that were not included in our study.

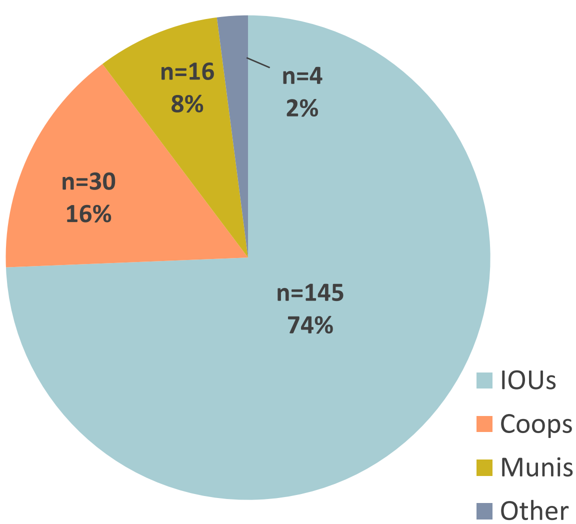
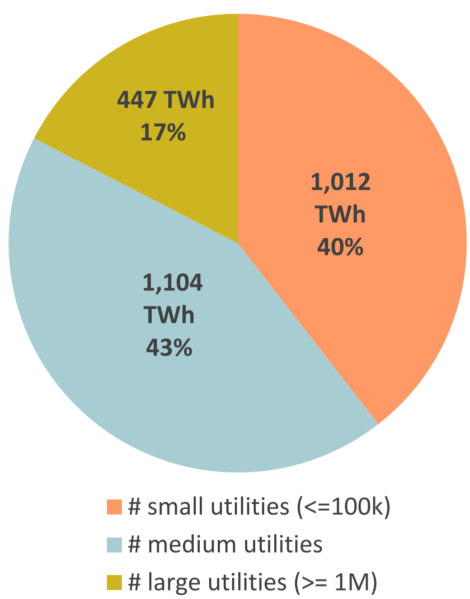


Figure 29: Number and proportion of utilities by ownership included in this study

[10] The "other" category refers to retail power marketers or political subdivisions, as defined by the EIA Form 861.

Figure 30 shows the mix of small- (≤ 100,000 customers), medium- (100,001 to 999,999 customers), and large- (≥ 1,000,000 customers) sized utilities represented as electricity sales (TWh) that are included and not included in this study. As shown in this figure, the utilities we included are almost evenly split between small- and medium-sized utilities (40% and 43%, respectively) and 17% large-sized utilities. 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). Figure 30 also shows that we have a smaller number of small-sized utilities in our study compared to the U.S. total (40% and 45%, respectively).



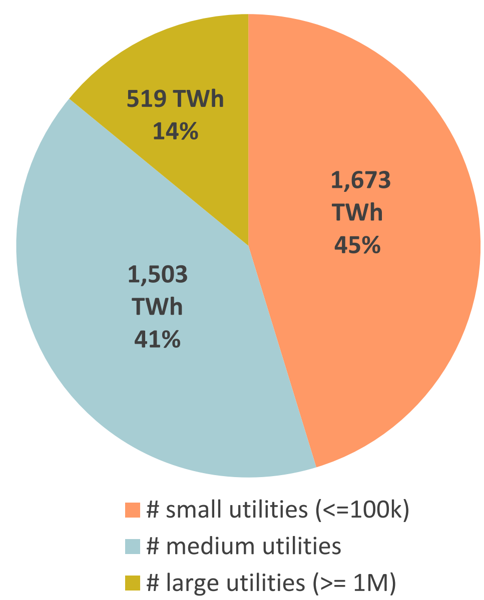


Figure 30. Represented sales (TWh) and proportion of utilities, by size, included (left) and for total U.S. (right) in this study

5.2. Are there remaining trends in reliability over time, which we cannot yet explain?

While the analysis we presented in Section 4 found strong correlations between many annual aspects of weather and the characteristics of utilities and reliability, we also found an independent, highly statistically significant correlation between year and SAIDI. The trend is statistically significant both when the annual average duration of power interruptions includes what utilities categorize as major events as well as when it excludes these events. Moreover, the trend is much larger when major events are included, which suggests that increases in either the number or severity of major events over time has been the principal contributor to the observed trend over time.

In view of the potential significance of this finding and to pave the way toward a more detailed analysis of this finding in the future, this subsection reviews the robustness of our findings regarding time trends in reliability both across models and through analysis of more selective sub-samples of the data.

Figure 31 and Figure 32 show the year coefficients for all seven SAIFI and SAIDI models, respectively, both without and with major events included. Figure 31 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 32 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.

To summarize, we found:

- essentially no trend in SAIFI, without or with major events included over time
- a small, but significant positive trend of increasing SAIDI without major events included over time
- a larger and significant positive trend of increasing SAIDI with major events included over time

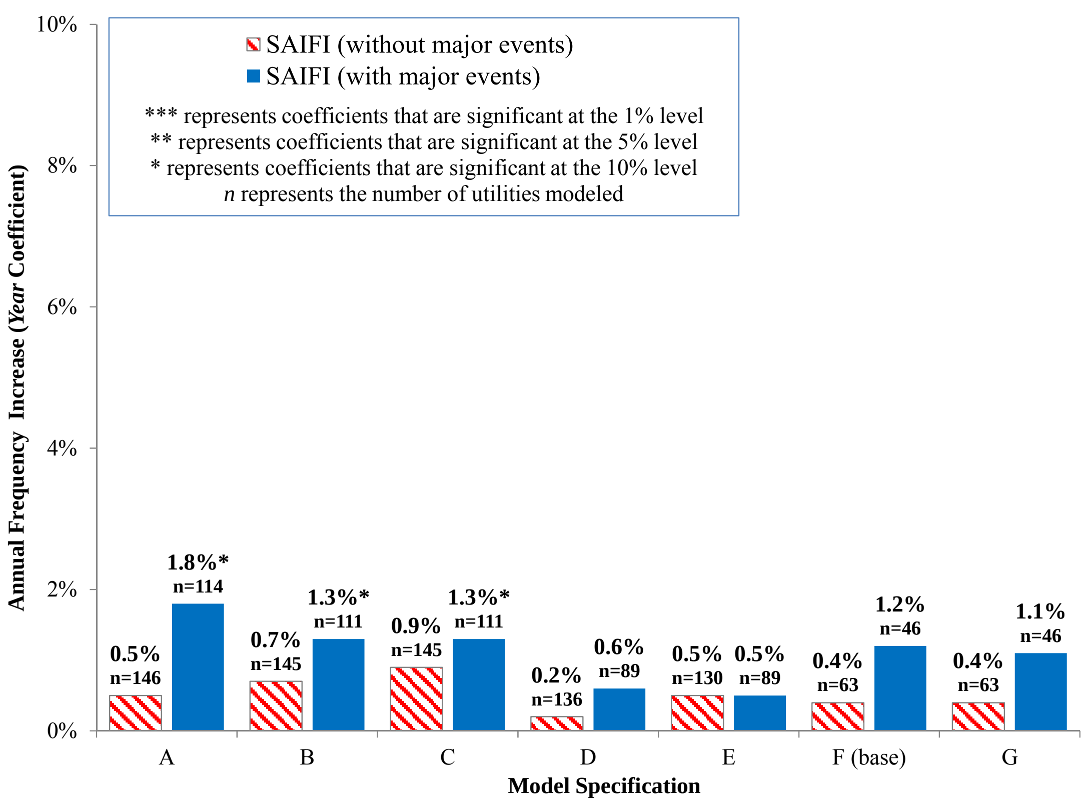


Figure 31: Annual increase in frequency of interruptions: all models considered

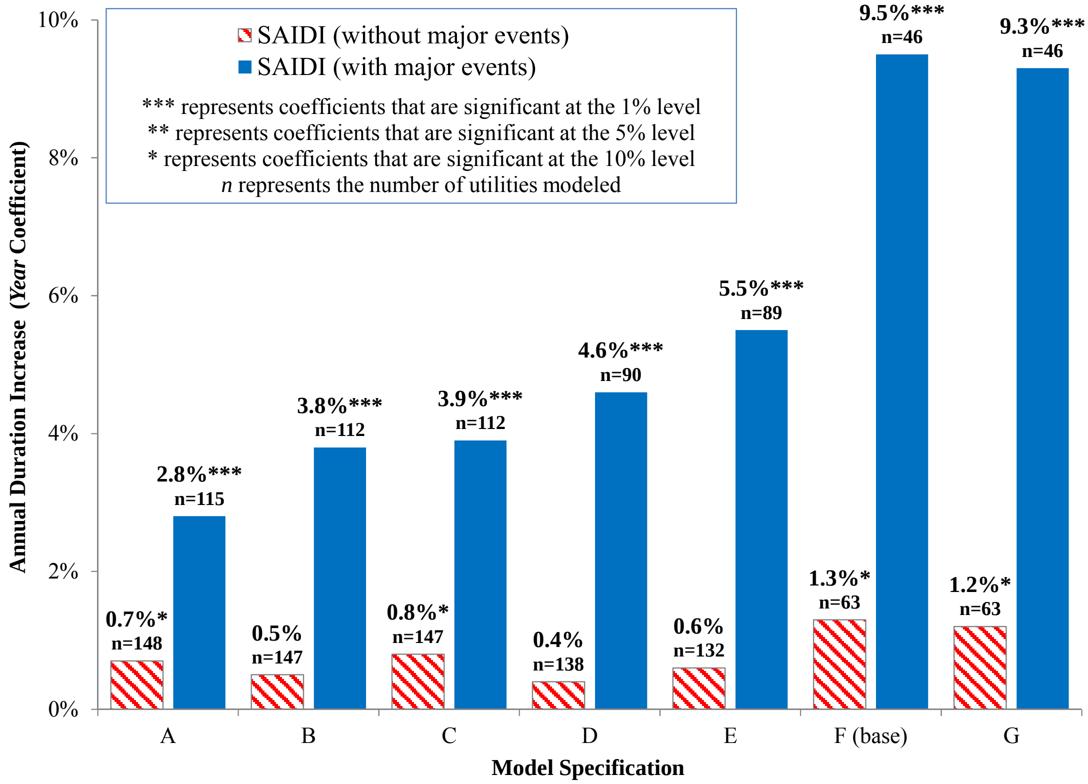


Figure 32: Annual increase in duration of interruptions: all models considered

We next evaluated sub-samples of utility data used in our analysis to further evaluate the robustness of this finding. Specifically, we sought to determine the extent to which changes in the composition of utilities involved in regression models might have an influence on our findings. For example, if our unbalanced panel included a number of utilities with: (a) less than 13 years of observations; (b) observations that were predominantly in later years (compared to utilities with complete datasets spanning all 13 years); and (c) higher SAIDI values on average compared to other utilities in the full dataset, then an increasing trend in SAIDI might be due solely to inclusion of these utilities in the analysis. Similarly, since the number of utilities included in the SAIDI regressions without and with major events differ, it is possible that differences between in the value of year coefficients might be due solely to the fact that different groups of utilities were included in each regression.

We examined the first possibility by restricting the regression analysis to only include utilities for which we had all 13 years of SAIDI data. We call this dataset the "partially restricted panel." We examined the second possibility by further restricting the regression analysis to the subset of these utilities which had both SAIDI without and with major events included. We call this dataset the "fully restricted panel." We conducted these analyses for both Models E and F because Model E allowed us to include more utilities in each dataset. We compare the resulting year coefficient to those from our original analysis, called the "unrestricted panel."

Table 9 shows that for both Models E and F, the year coefficient for SAIDI with major events is both consistently positive and statistically significant for all three panels. Similarly, the year coefficients for SAIDI without major events are also consistently positive but smaller and less statistically significant for all three panels. Technical Appendix D contains the full results from this analysis.

We conclude that SAIDI with major events is increasing over time in a manner not captured by the explanatory variables we have considered to date and that this finding is not influenced by restrictions we have placed on the utilities to take into account some of the potential inherent biases in the underlying data we analyzed.

Table 9: Fully restricted, partially restricted, and unrestricted panel regression results for annual trend (YEAR variable) for model F and model E

	Model F			Model E		
Reliability metric	**Unrestricted panel**	**Partially restricted panel**	**Fully restricted panel**	**Unrestricted panel**	**Partially restricted panel**	**Fully restricted panel**
SAIDI annual trend—*with* major events	9.5%***	9.8%***	9.3%***	5.5%**	4.8%**	3.9%*
SAIDI annual trend—*without* major events	1.3%*	1.9%*	1.9%*	0.6%	1.0%**	0.9%

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.

5.3. Discussion of findings for utility T&D spending

Our *a priori* expectation was that increased T&D spending in the previous year would be correlated (and statistically significant) with improvements in reliability in the following year. The regression output tables in Appendix D show that the coefficients on lagged T&D spending per customer were negative for 10 of the 12 regressions, which suggests that reliability improvements are negatively correlated with increased T&D spending in the previous year—of course, these results were generally not significant at the 90th percentile or above. We were surprised to find that T&D spending was not significantly correlated with interruption frequency or duration in Model F.[11]

Furthermore, we observed counter-intuitive results within the Model F regressions. For example, the coefficient for lagged T&D spending SAIDI models had a negative and positive sign when major events were and were not included, respectively. Although none of these coefficients were statistically significant, the Model F suggests that increased spending may be correlated with less frequent and shorter duration interruptions if major events are not included. If major events are included, increased

[11] It is important to note that the pooled SAIDI and SAIFI regressions (i.e., no fixed or random effects included) did find statistically significant correlations for lagged T&D spending.

spending may be correlated with less frequent and shorter interruptions. Consequently, we re-ran the models to confirm if these counter-intuitive findings persisted under alternative approaches for expressing lagged T&D spending (e.g., spending per line mile; spending per MWh delivered; spending per customer; spending from previous two years; distribution-only spending; transmission-only spending; % deviation in annual spending compared to 13-year average, etc.). We found that some of these alternatively formulated spending variables became statistically significant, but many still showed a mix of both positive and negative signs depending on the reliability metric (SAIDI or SAIFI) and whether or not major events were included.

Unfortunately, FERC Form 1 filings do not contain more detailed breakdowns on annual utility spending related to T&D. We suspect that reliability is affected differently depending on whether utilities spend relatively more on preventative maintenance when compared to reactive maintenance. The presence of "competing" effects within the utility spending data may be influencing the results and leading to the counter-intuitive findings. For example, a proactive utility may anticipate future reliability problems and then justify investing a large amount of capital now to reduce the likelihood of a future interruption. In this case, the utility would have higher (lagged) T&D spending and a relatively lower SAIDI and/or SAIFI. Alternatively, a reactive electric utility simply spends more on operations and maintenance as reliability problems arise. In this case, the utility would have higher (current year, not lagged) T&D spending and a relatively higher SAIDI and/or SAIFI. However, it is certainly possible that proactively investing in a new line may increase future utility exposure while not necessarily improving existing system reliability. In summary, it is possible that competing proactive versus reactive utility spending strategies could explain the aforementioned inconsistencies in the signs and poor statistical significance of our findings with respect to lagged T&D spending.

5.4. Comparison to previous findings

Eto et al. (2012) found that reliability, as measured by all four indices (SAIDI and SAIFI both without and with major events included) was getting worse over time and that the correlations were highly statistically significant. The study also found very limited and generally not highly statistically significant correlations with the weather- and utility-specific factors it considered.

The current study finds that only the correlations for the annual average duration of power interruptions with major events included is highly statistically significant with the time-trend variable. Moreover, the current study, in contrast to Eto et al. (2012), also finds several statistically significant correlations between reliability and a number of weather and utility-specific factors.

Table 10 summarizes the difference in the findings for the time-trend coefficients between the Eto et al. (2012) study and the current study.

Table 10: Comparison of annual trend in reliability metrics (% per year)

Reliability metric:	Eto et al. (2012)	Model F	Model E
SAIDI (with major events)	2.6%***	9.5%***	5.5%***
SAIDI (without major events)	6.5%***	1.3%*	0.6%
SAIFI (with major events)	2.1%***	1.2%	0.5%
SAIFI (without major events)	3.3%***	0.4%	0.5%

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.

5.5. Additional caveats when interpreting the study findings

There are a number of final caveats that should be considered when evaluating the results of our study. We summarize them briefly, as follows:

First, 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 (see, for example, IEEE 2012), utilities sometimes use other criteria to define them (Eto and LaCommare 2008; Eto et al. 2012). 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.

Second, there is also the possibility of selection bias affecting this analysis (Heckman 1979). As we discussed in Section 5.1, 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). Under-represented smaller utilities, which may include cooperatives and municipals, could have fundamentally different reliability than the sample of 195 utilities evaluated in this study. Many of these under-represented utilities do not collect and/or publish reliability performance metrics. For this reason, it is not appropriate to extend our findings to the entire population of U.S. electric utilities unless these potential sources of bias have been taken into account.

Third, although we believe that this econometric analysis is a significant improvement over the model originally specified in Eto et al. (2012), 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. There is also evidence of collinearity between the linear and non-linear weather terms—and, more generally, with the entire suite of weather variables. Multi-collinearity does not create bias, but it can lead to inflated standard errors and p-values (e.g., see Greene 2000 and Wooldridge 2002).

Fourth, there are other unobservable or intangible factors, which could significantly affect utility reliability. One example of an intangible factor might include the effect of “culture” for a utility (PA Consulting 2014) on reliability. It has been shown that some utilities take a “splintered approach” to addressing reliability problems, which can lead to inefficient use of company resources (APPA 2014). Another example of an unobservable factor is the share of utility customers who have installed smart grid technologies. These technologies could improve reliability, but penetration rates of smart grid technologies are not currently reported for a significant number of utilities.

6. Next Steps and Conclusion

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.

First, it is important to continue to explore the relationship between reactive and proactive T&D spending and reliability. Also, the relationship between reliability and the long-run deployment of other "smart" technologies should be explored further as new information becomes available.

Second, there may be more appropriate annual weather parameters available to 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).

Third, in addition to collecting more information from non-IOUs, it might be possible to address small utility selection bias using an approach similar to what was first proposed by Heckman (1979).

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. Others 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, on the one hand, planning and operations and, on the other hand, 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. In doing so, we hope that our findings will help to inform future public and private decisions that will influence the future reliability of the U.S. electric power system.

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Appendix A. IEEE definition and calculation of Major Event Days

To make year-to-year comparisons of reliability performance more meaningful, utilities and their regulators have developed methods for segregating reliability performance using a concept known as "major event days." The Institute of Electrical and Electronics Engineers (IEEE) defines them as follows:

> *"A **major event day** is a day in which the daily System Average Interruption Duration Index (SAIDI) exceeds a Major Event Day threshold value [called TMED]. For the purposes of calculating daily system SAIDI, any interruption that spans multiple calendar days is accrued to the day on which the interruption began. Statistically, days having a daily system SAIDI greater than TMED are days on which the energy delivery system experienced stresses beyond that normally expected (such as during severe weather). Activities that occur on Major Event Days should be separately analyzed and reported."* (IEEE Power Engineering Society 2012)

IEEE Std. 1366 uses the previous five years of a utility's daily SAIDI data in order to establish a threshold value for daily SAIDI values recorded in the current year. The equation for the threshold value, known as *Tmed*, is as follows:

$$Tmed = e^{(\alpha+2.5\beta)}$$

Where for each utility:

α is the log-normal average of the previous five years of daily SAIDI

β is the log-normal standard deviation of the previous five years of daily SAIDI

Application of the method involves first calculating *Tmed* for the current year (based on daily SAIDI values for the prior five years) and then comparing the daily SAIDI to this value. If daily SAIDI exceeds *Tmed*, that day is identified as an MED. Having partitioned some of the daily SAIDI values in this manner, the remaining daily SAIDI values are summed to an annual SAIDI without major events. Utilities sometimes report two annual SAIDI values: one without major events and one with major events.

Appendix B. Base model robustness tests

Table B - 1: Alternative specifications for SAIDI (without major events) regressions

Model specification:	Model 1-A	Model 1-B	Model 1-C	Model 1-D	Model 1-E	Model 1-F	Model 1-G
Intercept	-8.732 (7.915)	-5.959 (8.037)	-10.571 (7.766)	-2.895 (8.398)	-7.011 (8.218)	-21.218 (13.53)	-19.689 (13.167)
Electricity delivered (MWh per customer)	0.02*** (0.006)	0.021*** (0.006)	0.007*** (0.003)	0.022*** (0.006)	0.024*** (0.006)	0.002 (0.002)	0.002 (0.002)
Heating degree-days (#)	0 (0)						
Cooling degree-days (#)	0 (0)						
Outage management system?	0.092*** (0.03)	0.094*** (0.029)	0.086*** (0.029)	0.11*** (0.031)	0.108*** (0.031)	0.037 (0.049)	0.037 (0.049)
Years since outage management system installation	-0.002 (0.005)	0 (0.005)	-0.004 (0.005)	0.004 (0.005)	0.003 (0.005)	-0.007 (0.009)	-0.006 (0.008)
Year	0.007* (0.004)	0.005 (0.004)	0.008* (0.004)	0.004 (0.004)	0.006 (0.004)	0.013* (0.007)	0.012* (0.007)
Abnormally cold weather (% above average HDDs)		0 (0.001)	-0.002 (0.002)	-0.003 (0.002)	0 (0.001)	0.001 (0.001)	-0.003 (0.003)
Abnormally warm weather (% above average CDDs)		0 (0.001)	0.002 (0.002)	0.001 (0.001)	0 (0.001)	0 (0.001)	0.004 (0.004)
Abnormally high # of lightning strikes (% above average strikes)		0.001*** (0)	0.001** (0)	0.001*** (0)	0.001*** (0)	0.001 (0)	0.001** (0)
Abnormally windy (% above average wind speed)		0.004 (0.004)	0.024*** (0.007)	0.025*** (0.007)	0.023*** (0.007)	0.021** (0.009)	0.021** (0.009)
Abnormally wet (% above average total precipitation)		0.002* (0.001)	0 (0.002)	0 (0.002)	0.002** (0.001)	0.002 (0.002)	-0.006 (0.004)
Abnormally dry (% below average total precipitation)		0.001 (0.001)	0.006*** (0.002)	0.006*** (0.002)	0.001 (0.001)	0.001 (0.002)	0.004 (0.004)
Abnormally cold weather squared			0 (0)	0* (0)			0 (0)
Abnormally warm weather squared			0 (0)	0 (0)			0 (0)

Model specification:	Model 1-A	Model 1-B	Model 1-C	Model 1-D	Model 1-E	Model 1-F	Model 1-G
Abnormally windy squared			-0.002*** (0.001)	-0.002*** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.002** (0.001)
Abnormally wet squared			0 (0)	0 (0)			0 (0)
Abnormally dry squared			0** (0)	0** (0)			0 (0)
Lagged T&D expenditures ($2012 per customer)				-0.012 (0.051)	-0.01 (0.051)	-0.005 (0.026)	-0.006 (0.026)
Number of customers per line mile					0 (0)	-0.003 (0.003)	-0.004 (0.003)
Share of underground T&D miles to total T&D miles						-0.002 (0.004)	-0.003 (0.004)
Degrees of freedom:	1,479	1,463	1,604	1,327	1,260	523	519
Number of utilities:	148	147	147	138	132	63	63
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.78	0.79	0.04	0.80	0.80	0.05	0.08
Akaike Information Criteria (AIC)	1,181.2	1,163.5	1,517.4	1,024.1	779.4	443.4	496.7
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

Table B - 2: Alternative specifications for SAIDI (with major events) regressions

Model specification:	Model 2-A	Model 2-B	Model 2-C	Model 2-D	Model 2-E	Model 2-F	Model 2-G
Intercept	-50.288** (21.095)	-71.301*** (23.166)	-72.831*** (23.65)	-87.303*** (29.505)	- 105.128*** (29.124)	- 185.236*** (49.627)	-180.85*** (49.934)
Electricity delivered (MWh per customer)	0 (0.004)	0.012 (0.009)	0.011 (0.009)	0.004 (0.01)	0.007 (0.012)	0.004 (0.015)	0.003 (0.015)
Heating degree-days (#)	0*** (0)						
Cooling degree-days (#)	0*** (0)						
Outage management system?	0.295*** (0.089)	0.292*** (0.089)	0.289*** (0.089)	0.21** (0.09)	0.196** (0.09)	0.128 (0.136)	0.143 (0.136)
Years since outage management system installation	0.019 (0.015)	0.02 (0.015)	0.025* (0.015)	0.014 (0.017)	0.013 (0.017)	-0.02 (0.025)	-0.023 (0.025)
Year	0.028*** (0.011)	0.038*** (0.012)	0.039*** (0.012)	0.046*** (0.015)	0.055*** (0.015)	0.095*** (0.025)	0.093*** (0.025)
Abnormally cold weather (% above average HDDs)		-0.006** (0.003)	-0.009 (0.007)	-0.004 (0.008)	-0.004 (0.003)	0.004 (0.013)	-0.036 (0.028)
Abnormally warm weather (% above average CDDs)		-0.002 (0.002)	0.002 (0.005)	0.004 (0.005)	-0.003 (0.002)	-0.008* (0.004)	-0.006 (0.01)
Abnormally high # of lightning strikes (% above average strikes)		0.001* (0.001)	0.001 (0.001)	0.002** (0.001)	0.003*** (0.001)	0.001 (0.002)	0.001 (0.002)
Abnormally windy (% above average wind speed)		0.03*** (0.01)	0.103*** (0.022)	0.079*** (0.021)	0.081*** (0.021)	0.121*** (0.031)	0.118*** (0.031)
Abnormally wet (% above average total precipitation)		0.006*** (0.002)	0.018*** (0.004)	0.019*** (0.005)	0.007*** (0.003)	0.01* (0.005)	0.016* (0.009)
Abnormally dry (% below average total precipitation)		0.001 (0.002)	-0.006 (0.006)	-0.001 (0.006)	0.002 (0.003)	0.001 (0.005)	-0.007 (0.012)
Abnormally cold weather squared			0 (0)	0 (0)			0.004 (0.003)
Abnormally warm weather squared			0 (0)	0* (0)			0 (0)

Model specification:	Model 2-A	Model 2-B	Model 2-C	Model 2-D	Model 2-E	Model 2-F	Model 2-G
Abnormally windy squared			-0.007*** (0.002)	-0.005*** (0.002)	-0.006*** (0.002)	-0.007*** (0.002)	-0.006*** (0.002)
Abnormally wet squared			0*** (0)	0*** (0)			0 (0)
Abnormally dry squared			0 (0)	0 (0)			0 (0)
Lagged T&D expenditures ($2012 per customer)				-0.004 (0.047)	0.002 (0.046)	0 (0.07)	-0.005 (0.073)
Number of customers per line mile					0 (0)	0.006 (0.007)	0.006 (0.007)
Share of underground T&D miles to total T&D miles						-0.014** (0.007)	-0.014** (0.007)
Degrees of freedom:	1,124	1,091	1,086	820	813	335	331
Number of utilities:	115	112	112	90	89	46	46
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.06	0.09	0.10	0.13	0.12	0.14	0.15
Akaike Information Criteria (AIC)	3,013.0	2,936.5	2,992.7	2,195.3	2,126.8	945.8	996/5
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

Table B - 3: Alternative specifications for SAIFI (without major events) regressions

Model specification:	Model 3-A	Model 3-B	Model 3-C	Model 3-D	Model 3-E	Model 3-F	Model 3-G
Intercept	-10.03 (10.796)	-13.409 (10.247)	-17.161 (10.703)	-4.403 (9.217)	-10.661 (9.543)	-8.622 (15.225)	-8.573 (15.276)
Electricity delivered (MWh per customer)	0.004*** (0.002)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.003*** (0.001)	0.002 (0.002)	0.002 (0.002)
Heating degree-days (#)	0 (0)						
Cooling degree-days (#)	0 (0)						
Outage management system?	-0.038 (0.039)	-0.037 (0.039)	-0.04 (0.039)	-0.03 (0.041)	-0.043 (0.041)	0.003 (0.038)	0.003 (0.038)
Years since outage management system installation	0.002 (0.007)	0.004 (0.007)	0.004 (0.007)	0.012* (0.006)	0.01* (0.006)	-0.003 (0.006)	-0.004 (0.006)
Year	0.005 (0.005)	0.007 (0.005)	0.009 (0.005)	0.002 (0.005)	0.005 (0.005)	0.004 (0.008)	0.004 (0.008)
Abnormally cold weather (% above average HDDs)		0 (0.001)	0 (0.003)	-0.002 (0.003)	-0.001 (0.001)	-0.001 (0.001)	-0.003 (0.002)
Abnormally warm weather (% above average CDDs)		0 (0.001)	-0.001 (0.002)	0.001 (0.002)	0 (0.001)	0 (0.001)	0 (0.003)
Abnormally high # of lightning strikes (% above average strikes)		0 (0)	0 (0)	0 (0)	0.001 (0)	0 (0.001)	0 (0.001)
Abnormally windy (% above average wind speed)		0.005 (0.004)	0.025*** (0.009)	0.03*** (0.008)	0.03*** (0.009)	0.023** (0.011)	0.023** (0.011)
Abnormally wet (% above average total precipitation)		0 (0.001)	0 (0.002)	0 (0.002)	0 (0.001)	-0.001 (0.001)	-0.001 (0.003)
Abnormally dry (% below average total precipitation)		0.002* (0.001)	0.005* (0.002)	0.005* (0.002)	0.001 (0.001)	0.001 (0.001)	0 (0.002)
Abnormally cold weather squared			0 (0)	0 (0)			0 (0)
Abnormally warm weather squared			0 (0)	0 (0)			0 (0)
Abnormally windy squared			-0.002*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.002** (0.001)	-0.002** (0.001)

Model specification:	Model 3-A	Model 3-B	Model 3-C	Model 3-D	Model 3-E	Model 3-F	Model 3-G
Abnormally wet squared			0 (0)	0 (0)			0 (0)
Abnormally dry squared			0 (0)	0 (0)			0 (0)
Lagged T&D expenditures ($2012 per customer)				0.04 (0.031)	0.036 (0.031)	-0.02 (0.021)	-0.022 (0.022)
Number of customers per line mile					0 (0)	-0.004** (0.002)	-0.005** (0.002)
Share of underground T&D miles to total T&D miles						0.001 (0.002)	0.001 (0.002)
Degrees of freedom:	1,603	1,586	1,581	1,441	1,368	522	518
Number of utilities:	146	145	145	136	130	63	63
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.01	0.01	0.02	0.02	0.02	0.03	0.03
Akaike Information Criteria (AIC)	1,920.8	1,917.6	1,994.4	1,525.3	1,349.7	331.3	400.7
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

Table B - 4: Alternative specifications for SAIFI (with major events) regressions

Model specification:	Model 4-A	Model 4-B	Model 4-C	Model 4-D	Model 4-E	Model 4-F	Model 4-G
Intercept	-35.713* (21.044)	-26.117* (15.415)	-25.86 (15.734)	-12.806 (12.185)	-9.913 (14.793)	-23.488 (20.295)	-21.692 (20.263)
Electricity delivered (MWh per customer)	0.021*** (0.007)	0.005 (0.003)	0.004 (0.003)	0.004 (0.003)	0.021*** (0.008)	-0.005 (0.011)	-0.006 (0.011)
Heating degree-days (#)	0 (0)						
Cooling degree-days (#)	0 (0)						
Outage management system?	0.075 (0.047)	0.074* (0.039)	0.075* (0.039)	0.102** (0.041)	0.121*** (0.046)	-0.02 (0.051)	-0.015 (0.05)
Years since outage management system installation	-0.004 (0.01)	-0.005 (0.008)	-0.005 (0.008)	0.005 (0.007)	0.012 (0.009)	0 (0.012)	0.001 (0.012)
Year	0.018* (0.011)	0.013* (0.008)	0.013* (0.008)	0.006 (0.006)	0.005 (0.007)	0.012 (0.01)	0.011 (0.01)
Abnormally cold weather (% above average HDDs)		0 (0.002)	0.004 (0.004)	0.002 (0.003)	-0.001 (0.001)	0.002 (0.005)	-0.005 (0.012)
Abnormally warm weather (% above average CDDs)		0 (0.001)	0.002 (0.003)	0.003 (0.002)	-0.001 (0.001)	0 (0.001)	0.001 (0.003)
Abnormally high # of lightning strikes (% above average strikes)		0.001** (0.001)	0.001** (0.001)	0.001*** (0)	0.002*** (0)	0.002** (0.001)	0.001** (0.001)
Abnormally windy (% above average wind speed)		0.005 (0.006)	0.007 (0.013)	0.033*** (0.01)	0.032*** (0.01)	0.04*** (0.012)	0.04*** (0.012)
Abnormally wet (% above average total precipitation)		0.002* (0.001)	0.003 (0.002)	0.005** (0.002)	0.003*** (0.001)	0.002 (0.001)	0.003 (0.003)
Abnormally dry (% below average total precipitation)		0.003* (0.002)	0.007** (0.003)	0.004 (0.003)	0.002 (0.001)	0.003* (0.002)	0.004 (0.004)
Abnormally cold weather squared			0 (0)	0 (0)			0.001 (0.001)
Abnormally warm weather squared			0 (0)	0 (0)			0 (0)
Abnormally windy squared			0 (0.001)	-0.002*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)

Model specification:	Model 4-A	Model 4-B	Model 4-C	Model 4-D	Model 4-E	Model 4-F	Model 4-G
Abnormally wet squared			0 (0)	0 (0)			0 (0)
Abnormally dry squared			0 (0)	0 (0)			0 (0)
Lagged T&D expenditures ($2012 per customer)				0.028 (0.045)	-0.01 (0.119)	-0.069 (0.184)	-0.071 (0.188)
Number of customers per line mile					0 (0)	0.008 (0.005)	0.008 (0.005)
Share of underground T&D miles to total T&D miles						-0.001 (0.004)	0 (0.004)
Degrees of freedom:	1,009	1,091	1,086	820	727	292	288
Number of utilities:	114	111	111	89	89	46	46
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.49	0.03	0.04	0.09	0.65	0.71	0.71
Akaike Information Criteria (AIC)	1,644.8	1,739.1	1,817.9	818.9	662.4	251.8	313.8
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

Appendix C. Full regression results for Model F

Table C - 1: Results for SAIDI regressions

Explanatory variables:	Log of SAIDI (without major events)			Log of SAIDI (with major events)		
	Pooled	*Fixed Effects*	*Random Effects*	*Pooled*	*Fixed Effects*	*Random Effects*
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 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)

Explanatory variables:	Log of SAIDI (without major events)			Log of SAIDI (with major events)		
	Pooled	*Fixed Effects*	*Random Effects*	*Pooled*	*Fixed Effects*	*Random Effects*
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
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

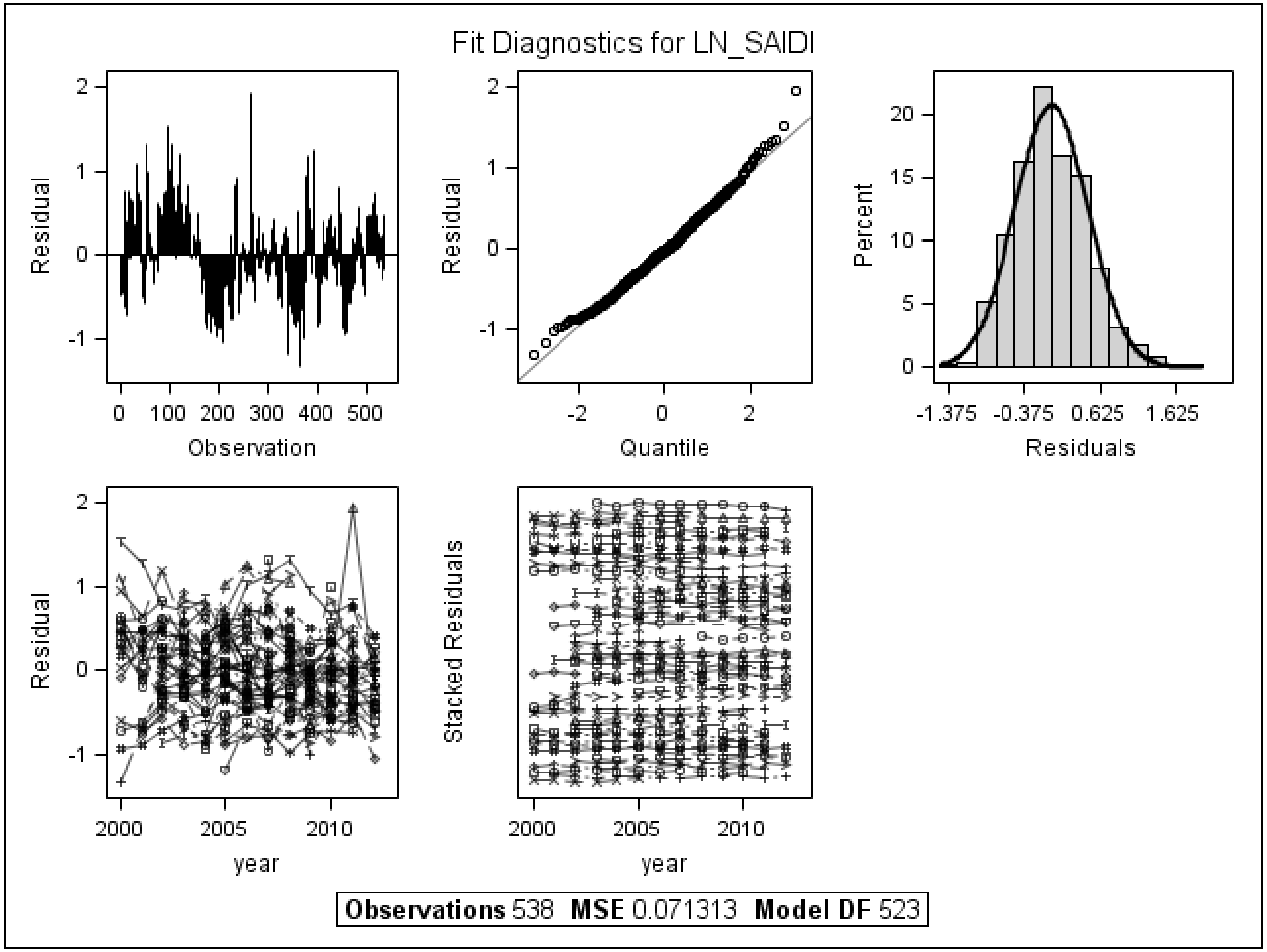

Figure C - 1: SAIDI base model fit diagnostics (without major events included)

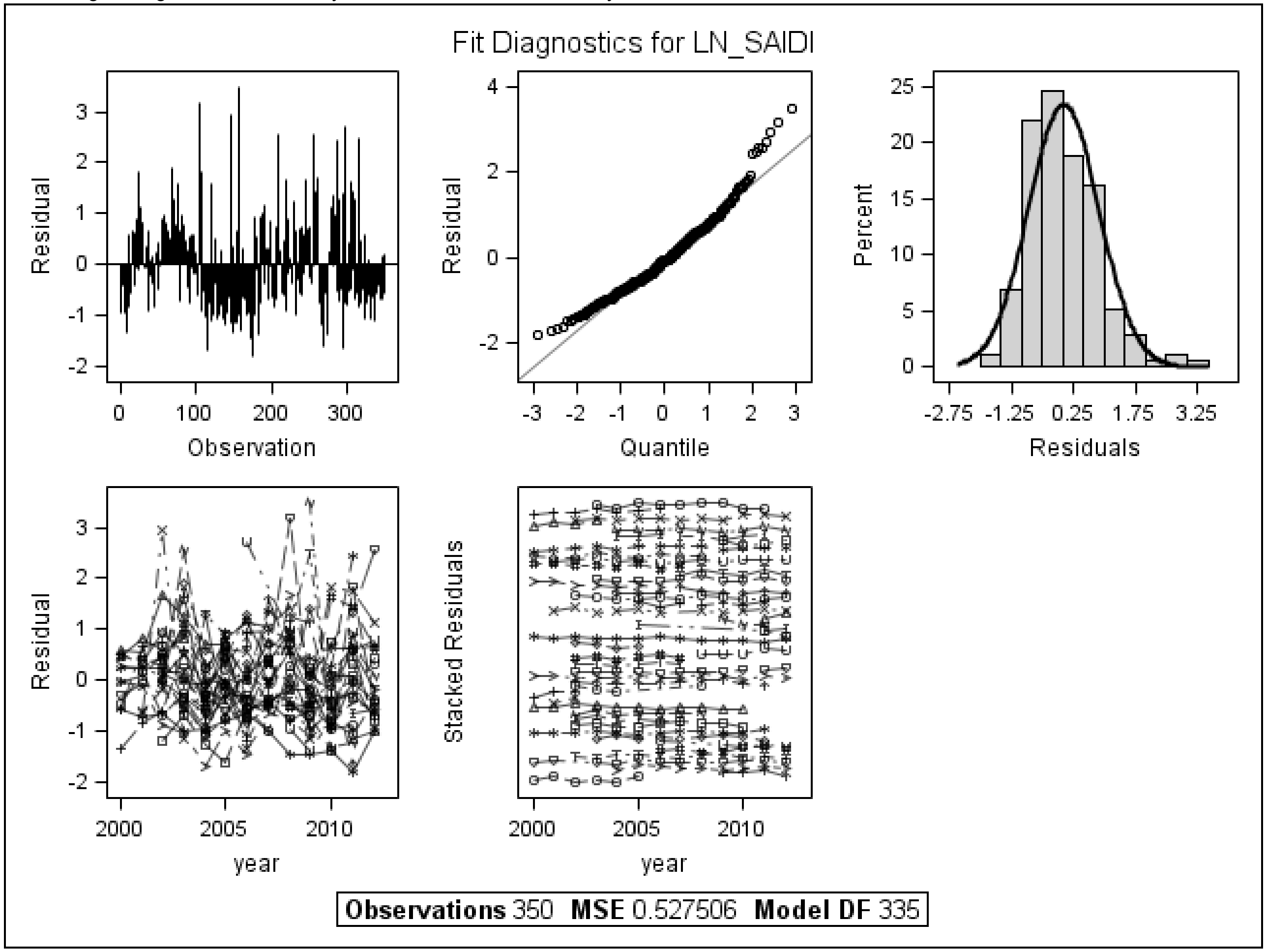

Figure C - 2: SAIDI base model fit diagnostics (with major events included)

Table C - 2: Results for SAIFI regressions

Explanatory variables:	Log of SAIFI (without major events)			Log of SAIFI (with major events)		
	Pooled	***Fixed Effects***	***Random Effects***	***Pooled***	***Fixed Effects***	***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 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

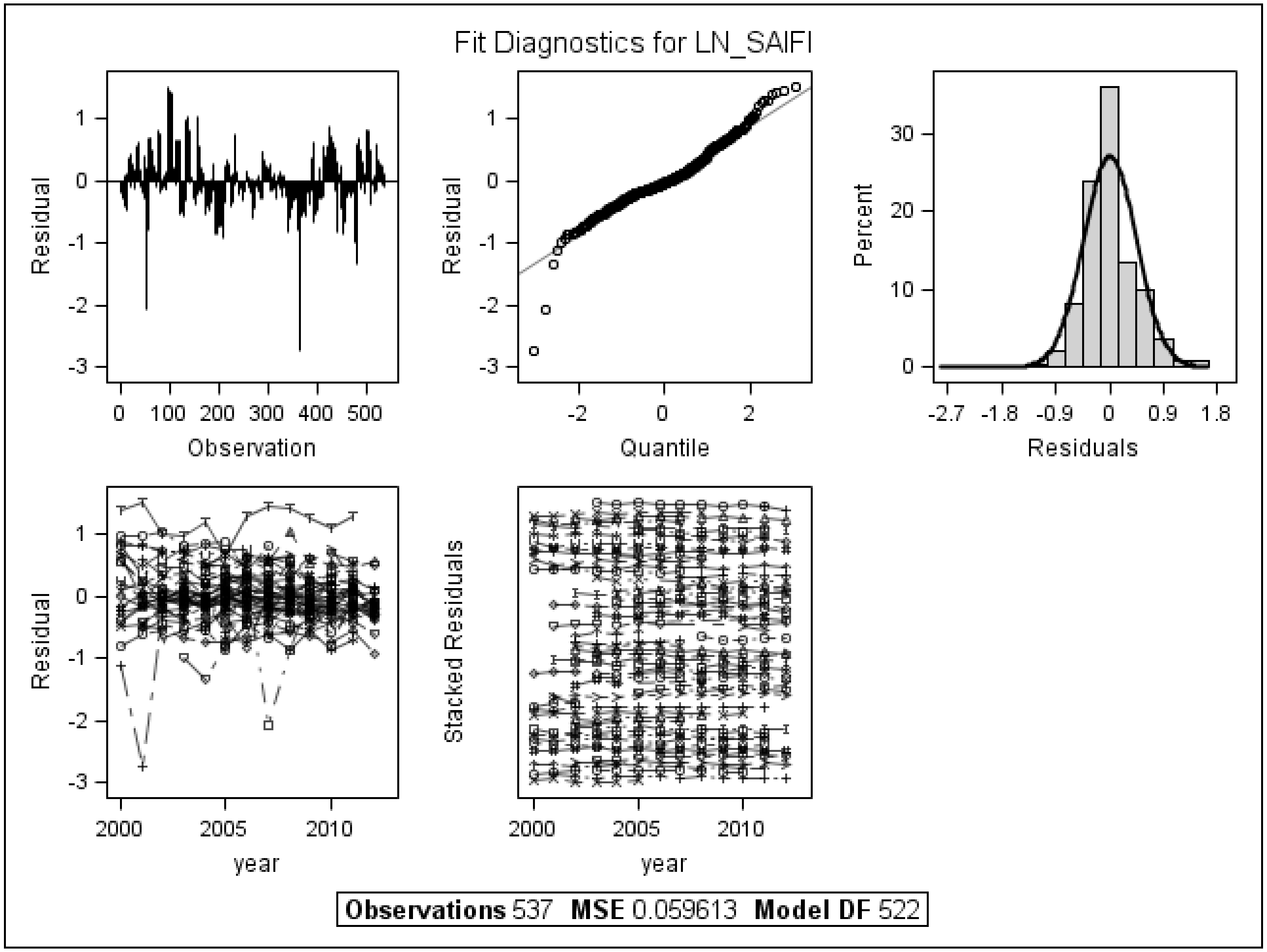

Figure C - 3: SAIFI base model fit diagnostics (without major events included)

Appendix D. Differences between utilities that have consistently reported reliability information and those that have not

This appendix evaluates the robustness of eight sets of model results (i.e., Models E and F multiplied by four reliability metrics) by comparing consistency of results between (1) an unrestricted panel data set; (2) a partially restricted panel data set; and (3) a fully restricted panel data set.

For the purposes of this analysis, the unrestricted panel data set includes utilities which have at least two years of coverage for all of the independent regressors and the reliability performance metrics.

Alternatively, the partially restricted panel data set only contains information for utilities who reported *all* 13 years of reliability data and at least two years of coverage for all of the independent regressors.

The fully restricted panel data set only contains information for utilities who reported *all* 13 years of reliability data and at least two years of coverage for all of the independent regressors. In addition, the fully restricted data set is limited to only those utilities which reported SAIDI (SAIFI) with *and* without major events included.

The intent of this analysis is to evaluate whether electric utility reliability performance—when major events are included—continues to decline regardless of whether utilities reported the full 13 years of reliability metrics (2000-2012) or an incomplete range of reliability information (e.g., no more than two years of missing reliability metrics, did not report reliability both with and without major events). Tables D.1 through D.4 compares the panel regression results under these three cases for SAIDI and SAIFI, respectively.

Table D - 1: Fully restricted, partially restricted and unrestricted panel data regression results (SAIDI; without major events)

Regression:	Unrestricted panel		Partially restricted panel		Fully restricted panel	
	Model E	***Model F***	***Model E***	***Model F***	***Model E***	***Model F***
Intercept	-7.011 (8.218)	-21.218 (13.53)	-15.727 (9.992)	-33.598 (20.875)	-13.164 (11.281)	-33.598 (20.875)
Electricity delivered (MWh per customer)	0.024*** (0.006)	0.002 (0.002)	0.012** (0.006)	0.015 (0.011)	0.025*** (0.008)	0.015 (0.011)
Abnormally cold weather (% above average HDDs)	0 (0.001)	0.001 (0.001)	0.001 (0.001)	0 (0.001)	0 (0.001)	0 (0.001)
Abnormally warm weather (% above average CDDs)	0 (0.001)	0 (0.001)	0.001 (0.001)	-0.002 (0.003)	0.001 (0.001)	-0.002 (0.003)
Abnormally high # of lightning strikes (% above average strikes)	0.001*** (0)	0.001 (0)	0.001 (0)	0.001* (0.001)	0.001 (0)	0.001* (0.001)
Abnormally windy (% above average wind speed)	0.023*** (0.007)	0.021** (0.009)	0.031*** (0.008)	0.034** (0.014)	0.03*** (0.009)	0.034** (0.014)
Abnormally windy squared	-0.002** (0.001)	-0.002** (0.001)	-0.002*** (0.001)	-0.003*** (0.001)	-0.002** (0.001)	-0.003*** (0.001)
Abnormally wet (% above average total precipitation)	0.002** (0.001)	0.002 (0.002)	0 (0.001)	-0.002 (0.001)	0 (0.001)	-0.002 (0.001)
Abnormally dry (% below average total precipitation)	0.001 (0.001)	0.001 (0.002)	0.002* (0.001)	0.002 (0.003)	0.002* (0.001)	0.002 (0.003)
Outage management system?	0.108*** (0.031)	0.037 (0.049)	0.147*** (0.036)	0.097 (0.07)	0.15*** (0.036)	0.097 (0.07)
Years since outage management system installation	0.003 (0.005)	-0.007 (0.009)	-0.002 (0.006)	0.007 (0.013)	0.004 (0.007)	0.007 (0.013)
Year	0.006 (0.004)	0.013* (0.007)	0.01** (0.005)	0.019* (0.01)	0.009 (0.006)	0.019* (0.01)
Lagged T&D expenditures ($2012 per customer)	-0.01 (0.051)	-0.005 (0.026)	0.084* (0.045)	-0.209** (0.095)	0.139* (0.074)	-0.209** (0.095)
Number of customers per line mile	0 (0)	-0.003 (0.003)	0 (0)	-0.003 (0.005)	0 (0)	-0.003 (0.005)
Share of underground T&D miles to total T&D miles		-0.002 (0.004)		-0.002 (0.007)		-0.002 (0.007)
Degrees of freedom:	1,260	523	678	223	611	223

Number of utilities:	132	63	56	25	55	25
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.80	0.05	0.10	0.10	0.75	0.10
Root mean square error	0.28	0.26	0.26	0.28	0.26	0.28
Utility effects:	Fixed	Random	Random	Random	Fixed	Random

Table D - 2: Fully restricted, partially restricted and unrestricted panel data regression results (SAIDI; with major events)

Regression:	Unrestricted panel		Partially restricted panel		Fully restricted panel	
	Model E	***Model F***	***Model E***	***Model F***	***Model E***	***Model F***
Intercept	-105.128*** (29.124)	-185.236*** (49.627)	-91.928** (44.745)	-191.25*** (64.892)	-74.808* (42.778)	-181.833*** (64.928)
Electricity delivered (MWh per customer)	0.007 (0.012)	0.004 (0.015)	0.013 (0.012)	0.017 (0.024)	0.017 (0.012)	0.022 (0.023)
Abnormally cold weather (% above average HDDs)	-0.004 (0.003)	0.004 (0.013)	-0.004 (0.01)	-0.006 (0.02)	-0.003 (0.01)	0 (0.019)
Abnormally warm weather (% above average CDDs)	-0.003 (0.002)	-0.008* (0.004)	-0.004 (0.003)	-0.009 (0.006)	-0.003 (0.003)	-0.005 (0.005)
Abnormally high # of lightning strikes (% above average strikes)	0.003*** (0.001)	0.001 (0.002)	0.003** (0.002)	0.002 (0.003)	0.004** (0.002)	0.005** (0.002)
Abnormally windy (% above average wind speed)	0.081*** (0.021)	0.121*** (0.031)	0.087*** (0.027)	0.101** (0.041)	0.094*** (0.027)	0.114*** (0.039)
Abnormally windy squared	-0.006*** (0.002)	-0.007*** (0.002)	-0.006*** (0.002)	-0.004* (0.002)	-0.006*** (0.002)	-0.005** (0.002)
Abnormally wet (% above average total precipitation)	0.007*** (0.003)	0.01* (0.005)	0.013*** (0.005)	0.032*** (0.009)	0.013*** (0.005)	0.028*** (0.008)
Abnormally dry (% below average total precipitation)	0.002 (0.003)	0.001 (0.005)	-0.002 (0.003)	-0.014** (0.006)	-0.003 (0.003)	-0.016*** (0.005)
Outage management system?	0.196** (0.09)	0.128 (0.136)	0.172 (0.125)	0.217 (0.214)	0.188 (0.119)	0.212 (0.191)
Years since outage management system installation	0.013 (0.017)	-0.02 (0.025)	0.06** (0.028)	-0.049 (0.051)	0.07** (0.027)	-0.04 (0.049)
Year	0.055*** (0.015)	0.095*** (0.025)	0.048** (0.022)	0.098*** (0.033)	0.039* (0.021)	0.093*** (0.033)
Lagged T&D expenditures ($2012 per customer)	0.002 (0.046)	0 (0.07)	0.056 (0.06)	-0.071 (0.118)	0.062 (0.061)	-0.076 (0.114)
Number of customers per line mile	0 (0)	0.006 (0.007)	0 (0)	-0.005 (0.014)	0 (0)	-0.009 (0.014)
Share of underground T&D miles to total T&D miles		-0.014** (0.007)		-0.025** (0.012)		-0.022* (0.012)
Degrees of freedom:	813	335	337	108	324	98

Number of utilities:	89	46	29	14	28	13
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.12	0.14	0.25	0.33	0.27	0.43
Root mean square error	0.74	0.73	0.70	0.64	0.68	0.53
Utility effects:	Random	Random	Random	Random	Random	Random

Table D - 3: Fully restricted, partially restricted and unrestricted panel data regression results (SAIFI; without major events)

Regression:	Unrestricted panel		Partially restricted panel		Fully restricted panel	
	Model E	*Model F*	*Model E*	*Model F*	*Model E*	*Model F*
Intercept	-10.661 (9.543)	-8.622 (15.225)	-31.342** (14.942)	-43.356 (27.454)	-31.313** (14.933)	-43.356 (27.454)
Electricity delivered (MWh per customer)	0.003*** (0.001)	0.002 (0.002)	0.004 (0.005)	-0.008 (0.009)	0.004 (0.005)	-0.008 (0.009)
Abnormally cold weather (% above average HDDs)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Abnormally warm weather (% above average CDDs)	0 (0.001)	0 (0.001)	0 (0.001)	0 (0.003)	0 (0.001)	0 (0.003)
Abnormally high # of lightning strikes (% above average strikes)	0.001 (0)	0 (0.001)	0 (0.001)	0 (0.001)	0 (0.001)	0 (0.001)
Abnormally windy (% above average wind speed)	0.03*** (0.009)	0.023** (0.011)	0.031*** (0.011)	0.029* (0.017)	0.032*** (0.011)	0.029* (0.017)
Abnormally windy squared	-0.002*** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.002** (0.001)	-0.002** (0.001)
Abnormally wet (% above average total precipitation)	0 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0 (0.002)	-0.001 (0.001)	0 (0.002)
Abnormally dry (% below average total precipitation)	0.001 (0.001)	0.001 (0.001)	0.003 (0.002)	0.001 (0.002)	0.003 (0.002)	0.001 (0.002)
Outage management system?	-0.043 (0.041)	0.003 (0.038)	-0.088 (0.066)	-0.046 (0.057)	-0.088 (0.066)	-0.046 (0.057)
Years since outage management system installation	0.01* (0.006)	-0.003 (0.006)	0.01 (0.01)	-0.02* (0.011)	0.01 (0.01)	-0.02* (0.011)
Year	0.005 (0.005)	0.004 (0.008)	0.016** (0.007)	0.022 (0.014)	0.016** (0.007)	0.022 (0.014)
Lagged T&D expenditures ($2012 per customer)	0.036 (0.031)	-0.02 (0.021)	0.136** (0.054)	-0.028 (0.099)	0.136** (0.054)	-0.028 (0.099)
Number of customers per line mile	0 (0)	-0.004** (0.002)	0 (0)	-0.003 (0.003)	0 (0)	-0.003 (0.003)
Share of underground T&D miles to total T&D miles		0.001 (0.002)		0.003 (0.004)		0.003 (0.004)
Degrees of freedom:	1,368	522	669	223	665	223

Number of utilities:	130	63	56	25	55	25
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.02	0.03	0.04	0.05	0.04	0.05
Root mean square error	0.33	0.24	0.37	0.29	0.37	0.29
Utility effects:	Random	Random	Random	Random	Random	Random

Table D - 4: Fully restricted, partially restricted and unrestricted panel data regression results (SAIFI; with major events)

Regression:	Unrestricted panel		Partially restricted panel		Fully restricted panel	
	Model E	*Model F*	*Model E*	*Model F*	*Model E*	*Model F*
Intercept	-9.913 (14.793)	-23.488 (20.295)	-23.783 (19.194)	-54.97** (23.396)	-17.972 (20.642)	-48.081* (26.848)
Electricity delivered (MWh per customer)	0.021*** (0.008)	-0.005 (0.011)	0.028*** (0.007)	-0.007 (0.009)	0.025*** (0.008)	-0.012 (0.011)
Abnormally cold weather (% above average HDDs)	-0.001 (0.001)	0.002 (0.005)	-0.002 (0.004)	0 (0.007)	-0.001 (0.004)	-0.003 (0.008)
Abnormally warm weather (% above average CDDs)	-0.001 (0.001)	0 (0.001)	-0.002 (0.002)	0 (0.002)	-0.002 (0.002)	0.003 (0.002)
Abnormally high # of lightning strikes (% above average strikes)	0.002*** (0)	0.002** (0.001)	0.001** (0.001)	0.002* (0.001)	0.002*** (0.001)	0.003** (0.001)
Abnormally windy (% above average wind speed)	0.032*** (0.01)	0.04*** (0.012)	0.035*** (0.011)	0.035*** (0.013)	0.037*** (0.012)	0.033** (0.015)
Abnormally windy squared	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.002** (0.001)	-0.003*** (0.001)	-0.001* (0.001)
Abnormally wet (% above average total precipitation)	0.003*** (0.001)	0.002 (0.001)	0.003** (0.001)	0.004** (0.002)	0.003** (0.001)	0.006* (0.003)
Abnormally dry (% below average total precipitation)	0.002 (0.001)	0.003* (0.002)	0 (0.002)	0 (0.002)	0 (0.002)	-0.001 (0.003)
Outage management system?	0.121*** (0.046)	-0.02 (0.051)	0.083 (0.052)	-0.004 (0.071)	0.108** (0.054)	0.059 (0.074)
Years since outage management system installation	0.012 (0.009)	0 (0.012)	0.031*** (0.012)	-0.028 (0.018)	0.035*** (0.013)	-0.034 (0.021)
Year	0.005 (0.007)	0.012 (0.01)	0.011 (0.01)	0.028** (0.012)	0.009 (0.01)	0.024* (0.014)
Lagged T&D expenditures ($2012 per customer)	-0.01 (0.119)	-0.069 (0.184)	0.066 (0.092)	-0.044 (0.06)	0.08 (0.091)	-0.173 (0.185)
Number of customers per line mile	0 (0)	0.008 (0.005)	0* (0)	-0.004 (0.007)	0* (0)	0.013 (0.016)
Share of underground T&D miles to total T&D miles		-0.001 (0.004)		-0.013*** (0.004)		-0.02*** (0.006)
Degrees of freedom:	727	292	321	119	297	86

Number of utilities:	89	46	30	15	28	13
Adjusted R^2 (fixed) / Generalized R^2 (random)	0.65	0.71	0.72	0.23	0.72	0.73
Root mean square error	0.31	0.26	0.29	0.24	0.29	0.23
Utility effects:	Fixed	Fixed	Fixed	Random	Fixed	Fixed

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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.

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 [6,42]. 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 [3,8] —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 [16].

Recent work has begun to address these limitations by examining trends in reliability data collected annually by electricity distribution companies [13,14]. 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 [12]. 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. [13,14] 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. [13,14] 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" [13,14].

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Ahvehag and Söder [2] 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” [2]; p. 910). However, the Ahvehag and Söder [2] 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. [13,14] and Ahvehag and Söder [2] 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. [25]; 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 [17]; Rocky Mountain Power [41]; Interstate Power and Light Company [27]; Jersey Central Power & Light [28]; Madison Gas and Electric Company [32]; Pacific Gas & Electric Company [38]; Portland General Electric [39]; PSE&G Services Corporation [40] and AEP Southwestern [1]. 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.

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 $\mathrm{Time_t}$, the number of customers affected by all interruptions in a given is $\mathrm{Affected_t}$, and the total number of customers served by the utility in a given year is $\mathrm{Customers_t}$.

$$SAIDI_t = \frac{\sum Time_t \times Affected_t}{Customers_t} \qquad (1)$$

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 $\mathrm{Affected_t}$ and the total number of customers served by the utility in a given year is $\mathrm{Customers_t}$.

$$SAIFI_t = \frac{\sum Affected_t}{Customers_t} \qquad (2)$$

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 [26]. 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 [12].[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. Fig. 1 shows the geographic coverage of the utilities we

[1] Previous work by Eto and LaCommare reviewed state utility commission reporting practices across the U.S. [12].

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 to 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)	

obtained data for represented by Census region.

Fig. 2 and Fig. 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 min (2 h and 20 min) per year and, for the set of data with major events included, slightly more than 370 min (6 h and 10 min) 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.

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. Fig. 4 shows the number of utilities we have data for use in this study by the length of the time series.

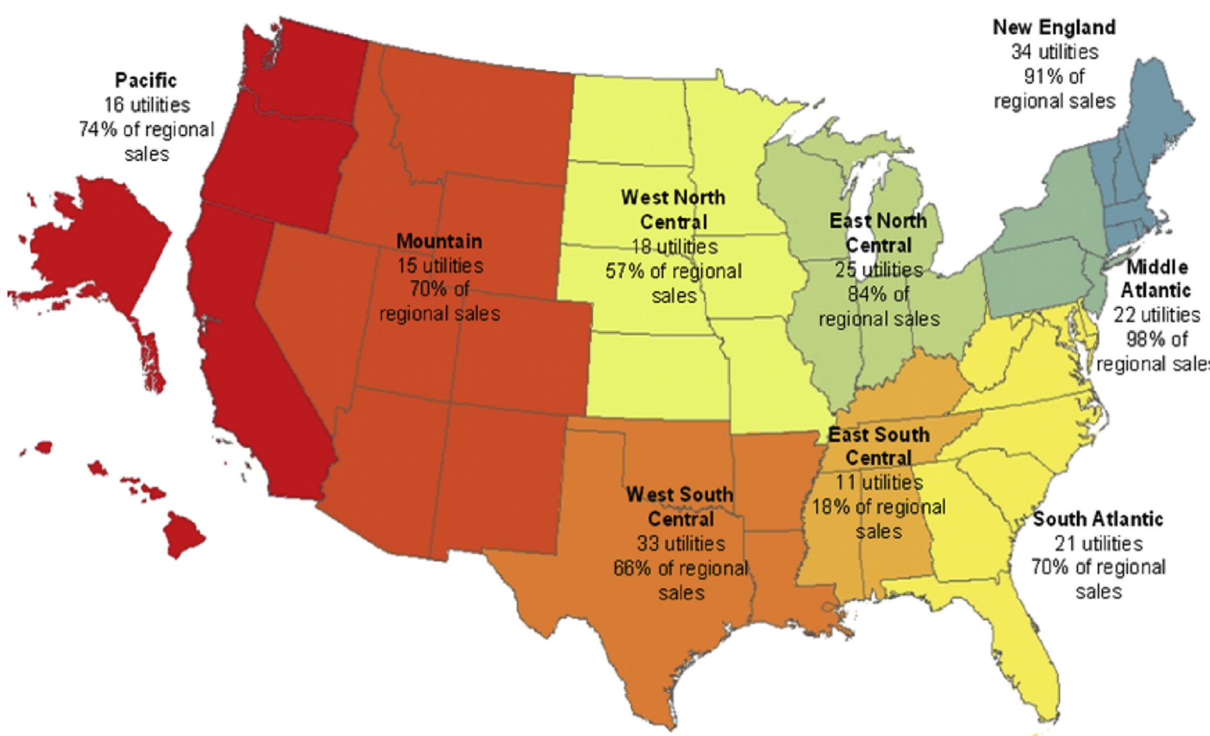


Fig. 1. Geographic coverage of utilities included in this study.

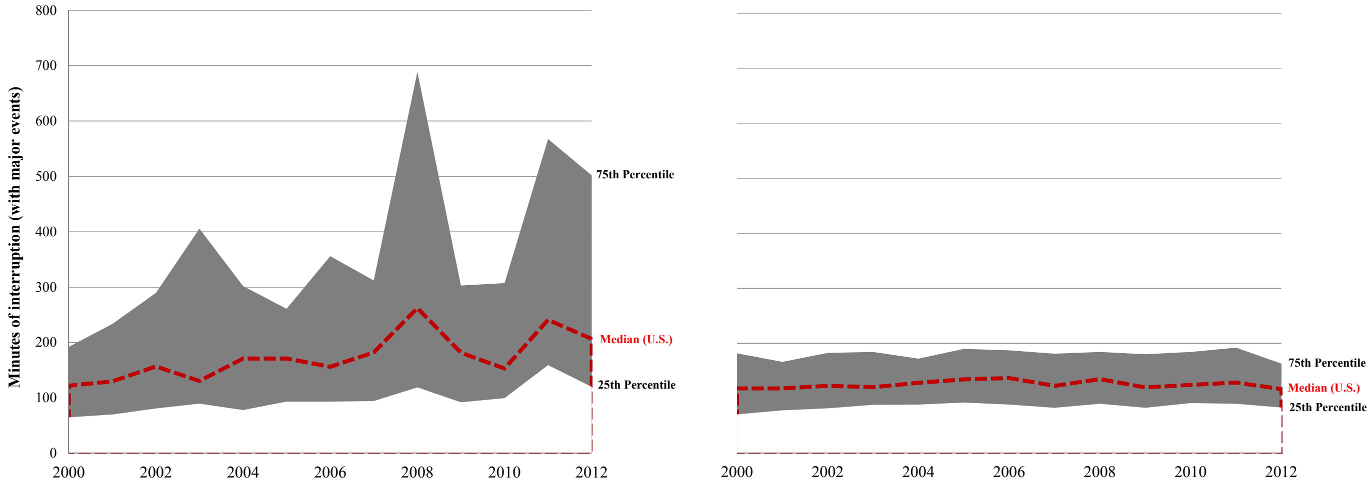


Fig. 2. Average minutes of interruption (SAIDI) with (left) and without (right) major events included.

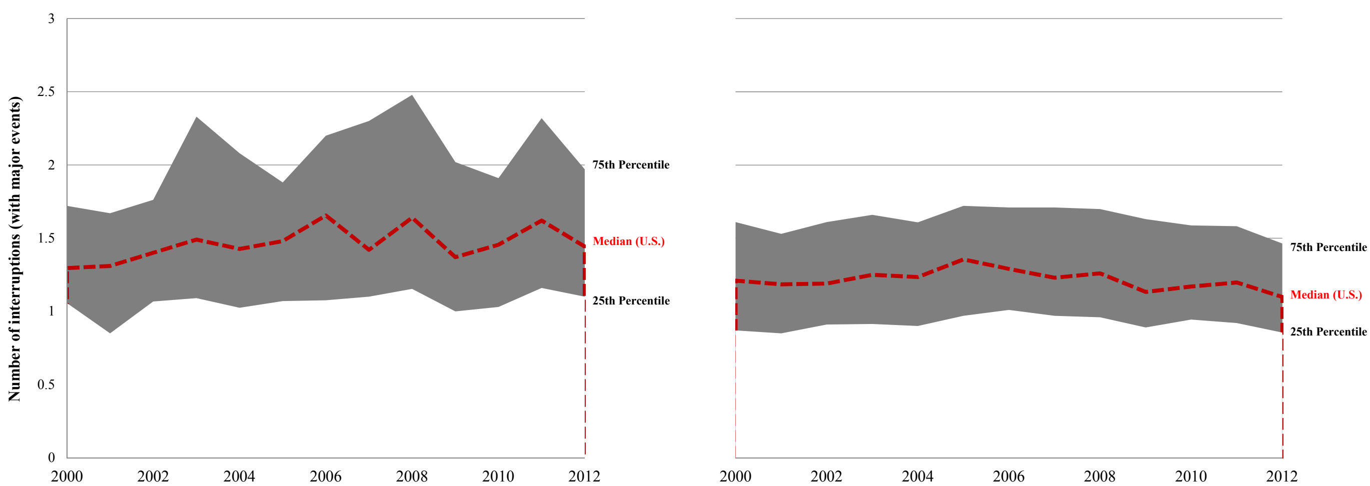


Fig. 3. Average number of interruptions (SAIFI) with (left) and without (right) major events included.

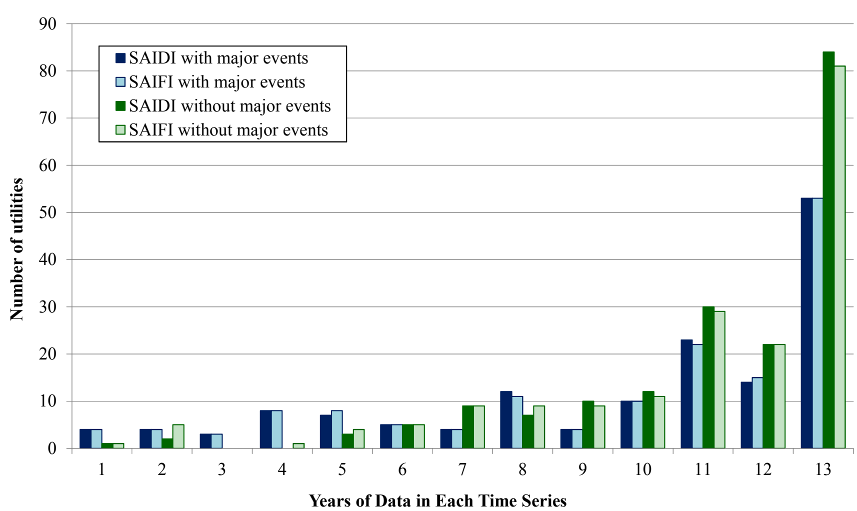


Fig. 4. Number of utilities with each number of years of successive data.

2.3. 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 [9]
Heating/Cooling degree-days	Utility-level	National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) [35]
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 [15]
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 [15]
Lightning data	Strike count summed to each utility by year	Vaisala National Lightning Detection Network [36]
Wind speed	Average for each utility by year	National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) [35]
Precipitation	Average for each utility by year	National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) [35]

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:

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

The general model specification described in Equation (3) above follows the general form used in earlier energy-related multivariate panel regressions [10,13]. 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]

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

[2] The presence of the α_i component within this model is “crucially important” [10] 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 [10]. 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.

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 [7]. 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” [46]. 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.

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 from the analysis.[3]

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 ($\overrightarrow{W}$) into pairs of positive (see Equation (5)) and negative (see Equation (6)) deviations from the 13-year average.

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

[3] Additional information detailing the analytical techniques used in this type of analysis can be found in Larsen et al. [30] and Larsen [31].

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)	2062	0[a]	143.1	125.6	1015.1	86.9
SAIFI (# of events)	2026	0.0[b]	1.4	1.2	20.9	0.9
HDD (# of degree days)	2210	198	4807.1	5020.7	9697.0	2023.7
CDD (# of degree days)	2210	0	1319.6	1026.0	4313.0	894.9
Lightning strikes (strikes per customer)	2181	0	0.5	0.1	189.9	5.2
Precipitation (inches)	2210	1.8	35.9	37.9	79.3	14.9
Wind speed (mph)	2210	3.4	7.3	7.0	12.7	1.5
T&D lines (customers per line mile)	2024	0	172.2	23.3	8942.6	672.8
Share of underground line miles (%)	840	0.1%	22.2%	20.4%	89.8%	15.3%
Delivered electricity (MWh per customer)	2288	1.1	26.7	25.0	181.7	14.4
T&D O&M spending ($2012 per customer)	2084	$4.4	$883.0	$239.8	$52,261.0	$2328.4

[a] 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.
[b] Raw value reported is 0.003.

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)	1438	1.2	372.2	173.0	14,437.6	825.8
SAIFI (# of events)	1440	0[a]	1.8	1.5	37.3	2.0
HDD (# of degree-days)	1794	198	5160.8	5329.0	9136.0	2000.6
CDD (# of degree-days)	1794	0	1168.1	897.0	4921.0	874.6
Lightning strikes (strikes per customer)	1748	0	0.5	0.1	189.9	5.8
Precipitation (inches)	1794	1.8	34.9	37.1	73.2	13.6
Wind speed (mph)	1794	3.2	7.0	6.9	12.1	1.6
T&D lines (customers per line mile)	1471	0.0	148.2	27.9	3832.1	409.9
Share of underground line miles (%)	648	0.6%	24.6%	23.4%	89.8%	16.1%
Delivered electricity (MWh per customer)	1856	1.1	27.3	24.2	257.3	22.8
T&D O&M expenditures ($2012 per customer)	1499	$4.4	$734.6	$235.1	$11,076.0	$1659.2

[a] 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.

$$\bar{\Delta}\overrightarrow{W}_{it}\begin{cases} 0: & \dfrac{(W_{it-}\overline{W}_i)}{\overline{W}_i}\times 100 \geq 0 \\ \dfrac{(W_{it-}\overline{W}_i)}{\overline{W}_i}\times 100: & \dfrac{(W_{it-}\overline{W}_i)}{\overline{W}_i}\times 100 < 0 \end{cases} \tag{6}$$

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. [13,14] 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 [24] surveyed the literature on the shape of weather-related infrastructure damage curves and concluded that the curves were nonlinear Larsen et al. [30] 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 [33] 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 [33] 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)).[4] 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,[5] multiplied

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

[5] 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 [11] 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 Ref. [20]. 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 [4]. Following the lead of Granger [18] and Sims [44]; a number of related testing procedures have been proposed within the context of evaluating exogeneity.

by the Handy-Whitman utility cost index (HW), and normalized by number of customers (see Equation (7)).

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

4. Model performance and selection

We developed a sequence of model specifications (each a distinct regression equation following the form outlined in Section 3) and conducted a series of robustness tests to evaluate them following procedures outlined in Hoen et al. [25]; which evaluated the impact of wind power projects on residential property values.[6] 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. [13,14]; 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" [25,37].

Model A, which is a close proxy to the Eto et al. [13,14] configuration, includes the following 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.[7] 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.

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.[30] 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. Fig. 5 through Fig. 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 Fig. 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

If major events are included (see Fig. 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

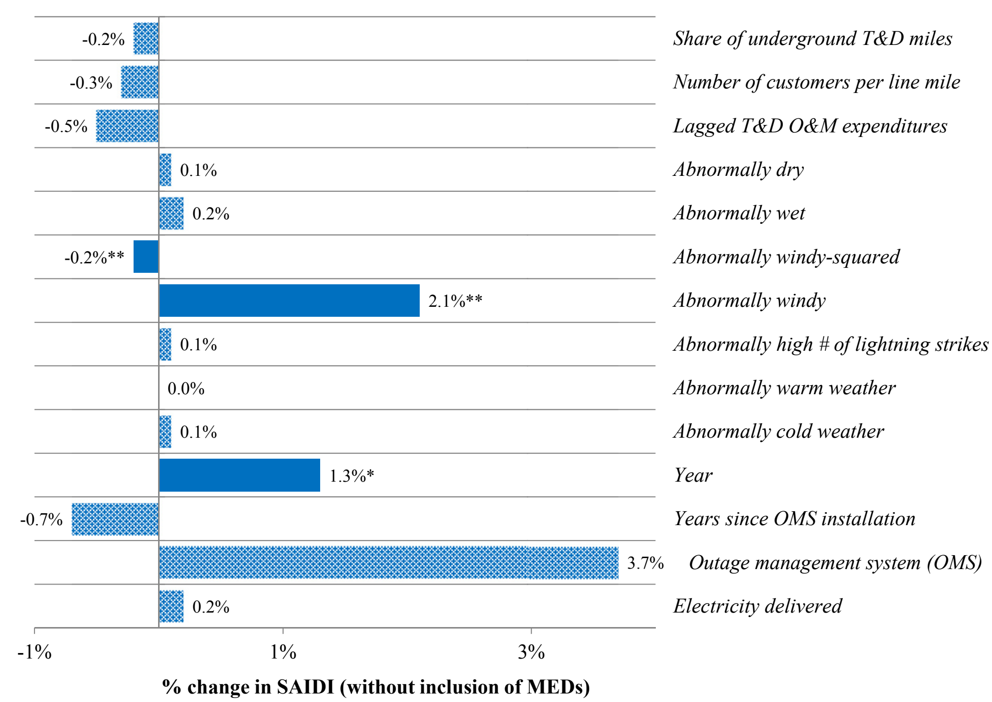
Independent of the above factors, each successive year over the analysis period is also correlated with a nearly 10% decrease in SAIDI.

[6] 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.

[7] There are some differences between Eto et al. [13,14] 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. [13,14] 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.

Table 5
Parameters included for base model and six alternatives.

Model	A [13,14]	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)		●	●	●	●	●	●
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						●	●



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.

Fig. 5. Percentage change in SAIDI (without 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 Fig. 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

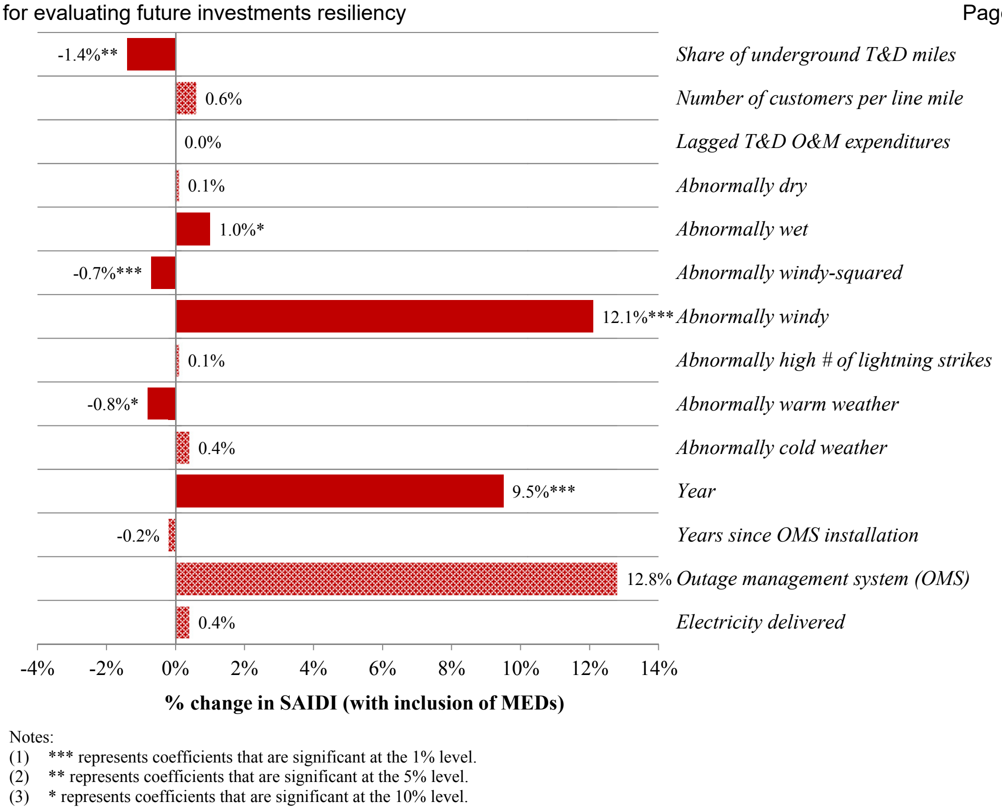


Fig. 6. Percentage change in SAIDI (with major events) corresponding to a change in the explanatory variable.

the frequency of interruptions.

If major events are included (see Fig. 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).

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. Fig. 9 and Fig. 10 show the year coefficients for all seven SAIFI and SAIDI models, respectively, both without and with major events included. Fig. 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.

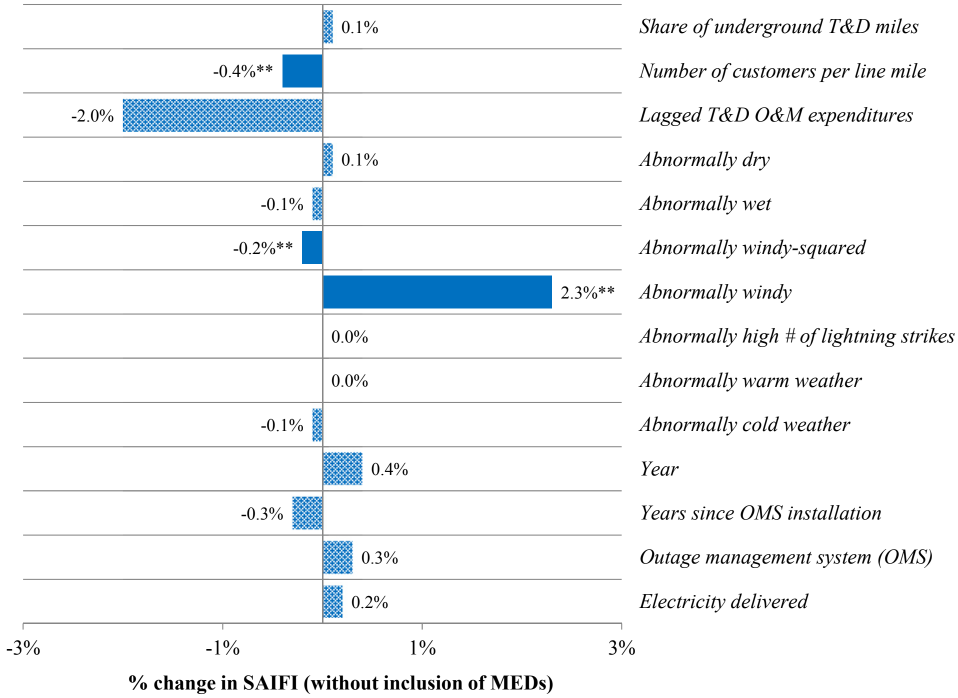
Fig. 10 shows that when major events are included in SAIDI, the year coefficients are always both positive and highly statistically significant for all seven models. It also shows that when major events are not included in SAIDI that the year coefficients, while positive, are both smaller and less statistically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

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.

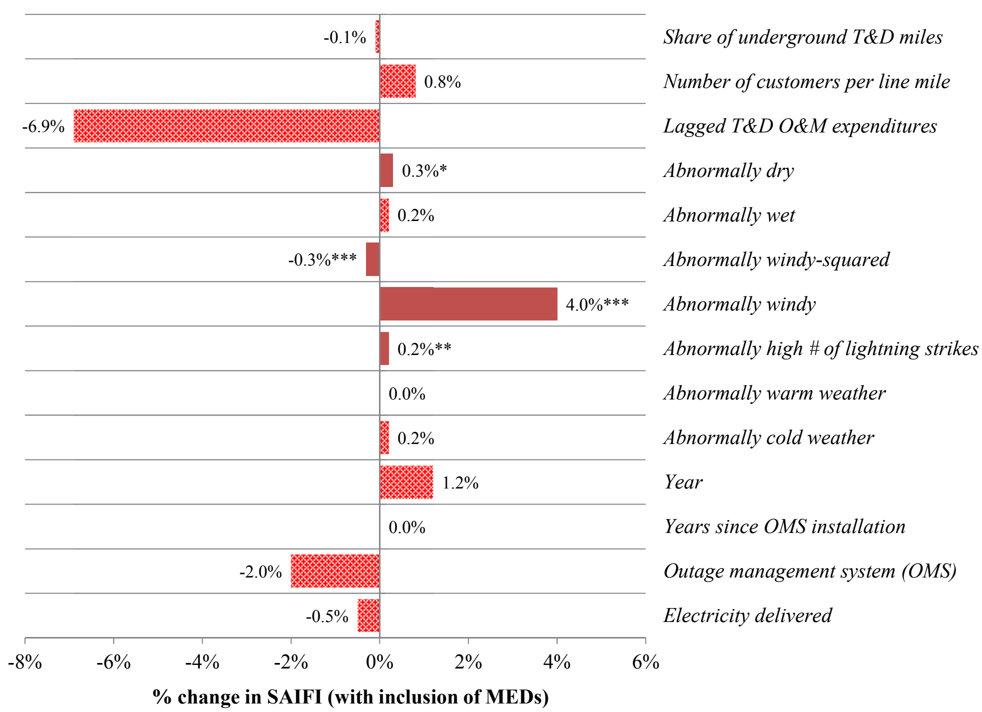
6.3. Important considerations when interpreting these findings

There are a number of caveats that should be considered when



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.

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



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.

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

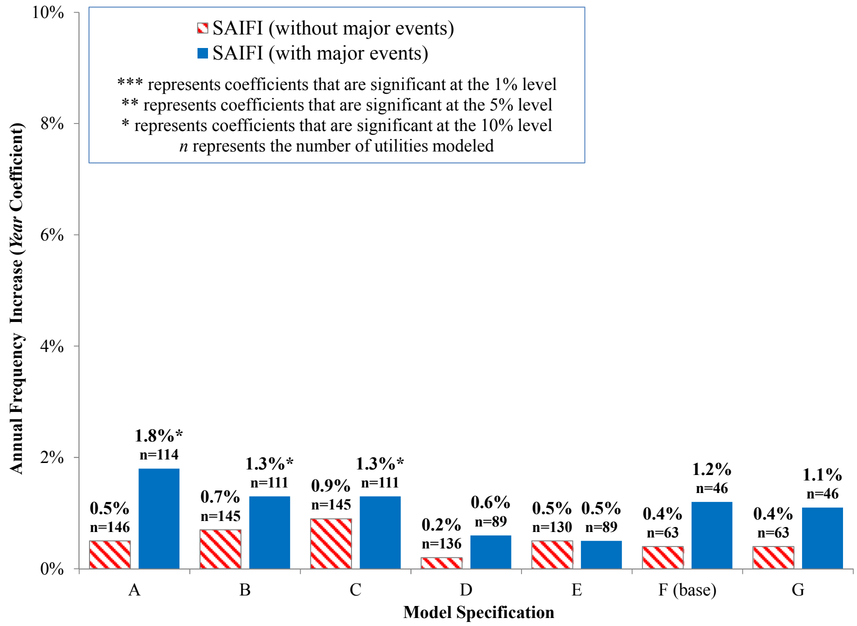


Fig. 9. Annual increase in frequency of interruptions: all models considered.

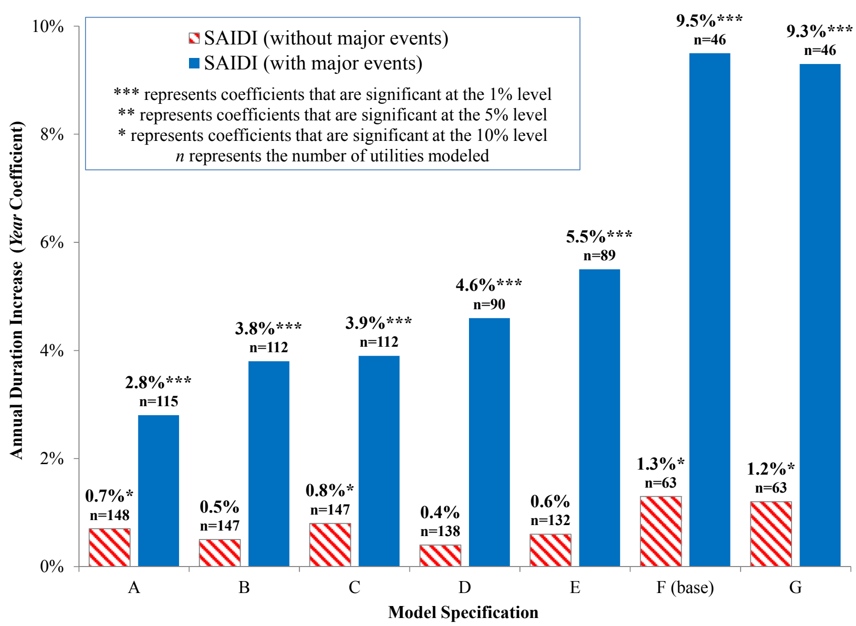


Fig. 10. Annual increase in total minutes customers are without power: all models considered.

evaluating the results of this study. Specifically, there is the possibility of selection bias affecting this analysis [23]. 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 [26], utilities sometimes use other criteria to define them [12,13]. 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. [13,14] and Alvehag and Söder [2], 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" [34]. 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 [31] 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 [31]. 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.[8]

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 [21] 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).

[8] 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.

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

Reliability metric	One-way fixed effect (utility)			
	F-value	Degrees of freedom (numerator/denominator)	Prob. > F	Reject null of no effects?
Log of SAIDI—without major events	16.8	62/461	<0.0001	Yes
Log of SAIDI—with major events	3.3	45/290	<0.0001	Yes
Log of SAIFI—without major events	18.8	62/460	<0.0001	Yes
Log of SAIFI—with major events	10.3	45/292	<0.0001	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 $p \leq 0.15$.[9] 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).[10]

Table A.2
Test results for the presence of random effects Ref. [21].

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

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

Dependent variable and criteria		A Ref. [13,14]	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
	Bayesian Information Criteria (BIC)	1186.5	1168.8	1523.3	1029.3	784.5	447.7	501.0
	Utility effects:	Fixed	Fixed	Random	Fixed	Fixed	Random	Random
	Degrees of freedom	1479	1463	1604	1327	1260	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)	3018.5	2942.0	2998.1	2200.3	2131.8	949.4	1000.1
	Utility effects:	Random	Random	Random	Random	Random	Random	Random
	Degrees of freedom	1124	1091	1086	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)	1926.8	1923.5	2000.4	1531.1	1355.5	335.5	404.9
	Utility effects:	Random	Random	Random	Random	Random	Random	Random
	Degrees of freedom	1603	1586	1581	1441	1368	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)	1649.8	1744.5	1823.3	823.8	667.0	255.5	317.5
	Utility effects:	Fixed	Random	Random	Random	Fixed	Fixed	Fixed
	Degrees of freedom	1009	1091	1086	820	727	292	288

[9] 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 [5]. Accordingly, we conduct the Hausman [21] 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 [22] 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.

[10] 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 [29]. 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 [21] 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.

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 [25,43]. 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.[30] 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).

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
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

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

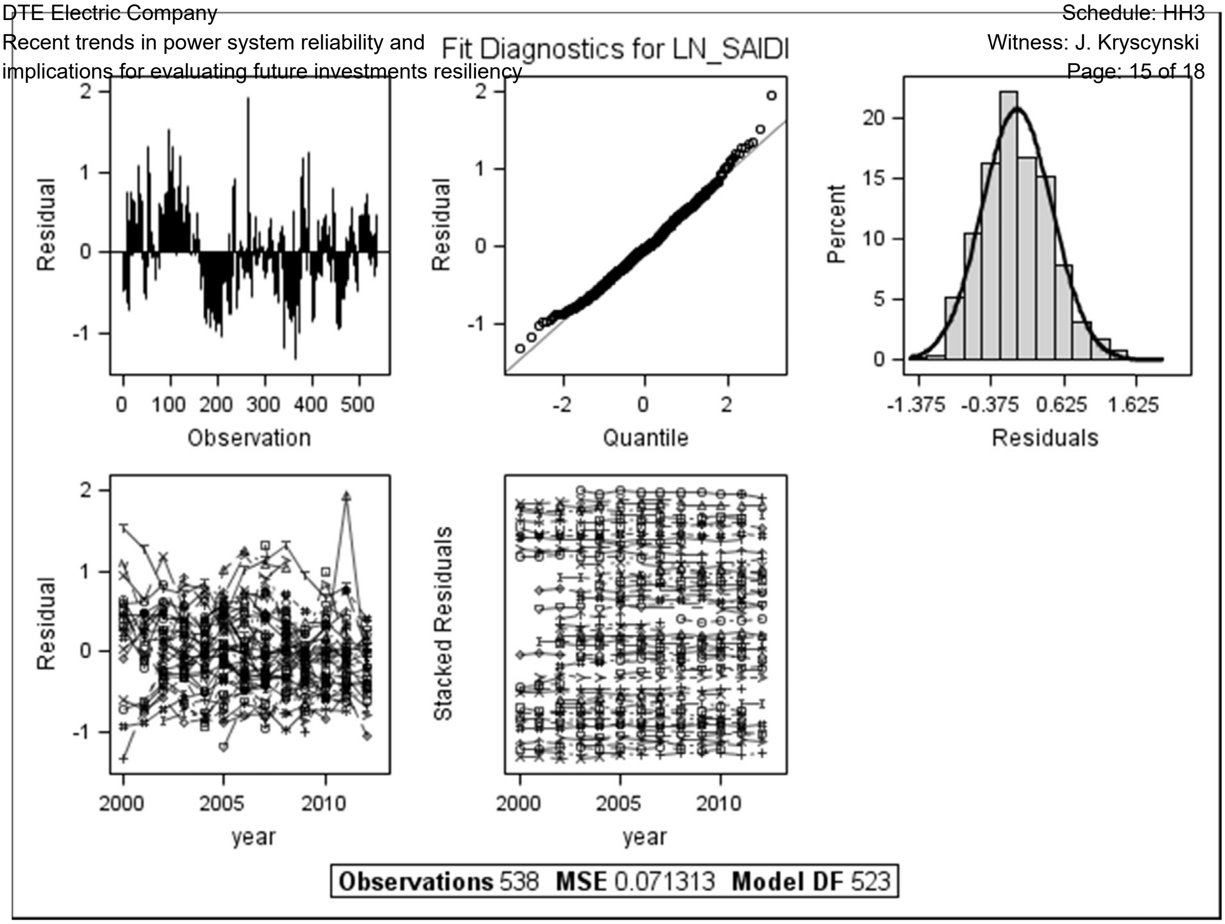

Fig. A.1SAIDI base model fit diagnostics (without major events included).

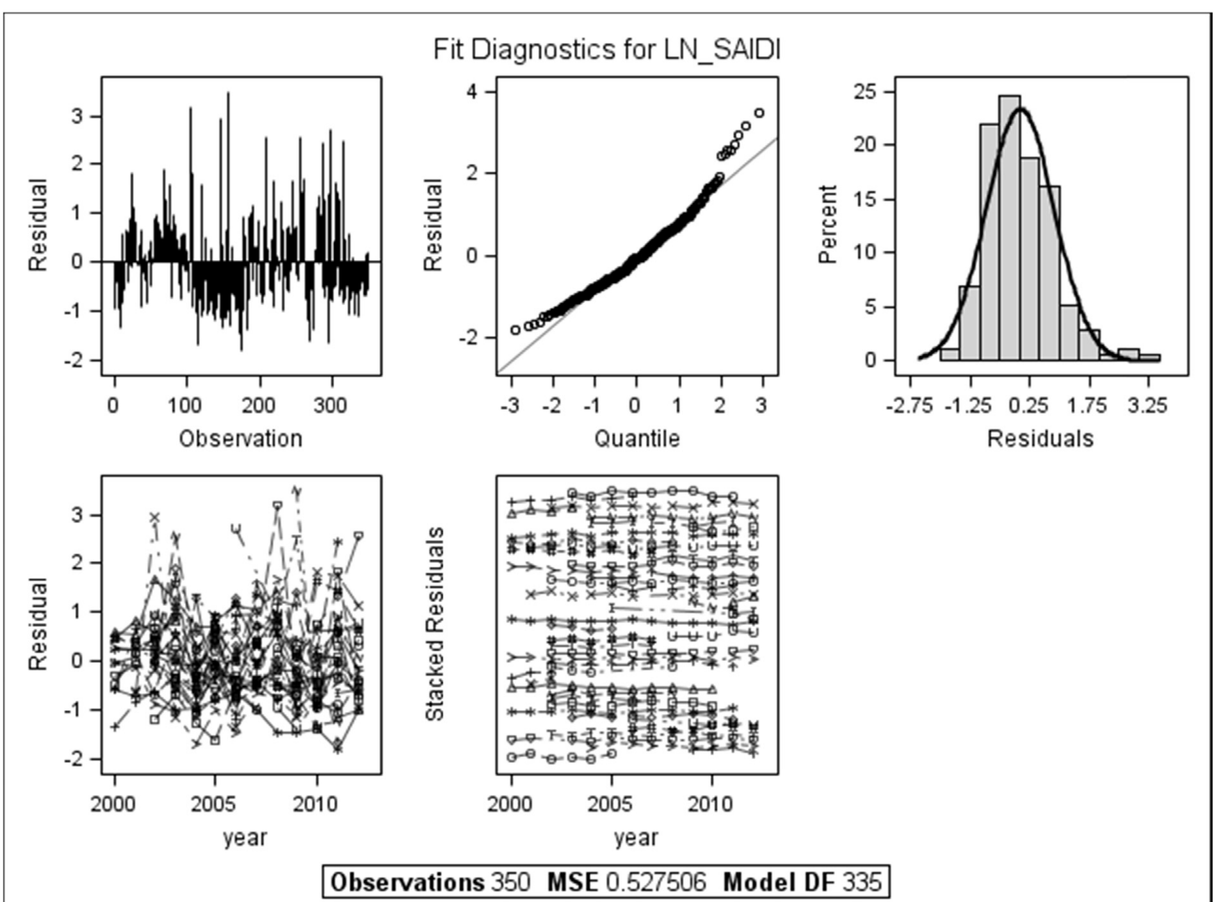

Fig. A.2SAIDI base model fit diagnostics (with major events included).

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

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

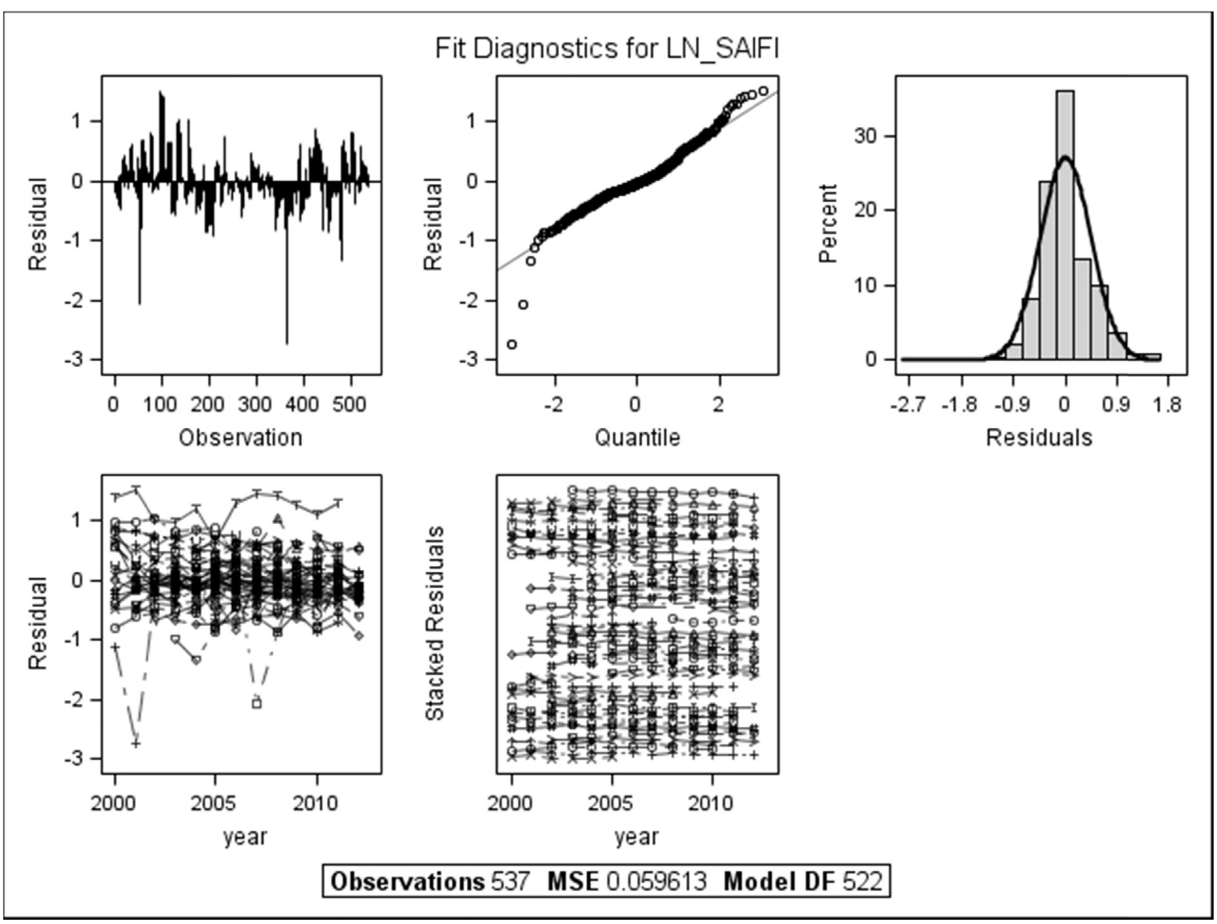

Fig. A.3SAIFI base model fit diagnostics (without major events included).

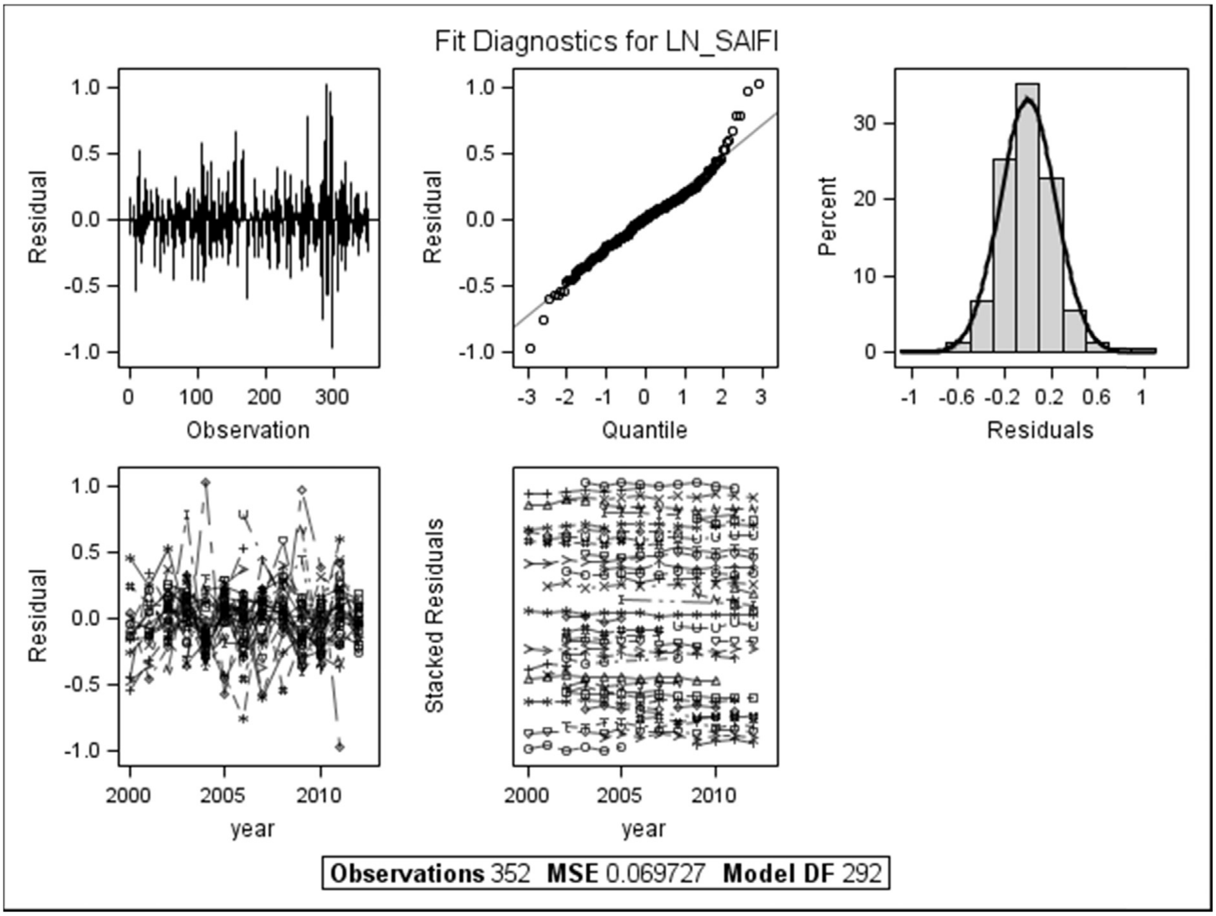

Fig. A.4SAIFI base model fit diagnostics (with major events included).

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EXHIBIT A-43 SCHEDULE HH4

The original model is voluminous such that attachment and entry in evidence is impracticable. As such, it is incorporated by reference herein and made available for examination by the parties pursuant to R792.10427 via hyperlink. Parties may review the model at:

Public
https://dteenergy.sharepoint.com/sites/DiscoveryPortal/Elec/U21534/Documents/Forms/AllItems.aspx?viewid=c5988175%2D3405%2D40fc%2Db0b8%2Da8fd6e0b646a

[redacted]

EXHIBIT A-43 SCHEDULE HH5

The original model is voluminous such that attachment and entry in evidence is impracticable. As such, it is incorporated by reference herein and made available for examination by the parties pursuant to R792.10427 via hyperlink. Parties may review the model at:

Public
https://dteenergy.sharepoint.com/sites/DiscoveryPortal/Elec/U21534/Documents/Forms/AllItems.aspx?viewid=c5988175%2D3405%2D40fc%2Db0b8%2Da8fd6e0b646a

MPSC Case No: U-21534	
Requester: MNSC	
Question No.: MNSCDE-12.8b	
Respondent: J. Kryscynski	
Page: 1 of 1	

Question: 8. Refer to Mr. Kryscynski's testimony at AJK-70:10, which identifies "Estimate impact of reliability programs" as a step employed by the Company's reliability improvement model.

b. Refer to the reliability improvement estimates by program provided in response to subpart (a) above. Provide the pilot results, workpapers, assumptions, estimates, calculations, and all other materials employed to design each program's reliability improvement estimate.

Answer: Please see the attached document.

Attachment: U-21534 MNSCDE-12.8b-01 Reliability Program Analysis

Co-Respondent(s): M. Elliott Andahazy,S. Hartwick,R. Steudle

Michigan Public Service Commission
DTE Electric Company
MNSCDE-12.8b - Reliability Program Analysis

TT

ExMED

2017-2022 10 Months (event volumes)

Year	Year_0	Year_1	Year_2	Year_3	Year_4
2017	123	66	101	61	92
2018	294	200	166	215	288
2019	565	272	357	413	0
2020	326	251	332	0	0
2021	178	97	0	0	0

Weights

	2017	2018	2019	2020	2021	2022
2017		7%	8%	11%	26%	
2018			20%	23%	32%	74%
2019				35%	41%	57%
2020					25%	29%
2021						13%

% change in events

	# of Circuits		2017	2018	2019	2020	2021	2022		
									N_1	775
7%	53	2017	0%	-46%	-18%	-50%	-25%		N_2	673
20%	152	2018		0%	-32%	-44%	-27%	-2%	N_3	479
35%	274	2019			0%	-52%	-37%	-27%	N_4	205
25%	194	2020				0%	-23%	2%		
13%	102	2021					0%	-46%		
100%	775									

% change in events number of years after program completion

	N+1	N+2	N+3	N+4	N+5	
Raw data calculation	-40%	-26%	-29%	-8.0%	NA	
Reliability Modeling (Smoothed)	-40%	-30%	-25%	-8%	0%	

Data are based on Jan to Oct from 2017 to 2022
Events are multiple customers and Tree related outage events

Michigan Public Service Commission
DTE Electric Company
MNSCDE-12.8b - Reliability Program Analysis

Hardening

ExMED

2017-2022 10 Months (event volumes)

Year	Year_0	Year_1	Year_2	Year_3	Year_4
2017	0	0	0	0	0
2018	59	14	6	8	17
2019	284	60	62	67	0
2020	515	129	113	0	0
2021	267	44	0	0	0

% change in events

	# of Circuits		2017	2018	2019	2020	2021	2022	N_1	72
0%	0	2017	0%	0%	0%	0%	0%		N_2	53
7%	5	2018		0%	-76%	-90%	-86%	-71%	N_3	23
25%	18	2019			0%	-79%	-78%	-76%	N_4	5
42%	30	2020				0%	-75%	-78%		
26%	19	2021					0%	-84%		
100%	72									

Weights

	2017	2018	2019	2020	2021	2022
2017		0%	0%	0%	0%	
2018			7%	9%	22%	100%
2019				25%	34%	78%
2020					42%	57%
2021						26%

% change in events number of years after program completion

	N+1	N+2	N+3	N+4	N+5	N+6	N+7	N+8	N+9	N+10	N+11	N+12	N+13	N+14	N+15
Raw data calculation	-78%	-79%	-79%	-71.2%	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Reliability Modeling (Smoothed)	-80%	-75%	-70%	-65%	-60%										-10%

Data are based on Jan to Oct from 2017 to 2022
Events are multiple customers and not Tree related outage events

Michigan Public Service Commission
DTE Electric Company
MNSCDE-12.8b - Reliability Program Analysis

CE(PTMM Estimate) ExMED

2017-2022 10 Months (event volumes)

Year	Year_0	Year_1	Year_2	Year_3	Year_4
2017	0	0	0	0	0
2018	0	0	0	0	0
2019	171	71	72	118	0
2020	411	327	367	0	0
2021	483	495	0	0	0

Weights

	2017	2018	2019	2020	2021	2022
2017		0%	0%	0%	0%	
2018			0%	0%	0%	0%
2019				10%	22%	100%
2020					38%	78%
2021						51%

% change in events

	# of Circuits		2017	2018	2019	2020	2021	2022		
									N_1	105
0%	0	2017	0%	0%	0%	0%	0%		N_2	51
0%	0	2018		0%	0%	0%	0%	0%	N_3	11
10%	11	2019			0%	-58%	-58%	-31%	N_4	0
38%	40	2020				0%	-20%	-11%		
51%	54	2021					0%	2%		
100%	105									

% change in events number of years after program completion

	N+1	N+2	N+3	N+4	N+5	N+6	N+7
Raw data calculation	-13%	-21%	-31%	0.0%	NA	NA	NA
Reliability Modeling (Smoothed)	-30%	-25%	-20%	-15%	-10%	-5%	0%

Data are based on Jan to Oct from 2017 to 2022
Events are multiple customers and not Tree related outage events

		Customer Benefits				
		Improved customer experience	**Ease in paying a past-due balance**	**Access to their channels of choice**	**Access to payment solutions and energy assistance**	**Keeping Customers Informed**
Category	**2024 and 2025 Improvement Description**					
Restore Electric Service Phase 2	Allow customers with two AMI meters disconnected for non-payment to reconnect both meters in one web transaction	X	X	X		
	Allow customers eligible for SER to reconnect with a down payment	X	X	X	X	
Lock (Hold) Status	Notify customers on the web once an agency payment has been applied to their account	X		X		X
	Incorporate web links on more existing notifications to encourage customers to check the website for lock status	X		X		X
Payment Extension (PE)	Provide customers with their shut-off date and the amount required to avoid disconnection when offering a Payment Extension	X	X	X		X
Payment Agreement (PA)	Offer eligible customers the ability to enroll in a Payment Agreement to pay down their past-due balance over a period of 3 to 6 months (in addition to paying their current charges)	X	X	X	X	
	Online Assistance Help: Educate customers on their eligible payment assistance programs and allow them to choose which program to enroll in	X		X	X	X
	Construct new eligibility API for Payment Agreement, split eligibility APIs by Collections transaction type, and build corresponding details APIs for each transaction to streamline use of APIs across all digital channels	X		X		
	Make additional customer-facing design enhancements	X		X		
Payment Improvements	Improve the payment experience for customers within the Collection transactions (e.g., restore, payment extension, payment agreement), which will reduce friction points	X	X	X		
Restore Electric Service Phase 3	Allow accounts with agency commitments to reconnect for $0	X		X	X	
Online Assistant Finder	Online Assistance Finder: Assist eligible customers to identify available programs and promote the best option for that customer (Next-Best Action), such as PA, PE, SER, etc.	X	X	X	X	
All	Remove defects to streamline processes that will improve customer's ability to complete digital transactions successfully. Expand eligibility criteria for existing digital transactions	X	X	X	X	X

Michigan Public Service Commission
DTE Electric Company
Projected Cost of Long-Term Debt
Projected 12 Month Period Ending December 31, 2025

Case No.: U-21534
Exhibit: A-45
Schedule: JJ1
Witness: T. J. Lepczyk

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)
Line No.	**Issue Name**	**Original Issue Date**	**Stated Maturity**	**Interest Rate %**	**Amount of Offering ($000)**	**Price to Public %**	**Expenses of Financing %**	**Net Proceeds to the Company %**	**Cost Based on Net Proceeds %**	**12/31/2025 Amount Outstanding ($000)**	**Annual Cost ($000)**
1	2002 Series B	10/23/02	10/15/32	6.350%	225,000	99.33%	1.0%	98.369%	6.47%	225,000	14,566
2	2005 Series BR	02/07/05	02/15/35	5.450%	200,000	99.59%	1.0%	98.562%	5.55%	200,000	11,098
3	2005 Series E	10/06/05	10/01/37	5.700%	250,000	99.40%	1.0%	98.420%	5.81%	250,000	14,523
4	2006 Series A	06/01/06	06/01/36	6.625%	250,000	99.95%	1.0%	98.954%	6.71%	250,000	16,766
5	2007 Series A	12/18/07	03/15/38	6.470%	50,000	100.00%	0.8%	99.168%	6.53%	50,000	3,266
6	2011 Series E	09/01/11	09/01/26	4.460%	77,000	100.00%	0.6%	99.411%	4.51%	77,000	3,476
7	2011 Series F	09/01/11	09/01/41	5.670%	46,000	100.00%	0.6%	99.411%	5.71%	46,000	2,627
8	2011 Series H	09/20/11	09/01/41	4.500%	140,000	98.87%	1.1%	97.814%	4.64%	140,000	6,490
9	2012 Series B	06/22/12	06/15/42	3.950%	250,000	99.57%	1.0%	98.541%	4.03%	250,000	10,086
10	2013 Series A	03/27/13	04/01/43	4.000%	375,000	99.55%	1.0%	98.500%	4.09%	375,000	15,327
11	2014 Series A	06/04/14	06/01/26	3.770%	100,000	100.00%	0.6%	99.392%	3.83%	100,000	3,834
12	2014 Series B	06/04/14	06/01/44	4.600%	150,000	100.00%	0.6%	99.392%	4.64%	150,000	6,957
13	2014 Series E	07/02/14	07/01/44	4.300%	350,000	99.85%	1.0%	98.832%	4.37%	350,000	15,296
14	2015 Series A	03/11/15	03/15/45	3.700%	500,000	99.77%	1.0%	98.735%	3.77%	500,000	18,854
15	2016 Series A	05/17/16	06/01/46	3.700%	300,000	99.93%	1.1%	98.824%	3.77%	300,000	11,297
16	2017 Series B	08/09/17	08/15/47	3.750%	440,000	99.95%	1.1%	98.850%	3.81%	440,000	16,784
17	2018 Series A	05/07/18	05/15/48	4.050%	525,000	99.55%	1.1%	98.456%	4.14%	525,000	21,736
18	2019 Series A	02/15/19	03/01/49	3.950%	650,000	99.20%	1.1%	98.111%	4.06%	650,000	26,385
19	2020 Series A	02/26/20	03/01/30	2.250%	600,000	99.88%	0.8%	99.042%	2.36%	600,000	14,148
20	2020 Series B	02/26/20	03/01/50	2.950%	500,000	99.96%	1.1%	98.893%	3.01%	500,000	15,031
21	2020 Series C	04/06/20	03/01/31	2.625%	600,000	99.83%	0.8%	99.004%	2.73%	600,000	16,387
22	2021 Green Series A 110087	03/29/21	04/01/28	1.900%	575,000	99.92%	0.9%	99.062%	2.04%	575,000	11,756
23	2021 Green Series B 110088	03/29/21	04/01/51	3.250%	425,000	99.17%	1.1%	98.062%	3.35%	425,000	14,250
24	1995CC 2021 Remarketing 110089	09/01/21	09/01/30	1.450%	82,350	100.00%	0.7%	99.317%	1.53%	82,350	1,261
25	2008ET2 2021 Remarketing 110090	09/01/21	08/01/29	1.350%	59,175	100.00%	0.7%	99.310%	1.44%	59,175	854
26	2022 Series A 110091	02/24/22	03/01/32	3.000%	500,000	99.60%	0.9%	98.696%	3.15%	500,000	15,764
27	2022 Green Series B 110092	02/24/22	03/01/52	3.650%	400,000	99.39%	1.1%	98.260%	3.75%	400,000	14,988
28	2023 Series A 110093	03/03/23	04/01/33	5.200%	600,000	99.79%	0.9%	98.908%	5.34%	600,000	32,045
29	2023 Series B 110094	03/03/23	04/01/53	5.400%	600,000	99.82%	1.1%	98.707%	5.49%	600,000	32,928
30	2023DT Series 110095	06/01/23	06/03/30	3.875%	100,000	100.00%	1.3%	98.730%	4.09%	100,000	4,085
31	2024 Series B	02/29/24	12/01/26	4.850%	500,000	99.98%	0.5%	99.455%	5.06%	500,000	25,308
32	2024 Series C	02/29/24	03/01/34	5.200%	500,000	99.95%	0.8%	99.124%	5.31%	500,000	26,570
33	2025 Series A	03/01/25	03/01/55	5.530%	800,000	100.00%	1.0%	99.00%	5.60%	800,000	44,794
34	2025 Series B	07/01/25	07/01/55	5.530%	500,000	100.00%	1.0%	99.00%	5.60%	500,000	27,996
									4.24%	12,219,525	517,531