SEVERE WEATHER, POWER OUTAGES, AND A DECISION TO IMPROVE ELECTRIC UTILITY RELIABILITY

A DISSERTATION
SUBMITTED TO THE DEPARTMENT OF MANAGEMENT SCIENCE AND ENGINEERING
AND THE COMMITTEE ON GRADUATE STUDIES
OF STANFORD UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Peter H. Larsen

March 2016

I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a dissertation for the degree of Doctor of Philosophy.

James Sweeney, Primary Adviser

I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a dissertation for the degree of Doctor of Philosophy.

John Weyant, Co-Adviser

I certify that I have read this dissertation and that, in my opinion, it is fully adequate in scope and quality as a dissertation for the degree of Doctor of Philosophy.

Lawrence Goulder

Approved for the Stanford University Committee on Graduate Studies.

Patricia J. Gumport, Vice Provost for Graduate Education

Abstract

Several studies have quantified the annual cost of United States power outages, with estimates ranging from tens to hundreds of billions of dollars. Despite the critical importance of reliable electricity to the economy, there has been little or no research conducted at the national level to determine if reliability is getting better or worse over time. The econometric model presented in this dissertation is the most comprehensive assessment of national reliability trends ever conducted. There has also been a general shortfall of peer-reviewed literature identifying methods to estimate the costs and benefits of strategies employed by utilities to improve reliability. This dissertation systematically evaluates the factors that affect the reliability of the U.S. power system and introduces—for the first time—an analysis framework to estimate the costs and benefits of implementing one strategy to improve reliability: undergrounding power transmission and distribution lines. It is shown that U.S. power system reliability is generally getting worse over time, due in large part to impacts associated with increasingly severe weather. 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.

This dissertation begins with an econometric analysis of the factors that are correlated with both the total minutes and frequency of power outages at nearly 200 utilities over a thirteen-year period. A number of factors were considered, including weather (temperature, precipitation, lightning, wind speed); transmission and distribution

operations and maintenance (O&M) spending; electricity sales; customers per line mile; the installation of outage management systems; and the share of underground line miles. Part Two surveys the literature on value-based reliability planning and concludes with results from a simple expert-elicitation exercise designed to evaluate the hypothesis that utility outage cost surveys may be inaccurate in their assessment of the aggregate value of lost load. Part Three introduces a general method to quantify the costs and benefits of undergrounding electricity infrastructure—a strategy that has been linked to improved reliability. Some researchers have found that the costs, in general, of undergrounding electric utility transmission and distribution (T&D) infrastructure far exceed the benefits from avoided outages. To test this finding, an infrastructure lifecycle simulation model is developed in order to evaluate the costs and benefits of undergrounding as existing overhead lines reach the end of their useful life. A number of impact categories are considered, including costs due to infrastructure replacement/conversion; changes in worker health and safety risk; and environmental restoration. Benefits from reduced power outages and increased property values are also considered as part of the cost-benefit framework. Part Four refines the undergrounding model for a specific utility, Cordova Electric Cooperative, which has spent the last forty years converting overhead lines to underground lines. An ex-post analysis of Cordova Electric Cooperative is conducted to determine if the benefits of undergrounding exceeded the costs. Initial and subsequent undergrounding model configurations highlight key criteria that must be met before policymakers should require that T&D lines be undergrounded. A short discussion follows on aspects of this study that should be taken into consideration when interpreting the results and additional research topics that should be explored in future analyses.

Acknowledgments

> *"I am no advocate of senseless and excessive cramming in studies, but a boy should work, and should work hard, at his lessons — in the first place, for the sake of what he will learn, and in the next place, for the sake of the effect upon his own character of resolutely settling down to learn it."*
>
> —Theodore Roosevelt (1901)

A number of people, from all walks—and in all stages—of life, influenced this manuscript, provided encouragement throughout my educational experience, and contributed to my success at Stanford University. Graduate students, like everyone else, experience the ups and downs of life over the course of several years. I was no exception. I lost a parent to cancer, experienced the birth of my daughter, moved from California to Montana—all while working full-time as an economist at Lawrence Berkeley National Laboratory (LBNL) and as a Stanford PhD student. I am indebted to so many people that writing this section is nearly as challenging as describing the technical content later in this manuscript. The following people come immediately to mind, but over the course of time, I know I will regret not formally acknowledging others.

First and foremost, I would like to thank my faculty advisors. Jim Sweeney, my major advisor, helped me in ways that cannot easily be put into words on a page. I vividly recall an especially difficult time when Jim's sage advice echoed the wisdom of Winston Churchill who said "if you're going through hell, keep going". Jim knew exactly when to push me to achieve depth in thinking and when to pull me back from the abyss, so that I never lost my footing or sight of the broader implications of my research. Jim is one of those very rare scientists who, in a different time and place, would have been comfortable working with both a microscope and telescope. I had the great privilege of studying under him for nearly five years. I owe a heartfelt and mindful thank you to another advisor, John Weyant. His international reputation for modeling the implications of climate change and energy policies—and his encouragement—influenced my decision to apply to the MS&E PhD program. I always looked forward to meeting with John, because he would tell interesting and personal stories about the founders of our field. He would also make seemingly offhand observations that, upon reflection, revealed a higher-level of thinking that one rarely comes across over the course of a lifetime. I am so grateful to Larry Goulder for agreeing to serve as a reader on my dissertation committee. In short order, Larry was able to identify and question an overlooked, but critical assumption that had a profound impact on my results. He also played a pivotal role in the final stages of this manuscript by encouraging me to emphasize a motif—much like a composer approaches classical music. Professors Charles Kolstad and Ram Rajagopal provided insightful and constructive suggestions during my oral defense. Other Stanford faculty including, but not limited to, Kenneth Arrow, Kate Bundorf, Hill Huntington, Christine Pal Chee, and Patrick Windham provided inspiration, mentorship, and guidance along the way. A number of staff at Stanford also contributed to the successful completion of my degree. Lori Cottle, Tim Keely, Sarah Jo Manson, Pam McCroskey, Amna Nazir, Catherine Vogel, and Juanita Winkleman are just a few names of people who, in their own way, make Stanford a *great* institution. I also had the pleasure of meeting, collaborating, and commiserating with an amazing group of graduate students including, but not limited to, John Bistline, Melanie Craxton, Danielle Davidian, Mike Delgado, Delavane Diaz, Ben Leibowicz, Juan Carlos Lopez, Christos Makridis, Maria Roumpani, Ryan Triolo, and Jordan Wilkerson.

A number of colleagues at LBNL were instrumental in supporting my graduate studies, providing technical assistance throughout my program, and giving moral support during especially challenging phases. The LBNL Tuition Assistance Program covered my tuition costs. Kim Williams, now the Chief Financial Officer of LBNL, was an early supporter of my desire to return to school. Kim also donated her valuable time to participate in a case study for one of my class projects. I owe a sincere thank you to my supervisor, Joe Eto, for accommodating my flexible schedule. Joe is a highly-regarded expert on the reliability of power systems. He spent a considerable amount of time mentoring me on this subject and helping shape the analysis in what would eventually become the first and second chapters. I could not have completed this program without his support, encouragement, and friendship. Chuck Goldman was always skeptical of my ability to balance work, school, and life and I am indebted to him for it. His subtle—and not so subtle—influence permeates throughout all facets of my professional life including this manuscript. Chuck has made me a better writer, improved my critical-thinking abilities, and, most importantly, taught me how to manage my time efficiently. My colleague, Juan Pablo Carvallo, helped solve the most difficult programming algorithm within the undergrounding economic analysis. I also owe a considerable amount of gratitude to my colleague and collaborator, Kristina LaCommare. Kristina collected and shared reliability performance statistics for all of the utilities represented in the first chapter of this manuscript. Kristina is a constant source of positivity and humor and I look forward to working with her in the future. Bill Morrow (LBNL), Amber Armentrout (Ventyx-ABB), and Sean Hedges (Ventyx-ABB) provided technical assistance by mapping annual weather observations to utility service territories. LBNL colleagues Pete Cappers, Liesel Hans, Ben Hoen, Anna Spurlock, and Annika Todd all provided insightful and constructive comments on the econometric framework and analysis. One of my better decisions involved eliciting the help of Dana Robson. Dana has a keen eye for detail, is a talented copy editor, and an expert at overcoming frustrations with Microsoft Word. The University of Georgia SAS-Listserv, Live Music Archive, and Organlive.com provided technical and inspirational assistance throughout the development of the SAS code and subsequent manuscript. Clay Koplin—CEO of the Cordova (Alaska) Electric Cooperative—

donated his time by providing constructive feedback on critical assumptions used throughout the Alaska case study. Simply put, the fourth chapter of this dissertation would not have been possible without his generosity. I would like to acknowledge Givey Kochanowski, from the U.S. Department of Energy (DOE) Office of Indian Energy Policy and Programs, who first introduced me to Clay during our study of rural Alaska energy challenges. Travis Kavulla, Montana Public Service Commissioner and President of the National Association of Regulatory Utility Commissioners, provided insight into what regulators consider when evaluating important investment decisions. The reliability trends analysis was originally funded by the Office of Electricity Delivery and Energy Reliability, National Electricity Delivery Division of U.S. DOE. I am grateful to U.S. DOE staff Rakesh Batra, Caitlin Callaghan, Larry Mansueti, David Meyer, David Ortiz, Joe Paladino, and Matt Rosenbaum for technical and/or financial support of related research at LBNL. I would like to acknowledge staff at the electric utilities and public utility commissions who shared reliability performance metrics with our team. Without this assistance, the first chapter of this dissertation and corresponding LBNL report would not have been possible.

I sincerely thank all of my close friends and family—you know who you are—for reminding me to laugh during funny times, for consoling me during sad times, for encouraging me during challenging times, and for traveling with me during this unique experience. Finally, I owe the greatest debt to my beautiful wife, Meghan. Meghan propped me up when I fell down and grounded me when I began to soar. She is *the* reason that I decided to apply, persevere through, and ultimately complete this degree. Perhaps Nicholas Sparks said it best when he wrote: “I love you more than there are stars in the sky.”

The following is dedicated to the memory of my dad and the promise of my daughter.

Helena, Montana
March 2016

“There is geometry in the humming of the strings; there is music in the spacing of the spheres.”

—Pythagoras (unknown date)

Table of Contents

List of Tables

List of Figures

Introduction

Severe weather, power outages, and an opportunity to improve reliability

Power system outages and severe weather have been inextricably linked for nearly one hundred and fifty years—all the way back to the 1880s and the founding of the Edison Illuminating Company. And since that time, electrical engineers, system planners, policymakers, industrial inventors, and even backyard tinkerers, have experimented with technologies designed to protect critical power system infrastructure from the elements. This dissertation evaluates the role that severe weather and other key factors play in the reliability of the U.S. power system. It also considers how widely-deployed technologies, including outage management systems (OMS) and undergrounded infrastructure, impact the frequency and total annual duration of power interruptions. For nearly sixty years, researchers have acknowledged that reliable electric service (or lack thereof) has economic benefits (costs) to society. As the electric industry evolved over this time period, so have the methods used by researchers to value reliability. Accordingly, a comprehensive literature review is conducted of studies that have estimated the value of reliability under a wide range of conditions and scenarios. The role of utility operations and maintenance (O&M) spending and the societal costs and benefits of investing in one type of technology (undergrounded lines), are also investigated within the context of power system reliability.

The empirical techniques demonstrated and results presented throughout this document are also timely given the backdrop of climate change and associated policies designed to address future vulnerabilities. The United States Department of Energy (DOE) reports that weather is the most common cause of power outages and that weather-related outages have significantly increased over the past twenty years (U.S. DOE 2015). Furthermore, the United States Global Change Research Program and National Science and Technology Council convened over three hundred experts, including members of the National Academy of Sciences, to evaluate climatic changes already occurring across the United States and additional changes expected over the coming decades. The 2014 National Climate Assessment found that "some extreme weather and climate events have increased in recent decades…extreme weather events and water shortages are already interrupting energy supply and impacts are expected to increase in the future" (Melillo et al. 2014).

Given the interdisciplinary nature of this research topic, this manuscript builds on insights from a number of different academic disciplines—including power system engineering, meteorology, and economics—to answer a number of important questions that transcend any one field of research.

Research questions

Electric utilities are often mandated by public utility commissions or other regulatory bodies to submit documentation (e.g., reliability reports) about historical power system interruptions as well as the factors that contributed to the historical outages. Individual utilities or collections of utilities under the jurisdiction of a single regulatory institution are typically aware of the factors that influence local and/or regional reliability. However, very little research—with a notable exception (Eto et al. 2012)—has been undertaken to evaluate long-term *national* trends in reliability and the factors that may be influencing power system reliability. This dissertation answers a number of important, yet unanswered, questions related to the reliability of the U.S. power system including:

- Are there trends in reported electricity reliability over time?
- Are there utility-by-utility differences in reported electricity reliability?
- Is the share of underground line miles correlated with reliability?
- Do reliability improvements occur after the installation of OMS?
- Is the total amount of electricity delivered correlated with changes in utility reliability?
- How does abnormal weather affect the frequency of outages and the total minutes customers are without power?
- Are previous year annual transmission and distribution O&M expenditures correlated with the frequency and total annual minutes of system interruptions?

Not surprisingly, utilities are actively involved in efforts to improve system reliability for their customers. Undergrounding all overhead transmission and distribution lines is one such strategy being undertaken by utilities. Opponents of undergrounding commonly cite excessively high capital and annual O&M costs as the primary reason why undergrounding is not pursued by most utilities. Yet, utilities as far apart—both geographically and characteristically—as Cordova, Alaska and Washington, D.C. are actively undergrounding all power distribution lines. Unfortunately, there are no known analytical frameworks to evaluate the societal costs and benefits of this strategy. Accordingly, a number of questions related to power system undergrounding are systematically evaluated in this dissertation including:

- Do the all-in costs of undergrounding power lines exceed the benefits?
- What are the lifecycle costs of undergrounding all existing and new transmission and distribution lines at the end of their useful lifespan?

- Could increasing the share of underground T&D lines lead to improved power system reliability, and are there corresponding monetary benefits from this improvement?
- Are there benefits to property values from reducing the number of overhead lines?
- How much might health and safety costs increase if there is an extensive conversion of overhead-to-underground lines?
- How much might undergrounding transmission and distribution (T&D) lines increase (decrease) ecosystem restoration costs?
- How important are assumptions, including value-of-lost-load estimates, relative to one another within a decision to underground power lines?
- What are the minimum conditions necessary for a targeted undergrounding initiative to have net social benefits?

The above questions are answered using a range of analytical methods and empirical techniques including econometrics, lifecycle cost estimation, cost-benefit analysis, backward induction, and one-way and simultaneous assumption sensitivity analyses.

Analytical methods and empirical techniques

The information presented in this dissertation refines and extends analytical methods and empirical techniques first presented in earlier research. Eto et al. (2012) developed an early econometric model of U.S. power system reliability by including basic measures of weather (heating and cooling degree-days), utility sales per customer, and the presence of OMS. The first part of this dissertation builds on Eto et al. (2012) by expanding the list of utilities evaluated, increasing the number of possible regressors, and conducting a more rigorous approach to model specification. Larsen et al. (2008) developed a lifecycle cost estimation model to quantify the risk to Alaska's public infrastructure, including electricity system infrastructure, from projected climate change. This dissertation improves upon the Larsen et al. (2008) lifecycle cost estimation technique in two ways, by: (1) discounting costs in the actual year of replacement—i.e., not annualizing the replacement costs and discounting each year back to the present, and (2) considering *both* capital and O&M costs when evaluating future infrastructure costs. Sathaye et al. (2013) evaluated the risk to power line efficiency under projected climate change. Both Larsen et al. (2008) and Sathaye et al. (2013) conducted a Monte Carlo numerical simulation to characterize the range of possible impacts under alternative combinations of model inputs. A Monte Carlo numerical simulation is also carried out in the analysis that follows. But in this case, a larger number of model assumptions—when compared to Larsen et al. (2008) and Sathaye et al. (2013)—are varied simultaneously to explore, among other things, the relative influence of one assumption on the cost-benefit estimates over the others.

Dissertation organization

This dissertation is organized into a number of sections that build on one another. Part One introduces the factors that affect both the total customer minutes and frequency of power system interruptions. More specifically, an empirical model of U.S. power system reliability is proposed and alternative specifications are evaluated for performance, parsimony, and consistency following a technique described by Hoen et al. (2009). Part Two contains a historical review of the literature on value-based reliability planning. Value-based reliability planning is the concept that reliable electric service and strategies to improve reliability have value to society (or utility customers) and these values can be measured using a number of different techniques, including proxy methods, market-based methods, after-the-fact-measurement, and survey-based methods (Burns and Gross 1990). Part Two concludes with results from a simple expert-elicitation exercise designed to evaluate the hypothesis that utility outage cost surveys may be inaccurate in their assessment of the value of lost load (see, e.g., London Economics 2013; Growitsch et al. 2014; Rose et al. 2005). In Part Three, a cost-benefit framework is developed to evaluate whether the societal benefits of undergrounding Texas investor-owned utility power lines exceed the all-in costs. Part Three integrates findings from part one about the role that underground line miles play in power system reliability and the value of lost load reported from utility outage cost surveys identified in Part Two. Part Four is a case study of Cordova (Alaska) Electric Cooperative’s efforts over the past forty years to transition from an overhead power system to a fully undergrounded system. Based on feedback from utility staff, the undergrounding model presented in Part Three is reconfigured and the assumptions are adjusted to reflect observed conditions in Cordova. An ex-post analysis is conducted to determine if the benefits of undergrounding exceeded the costs for this specific utility. Finally, results for all sections are summarized and additional research ideas are presented in the conclusion section.

Part 1: Recent Reliability of the U.S. Power System

1.1 Context

Several studies have quantified the annual cost of U.S. power outages with estimates ranging from $28 billion to $209 billion (LaCommare and Eto 2005, 2006; Swaminathan and Sen 1998; Primen 2001). There are a number of factors that could affect the long-term reliability of U.S. electric utilities including, but not limited to: abnormal weather; presence of wildlife; transmission and distribution maintenance and capital expenditures; electricity sales; and the installation of outage management systems. Despite the high costs attributed to power outages, there has been little or no research conducted to determine which factors are statistically correlated with the frequency and total number of minutes of outages across the United States.

Eto et al. (2012) first developed a basic panel dataset and preliminary econometric framework to evaluate some factors that may be correlated with more frequent and lengthy service interruptions. It was shown that (1) the frequency and total number of minutes of reliability events increased ~2% annually; (2) increases in cooling degree-days (i.e., hot weather) are correlated with increased frequency of outages; and (3) outage management systems are initially correlated with an increased amount of time customers are without power, but electric utilities appear to be "learning" from these systems over time. The Eto et al. (2012) paper also acknowledged that additional factors should be evaluated in future studies including a larger sample of utilities and

> "…more disaggregate measures of weather variability (e.g., lightning strikes and severe storms), utility characteristics (e.g., the number of rural versus urban customers, and the extent to which transmission and distribution lines are overhead versus underground), and utility spending on transmission and distribution maintenance and upgrades, including advanced technologies."

1.2 Research Questions

The overall purpose of this specific analysis is to expand on research by Eto et al. (2012) by systematically evaluating the factors that affect the long-term reliability of U.S. electric utilities.

Furthermore, this analysis attempts to answer the following questions:

- Are there utility-specific differences in reported electricity reliability?
- Is the share of underground distribution miles to total line miles correlated with reliability?
- Do reliability improvements occur after the installation of an automated outage management system (OMS)?
- Is the total amount of electricity delivered correlated with changes in utility reliability?
- How does abnormal weather affect the frequency and total annual minutes of system interruptions?
- Are previous year annual transmission and distribution expenditures correlated with the frequency and total annual duration of system interruptions?
- Are there unexplained trends in reported electricity reliability over time?

1.3 Section Organization

Part One is organized as follows: Sections 1.4 and 1.5 provide background on what is known about the factors that affect the reliability of electric utilities, as well as how electric utility reliability is typically measured. The empirical method, data sources, and econometric techniques are described in Sections 1.6. and 1.7. Section 1.8 presents results and Section 1.9 contains a short discussion and list of caveats that should be considered when interpreting the results.

1.4 Factors that Affect the Reliability of Bulk Power Systems

This section provides background on what is known about the factors that affect the reliability of electric utilities as well as how reliability is typically measured. Not surprisingly, there are 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 (2013); Rocky Mountain Power (2011); Interstate Power and Light Company (2013); Jersey Central Power & Light (2013); Madison Gas and Electric Company (2013); Pacific Gas & Electric Company (2011); Portland General Electric (2012); PSE&G Services Corporation (2013); and AEP Southwestern (2012). Table 1 provides information on the range of categories used by a selected number of utilities introduced above.

Causes of reliability events are not consistently reported across utilities

Electric utilities report the causes of reliability events with varying levels of detail (see Table 1). For example, Portland General Electric (PGE) reports causes by individual feeder using the following eleven general categories: equipment; lightning; loss of supply (substation); loss of supply (transmission); other; planned; public; unknown; vegetation; weather; and wildlife. In addition, PGE provides more granular information on the individual causes within each general category (e.g., the types of components that failed within the PGE "equipment" category). Other utilities report the causes in a less-granular format. AEP Southwestern, for example, identifies seven general causes: animals and birds; people; unknown; utility-owned equipment; other; vegetation; and weather (including lightning).[1]

Pacific Gas and Electric (PG&E), which is not included in Table 1, did not report the cause of their outage events using general categories. Instead, PG&E qualitatively describes the ten largest reliability events for each year over the past decade. Interestingly, the ten largest outage events in 2010 were directly related to adverse weather. In January, a major storm produced wind speeds in excess of fifty miles per hour for three straight days (January 18–20), heavy rainfall and lightning for four days (January 18–21), and heavy snowfall in the Sierra Nevada mountains (January 20–21). This storm affected nearly 1.2 million PG&E customers and ~4,000 employees were dispatched to restore service.

The New York Department of Public Service's (NYDPS) electric reliability performance report (NYDPS 2013) indicated that most of each utility's interruptions are a result of the following categories: major storms, tree contacts, equipment failures, and accidents. It was noted that "2012 was by far the worst year ever for storm effects in the twenty-four years of staff recordkeeping, taking that distinction from last year" (NYDPS 2013). Hurricane Sandy caused most, but not all, storm-related system outages during 2012. Approximately 170 million hours of customer interruptions (or nearly a quarter of the total number of hourly interruptions since 1989) were attributed to Hurricane Sandy (NYDPS 2013). It was reported that over two million customers were affected by this specific storm, but other storms also significantly affected system reliability—including a major blizzard in January and severe thunderstorms in the summer.

---

[1] Although AEP Southwestern does not break out the frequency or duration of outages causes by lightning strikes, other utilities, including companies not represented in Table 1, do report the effect of lightning strikes on reliability.

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

Utility name	Reporting year	Metric	Causal categories	Comments
Madison Gas & Electric Company (Wisconsin)	2012	SAIFI	Cable failures; equipment failures; storm-related; substations; tree-related; wildlife-related; other	Reported by worst performing circuit.
Florida Public Utilities Company (Florida)	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)	2011	SAIDI (% share); SAIFI (% share)	Weather; animals; environment; equipment; interference; loss of supply; operational; other; planned; trees	
Interstate Power & Light (Iowa/Minnesota)	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)	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)	2012	Number of customer hours	Trees; construction (underground); construction (overhead); supply and station equipment; other; lightning; outside plant equipment; external; animals; weather	Causes were reported from 2003-2012 and across four divisions within service territory.
Portland General Electric (Oregon)	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)	2011	% of interruptions	Animals and birds; people; unknown; utility-owned equipment; other; vegetation; weather (including lightning)	

Inconsistent definitions of "major events"

Utilities are typically allowed to exclude major events, like severe storms, from the reliability performance calculations, because "they are circumstances over which the utilities have limited control" (NYDPS 2013). In New York state, major events are excluded when an event "causes service interruptions of at least 10% of customers in an operating area, and/or interruptions with duration of 24 hours or more" (NYDPS 2013). PSE&G defines a major event as "a sustained interruption of electric service resulting from conditions beyond the control of the Electrical Distribution Company (EDC), which may include, but is not limited to thunderstorms, tornadoes, hurricanes, heat waves or snow and ice storms, which affect at least 10% of the customers in an operating area" (PSE&G 2011). In contrast, the California Public Utilities Commission defines a major event as an "event that meet[s] either of the two following criteria: (a) the event is caused by earthquake, fire, or storms of sufficient intensity to give rise to a state of emergency being declared by the government, or (b) any other disaster not in (a) that affects more than 15% of the system facilities or 10% of the utility's customers, whichever is less for each event" (PG&E 2009). The inconsistent exclusion of major events creates challenges in the analysis and interpretation of reliability metrics across the country. For this reason, the Institute of Electrical and Electronics Engineers (IEEE) provides voluntary guidance on how utilities should define and exclude major events. IEEE standard 1366-2012 defines a major event from a statistical standpoint as a "day in which the daily System Average Interruption Duration Index (SAIDI) exceeds a Major Event Day threshold value[2] …activities that occur on Major Event Days should be separately analyzed and reported".

Regardless of inconsistencies in the definition of major events, electric utilities report a number of general causes for reliability events including: planned outages, weather, wildlife, T&D equipment failure, human error, vegetation, and other/unknown/external. Figure 1—which is an aggregation of information provided

[2] See IEEE 1366-2012 for more information about the quantitative method used to estimate the Major Event Day threshold value.

by the utilities listed in Table 1—shows that equipment failure (25%), vegetation (21%), other/unknown/external (20%), and weather (15%) are the top factors which affect the *duration* of reliability events. Figure 2 shows that equipment failure (25%), vegetation (24%), other/unknown/external (17%), and weather (15%) are the top factors which affect the *frequency* of reliability events. Interestingly, wildlife was listed as the cause in 11% of the total number outages, but only 4% of duration of the event was attributed to this factor. This finding implies that wildlife (e.g., squirrels, birds) cause reliability events relatively frequently, but wildlife-related causes do not necessarily lead to prolonged outages.

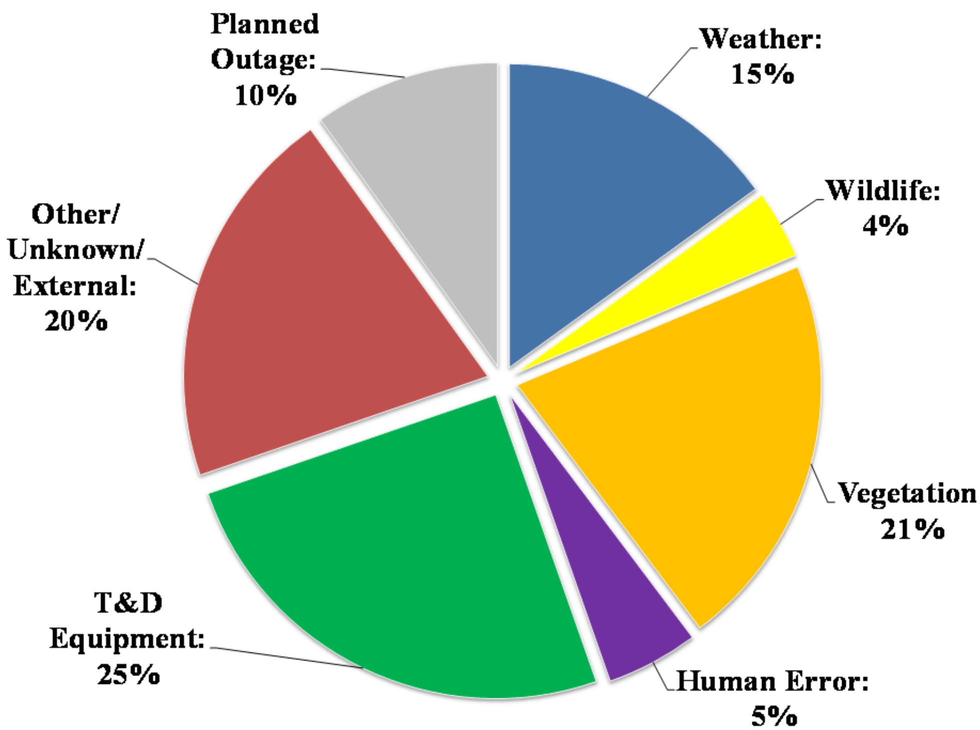

Figure 1. Factors that increase the duration of reliability events (n=5)

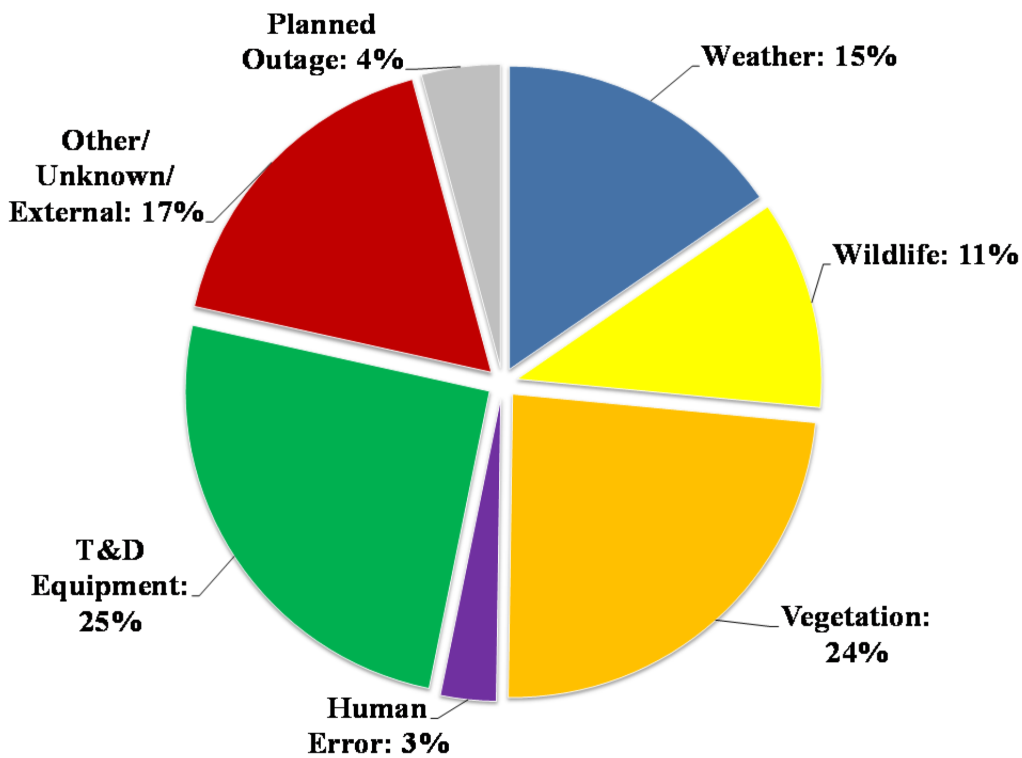

Figure 2. Factors that increase the frequency of reliability events (n=5)

1.5 Metrics Used to Measure Electric Utility Reliability

IEEE 1366-2012 formally defines a number of metrics to track electric utility reliability. The System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) are two of the most commonly used metrics to assess electric utility reliability (Eto et al. 2012). Equation 1 shows that annual SAIDI for a utility is calculated by summing all annual customer interruption durations and dividing this number by the total number of customers served. In this equation, the restoration time for each interruption event in a given year is represented by Time_t, the number of customers affected by all interruptions in a given is Affected_t, and the total number of customers served by the utility in a given year is Customers_t.

$$\text{SAIDI}_t = \frac{\sum \text{Time}_t \times \text{Affected}_t}{\text{Customers}_t} \tag{1}$$

For context, the IEEE recently conducted a survey of 106 utilities and found that the median 2012 SAIDI value is 236 minutes (or approximately four hours) (IEEE 2013). However, it was noted that "data may not be directly comparable since data collection and system differences exist; and certain exclusion differences can occur" (IEEE 2013). In other words, it is likely that some survey respondents may have reported SAIDI values with major events included and some reported SAIDI with major events excluded.

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

$$\text{SAIFI}_t = \frac{\sum \text{Affected}_t}{\text{Customers}_t} \qquad (2)$$

The aforementioned IEEE survey of 106 utilities found that the median 2012 SAIFI value is 1.5 interruption events (IEEE 2013), but similar caveats apply to the comparability of these results.

1.6 Data Sources

Larsen et al. (2015) introduced a range of plausible utility-specific and weather-related factors, which may be correlated to changes in the reliability of electric utilities.[3] Table 2 summarizes key information sources used in this section.

Table 2.Summary of data sources

Variable (units)	Years	Source
SAIDI (total minutes)	2000-2012	Public utility commissions, press releases, etc.
SAIFI (# of events)	2000-2012	Public utility commissions, press releases, etc.
HDD (# of degree days)	2000-2012	Ventyx Velocity Suite via National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC/Ventyx 2013)

[3] Sections 1.6 through 1.9 contain several passages that are nearly identical to those discussed in Larsen et al. (2015).

CDD (# of degree days)	2000-2012	Ventyx Velocity Suite via National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC/Ventyx 2013)
Lightning strikes (strikes per customer)	2000-2012	Vaisala National Lightning Detection Network (NLDN) (NLDN/LBNL 2013)
Precipitation (inches)	2000-2012	Ventyx Velocity Suite via National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC/Ventyx 2014)
Wind speed (mph)	2000-2012	Ventyx Velocity Suite via National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC/Ventyx 2014)
T&D lines (customers per line mile)	2000-2012	Ventyx Velocity Suite via FERC (2014) or U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx (2015)
Share of underground (%)	2000-2012	Ventyx Velocity Suite via FERC (2014) or U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx (2015)
Delivered electricity (MWh per customer)	2000-2012	U.S. Energy Information Administration via Form 861 (EIA 2013)
T&D O&M spending ($2012 per customer)	2000-2012	Ventyx Velocity Suite via FERC (2014) or U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx (2015)
Presence of outage management systems (year)	First year reported	Public utility commissions, press releases, etc.

1.6.1 Reliability Metrics

This analysis considers four distinct ways of reporting reliability performance independently of one another including: (1) SAIDI without major events; (2) SAIDI with major events; (3) SAIFI without major events; and (4) SAIFI with major events.

State-by-state utility regulatory commissions were the primary source for utility-reported reliability performance information, because these commissions typically require regulated utilities to report reliability information—and commissions typically make this information publicly available.[4] Larsen et al. (2015) also obtained reliability performance data via online press releases and other materials that may have been posted by the utility—especially in cases where utilities were not under the jurisdiction of state PUCs (municipality-owned utilities, cooperatives, etc.) or when

[4] Eto and LaCommare (2008) contains a review of state utility commission reporting practices as it relates to reliability.

PUC-mandated reliability data was not publicly-available. Larsen et al. (2015) collected reliability data for 195 different utilities located across the United States with 152 of the utilities being investor-owned and 43 as municipality-owned or electric cooperatives. Figure 3 and Figure 4 show the middle 50% range of SAIDI values for utilities used in this study without and with major events included, respectively.

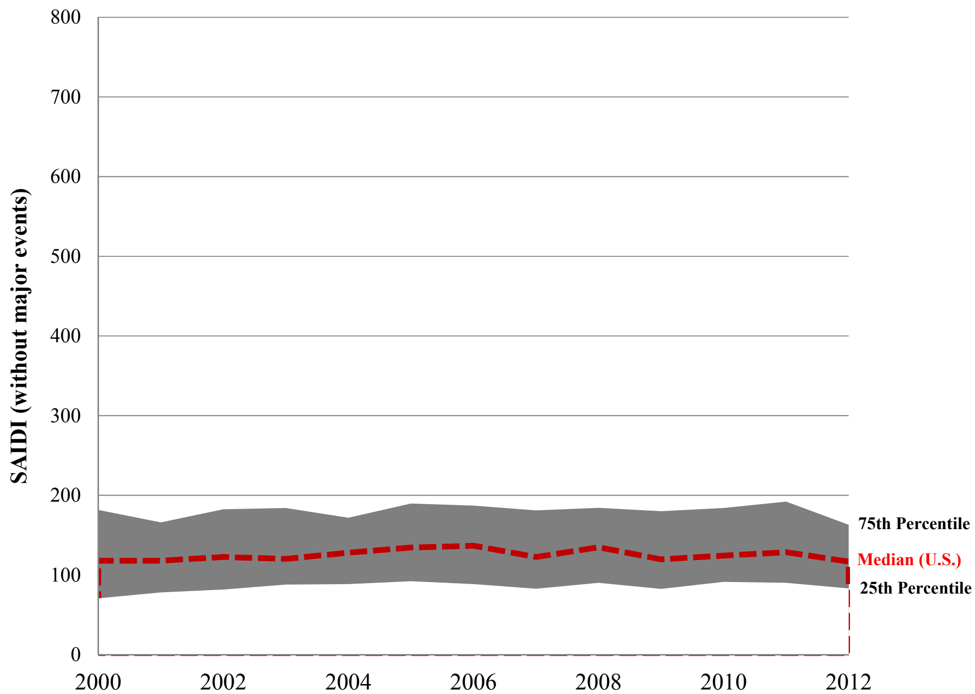

Figure 3. System average interruption duration index over time (all utilities in this study; without major events; minutes)

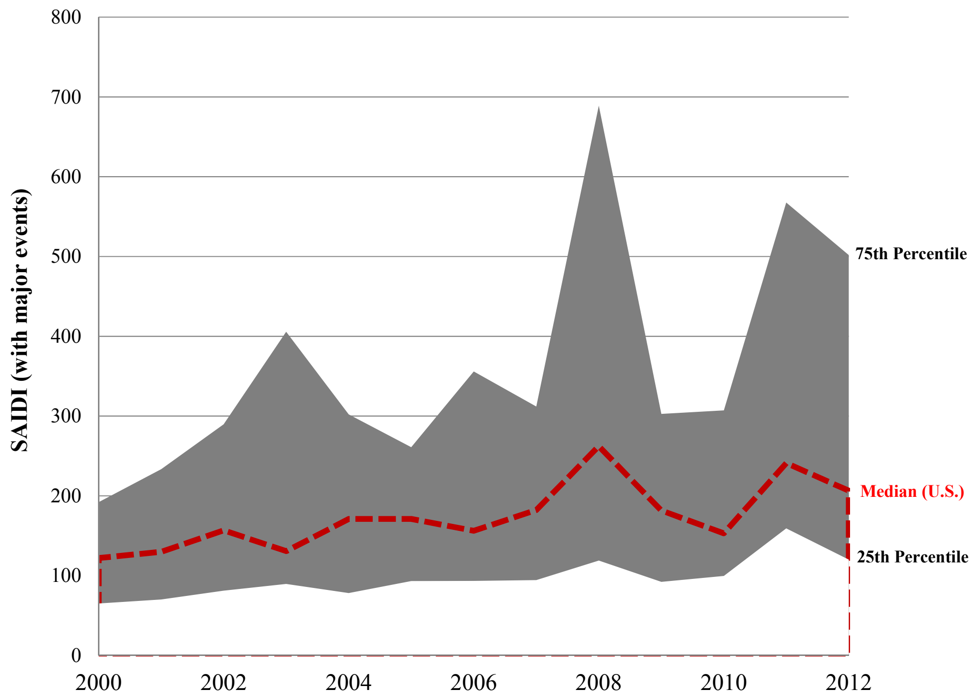

Figure 4. System average interruption duration index over time (all utilities in this study; with major events included; minutes)

Figure 5 and Figure 6 show the middle 50% range of SAIFI values for utilities used in this study without and with major events included, respectively. The pronounced effect of major events (i.e., storms) on the duration and frequency of outages can be seen in Figure 4 and Figure 6, respectively. The figures also show a fairly flat time trend for the reliability data without major events, but a slightly increasing trend for outages with the inclusion of major events.

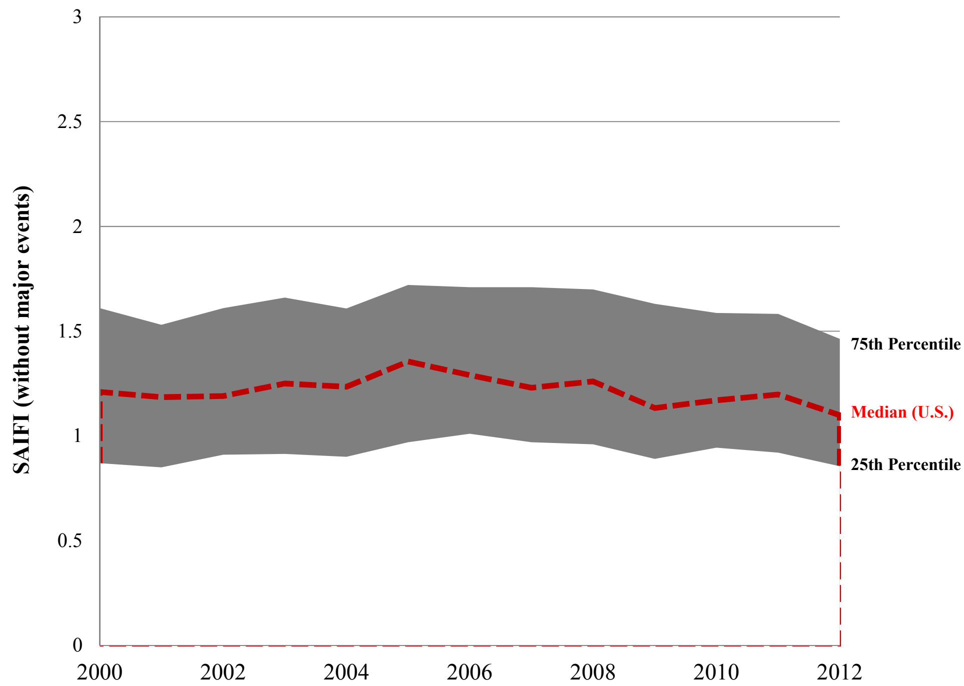

Figure 5. System average interruption frequency index over time (all utilities in this study; without major events)

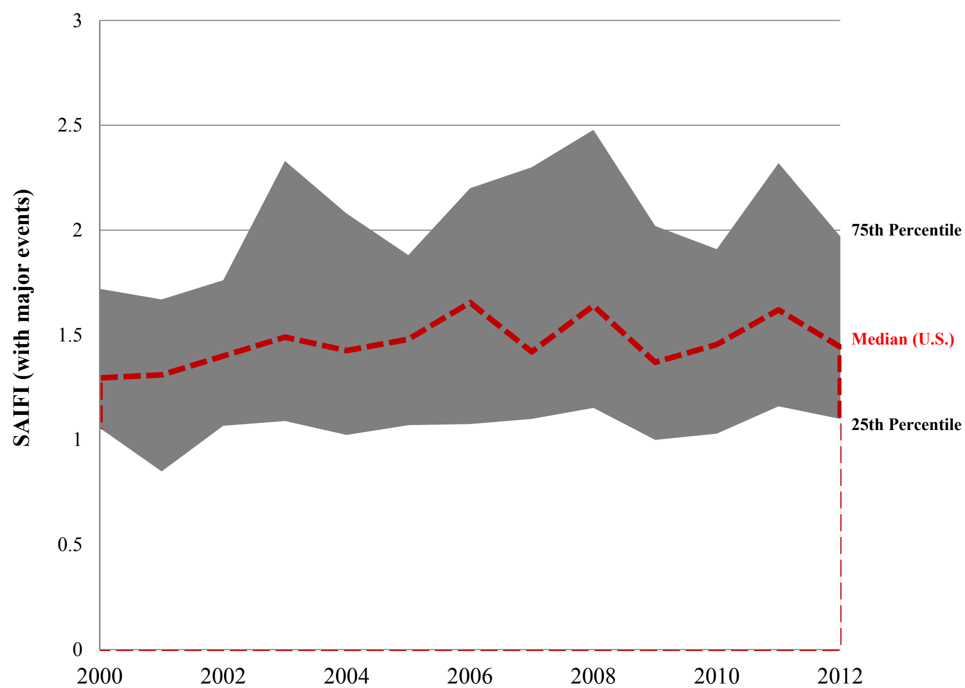

Figure 6. System average interruption frequency index over time (all utilities in this study; with major events)

1.6.2 Utility Characteristics

Larsen et al. (2015) also collected important characteristics of utilities that might be correlated with long-term reliability including:

- Annual operations and maintenance (O&M) expenditures on transmission and distribution (T&D)
- Total number of miles of T&D lines
- % share of the utility lines that are underground versus overhead
- Retail electricity sales
- Year when the utility installed/upgraded an automated outage management systems (OMS)

Information about total annual T&D O&M spending was collected from the fee-based Ventyx Velocity Suite system via FERC Form 1 (FERC 2014) and the U.S. Department of Agriculture Rural Utilities Service (U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx 2015). Total T&D O&M spending includes both fixed and variable expenses[5] and was converted to real 2012 dollars using the Handy-Whitman index of T&D costs (Whitman, Requardt and Associates 2013). T&D line miles, which are also reported on FERC Form 1, were also collected from the Ventyx Velocity Suite.

Larsen et al. (2015) also collected information from publicly-available sources identifying the year when the utility installed/upgraded an OMS. OMS are automated technologies that collect information on utility reliability (Larsen et al. 2015; Eto et al. 2012). More specifically, OMS record the number of customers who are without power as well as the duration of the interruption. Eto et al. (2012) found that OMS

[5] Larsen et al. (2015) combined transmission and distribution O&M expenses into a single metric. In the future, however, it might be useful to decouple the combined expenditures into four distinct categories: (1) proactive transmission expenditures; (2) reactive transmission expenditures; (3) proactive distribution expenditures; and (4) reactive distribution expenditures.

installations or upgrades were correlated with a decrease in reported reliability in the following year. Eto et al. (2012) attributed this to a change in the accuracy of reliability reporting and not necessarily to a change in reliability experienced by customers.

Larsen et al. (2015) obtained retail electricity sales for each utility from information collected by the U.S. Energy Information Administration via Form 861 (EIA 2013). Information was also collected on total annual number of residential, commercial, and industrial customers served by each utility from the same EIA form.

1.6.3 Annual Measures of Weather

Weather is, perhaps, the most obvious cause of power interruptions. Eto et al. (2012) identified the need to collect more robust information on a wide variety of weather variability measures—and to evaluate how these measures were related to reliability. Specifically, Larsen et al. (2015) assembled annual weather information for each utility's service territory including:

- heating degree-days
- lightning strikes
- wind speeds
- precipitation
- cooling degree-days

Information on lightning strikes is collected from the Vaisala National Lightning Detection Network (NLDN) (NLDN/LBNL 2013). NLDN provides flash detection efficiency of 95% and thunderstorm detection efficiency greater than 99%. Larsen et al. (2015) 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 the analysis dataset. Utility lightning strikes were then aggregated to an annual total for each utility in the study.

Annual precipitation data across the United States is collected by the National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) and then made available through the Ventyx Velocity Suite database (NCDC/Ventyx 2014). Ventyx analysts, working with LBNL staff, then compiled the daily precipitation data for each weather station within each utility service territory for every year (2000–2012). Ventyx summed up daily precipitation at each station in a given year and then finally calculated an average across all stations to estimate an annual total precipitation value per utility (Larsen et al. 2015).

The NCDC also collects data for wind speeds for thousands of weather stations across the country. Ventyx analysts, working with LBNL staff, assigned wind speed measurements to utilities identified in this analysis (NCDC/Ventyx 2014). This data was averaged in a manner similar to the technique described above for precipitation.

Annual heating (HDD) and cooling degree-days (CDD) were collected for each utility service territory in order to examine the relationship between high (low) temperatures and electricity reliability.[6] Larsen et al. (2015) obtained temperature data from the Velocity Suite database via the National Oceanic & Atmospheric Administration's National Climatic Data Center (NCDC) (NCDC/Ventyx 2013). Ventyx analysts provided Larsen et al. (2015) with HDD and CDD data at the utility service territory level within each state.

[6] HDD and CDD were originally developed to assess heating or cooling requirements for facilities. HDD and CDD are measures of temperature that are calculated by subtracting the average between the daily high and low temperature from a reference value (e.g., 65 degrees Fahrenheit). The reference point is intended to represent the temperature below or above which heating or cooling is required, respectively.

1.7 Analysis Method and Base Model

The analysis framework described in this section is predicated on follow-up research identified by Eto et al. (2012). A number of effects are evaluated including more disaggregated measures of weather variability (e.g., lightning strikes and severe storms), other utility characteristics (e.g., the number of customers per line mile, and the extent to which transmission and distribution lines are overhead versus underground), and utility spending on transmission and distribution operations and maintenance. This section begins with a description of the generalized method used for the econometric regression. Next, a base set of models are identified through the use of robustness testing and characteristics of the untransformed data set are presented.

1.7.1 Generalized Analysis Method

As originally discussed in Eto et al. (2012), the type of panel data used in this study is considered "short" (Cameron and Trivedi 2009) because the data structure has 150–200 utilities, but a relatively small number of temporal points (i.e., thirteen years). In addition, the dataset is also "unbalanced" (Wooldridge 2002) because there are missing reliability metrics—and other regressors—for a number of utility-year combinations. In summary, the analysis that follows is based on a short, unbalanced panel data set.

A multivariate regression technique is employed to generate quantitative estimates of the correlation between a dependent variable (e.g., SAIDI or SAIFI) and a set of independent—or explanatory—variables. The following regression equation was used in order to analyze the effect of weather observations; T&D O&M expenditures; sales; the presence of outage management systems (OMS); and line miles—above and below ground—on the frequency and total annual number of minutes of electric utility reliability events.

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

The general model specification described in Equation (3) above follows the general form used in earlier energy-related multivariate panel regressions (e.g., see Erdogdu 2011; Eto et al. 2012). In Equation (3), annual utility reliability is represented by the dependent variable: Y_{it}—which is logged. Electric utility and reporting year are represented by subscript $_i$ and $_t$, respectively. Subscript $_d$ and $_f$ are used to differentiate between observed and unobservable variables, respectively—and X_{di} and Z_{fi} represent observed and unobservable variables. For example, variables in X may include annual T&D expenditures 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 to capture an annual time trend.

As indicated above, the array of Z_{fi} variables are unobservable. Accordingly, a new term is defined, 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.

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

The presence of the α_i component within this model is "crucially important" (Erdogdu 2011), because it assumes that not all of the explanatory variables are captured in the array of X observable variables. If all explanatory variables were captured in the array of observable variables, then the α_i term may be eliminated from the model and a pooled ordinary least squares (OLS) regression technique would be appropriate (Erdogdu 2011). As indicated earlier, there are a number of explanatory factors, which have not been collected by electric utilities with any degree of precision or consistency. For this reason, it is appropriate to leave the α_i term in the model and conduct the econometric analysis assuming the presence of unobservable fixed (or random) effects.

1.7.2 Raw Data Characteristics

Table 3 and Table 4 below contain summary statistics for the raw panel datasets without and with major events, respectively. For example, these tables show that the average total annual duration of customer interruptions (SAIDI) is 140 minutes (two hours and twenty minutes) when major events are not included from the metric, but 372 minutes (six hours and twelve minutes) when major events are 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 operations and maintenance (O&M) expenditures ($2012 per customer)	2,084	$4.4	$883.0	$239.8	$52,261.0	$2,328.4

These tables also show that the average annual frequency of customer interruptions (SAIFI) is 1.4 events when major events are excluded from the metric, and 1.8 events when major events are included. Interestingly, these two tables show that inclusion of major events in the calculation of reliability increases the average frequency of interruptions by approximately 30% and the average duration of interruptions by more than 250%.[7]

[7] 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.,

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 O&M expenditures ($2012 per customer)	1,499	$4.4	$734.6	$235.1	$11,076.0	$1,659.2

1.7.3 Data Transformations

A number of these independent variables are transformed before conducting the regression analysis. First, new correlates are developed to evaluate the effect of abnormal weather. Next, a number of quadratic weather terms are incorporated to explore the possibility that reliability and abnormal weather is related in a non-linear

---

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, extreme outliers were investigated 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 (regression software) or manually (author) 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, Seven more utilities were manually excluded that had covariates and dependents containing at least three years of continuous data, but the blocks of annual data were misaligned (i.e., unbalanced). Finally, two additional utilities were excluded prior to conducting the first econometric analysis, because (1) these utilities failed the outlier screen and (2) it was not possible to independently confirm that their reported reliability performance metrics were inaccurate.

fashion. Finally, the possibility that previous year expenditures affect subsequent year reliability performance metrics is considered.

Incorporation of metrics to capture "abnormal" annual weather

A hypothesis was tested to evaluate whether utilities make strategic decisions related to reliability partially based on normal (i.e., average) weather conditions. In other words, it was hypothesized that warmer/cooler/wetter/drier/windier/etc.-than-average years will be correlated with measurable changes in the duration and/or frequency of power interruptions. To test this hypothesis, a number of metrics were developed to capture "abnormal" atmospheric conditions. The vector of weather correlates ($\vec{\boldsymbol{W}}$) were transformed into pairs of positive (see Equation 5) and negative (see Equation 6) deviations from the thirteen-year average.

$$\overset{+}{\Delta}\vec{\mathrm{W}}_{it}\begin{cases}\dfrac{\left(\mathrm{W}_{it}-\overline{\mathrm{W}}_{i}\right)}{\overline{\mathrm{W}}_{i}}\times 100, \text{ if} & \dfrac{\left(\mathrm{W}_{it}-\overline{\mathrm{W}}_{i}\right)}{\overline{\mathrm{W}}_{i}}\times 100>0\\ 0, \text{ if} & \dfrac{\left(\mathrm{W}_{it}-\overline{\mathrm{W}}_{i}\right)}{\overline{\mathrm{W}}_{i}}\times 100\leq 0\end{cases} \tag{5}$$

Positive deviations in annual HDDs and CDDs were calculated by subtracting a utility's HDDs (CDDs) in a given year from the utility's historical average for 2000–2012. Accordingly, a pair of abnormally cold (hot) temperature deviation variables were created to test this hypothesis. If the cooling (heating) degree-days in a given year were less than the thirteen-year average, the positive deviation variable was coded with a zero.

Like the temperature variables discussed above, it is assumed that more lightning strikes than an average year will be correlated with measurable reductions in utility reliability. Accordingly, a positive deviation lightning strike variable was created to test this hypothesis. If the lightning strikes in a given year were less than the thirteen-year average, the positive deviation variable was coded with a zero.

It is also hypothesized that higher wind speeds than an average year will be correlated with measurable reductions in utility reliability. Accordingly, a positive deviation wind speed variable was created to test this hypothesis. If the average wind speed in a given year was less than the thirteen-year average, the positive deviation variable was coded with a zero.

Deviations in annual precipitation were calculated by subtracting a utility's precipitation in a given year from the average annual precipitation for 2000–2012. The hypothesis is that wetter (or drier) years than average will be correlated with measurable reductions in utility reliability. In this specific case, a pair of abnormal precipitation deviation variables were created to test this hypothesis. If the total precipitation in a given year (W_{it}) was greater than the thirteen-year average ($\overline{W}_i$), the negative deviation variable was coded with a zero and the positive deviation variable was coded with the percentage difference above the average. Conversely, if the total precipitation in a given year (W_{it}) was less than the thirteen-year average ($\overline{W}_i$), the positive deviation variable was coded with a zero to reflect a drier than normal year and the negative deviation variable was coded to reflect the percentage difference below the average.

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

Addition of non-linear weather metrics

It is possible that the relationship between weather, including temperature, precipitation, and wind—and any corresponding changes in system reliability—are not linear. Hitz and Smith (2004) surveyed the literature on the shape of weather-related infrastructure damage curves concluding that these curves were nonlinear. Larsen et al. (2008) argued that using non-linear indicators would be a "more appropriate" choice for estimating damage to infrastructure. Accordingly, there is a possibility that the weather metrics, with the exception of lightning strikes, are more appropriately modeled 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, this analysis follows the lead of McIntosh and Schlenker (2006) by “first demeaning the covariate and then squaring it, rather than squaring then demeaning”. It is assumed that increases in lightning strikes had a linear relationship with reliability (i.e., lightning strikes affect reliability in a similar fashion regardless of whether there was a 1% increase in the number of strikes or a 5% increase).

Previous year expenditures affecting subsequent year reliability metrics

In addition, fixed and variable O&M costs are lagged by one year to test the hypothesis that expenditures would not have an effect on reliability performance metrics until the following year. 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, multiplied by the Handy-Whitman utility cost index (HW), and normalized by number of customers (see Equation 7).

$$\text{Expenditures}_{\text{it-1}} = \left(\frac{\text{TFC}_{\text{it-1}} + \text{TVC}_{\text{it-1}} + \text{DFC}_{\text{it-1}} + \text{DVC}_{\text{it-1}}}{\text{Customers}_{\text{it}}} \right) \times \left(\frac{\text{HW}_{2012}}{\text{HW}_{\text{t-1}}} \right) \tag{7}$$

1.7.4 Testing for the Presence of Cross-sectional and Random Effects

A two-step process is carried out to determine the preferred effects model for each of the four regressions: (1) SAIDI without major events; (2) SAIDI with major events; (3) SAIFI without major events; and (4) SAIFI with major events. First, an F-test was conducted to detect the presence of cross-sectional effects (i.e., utility-specific effects). Next, if the F-test failed to reject the null hypothesis of no utility effects, a Hausman (1978) test was used to determine whether a fixed effects or random effects model was more appropriate for each of the four reliability metrics evaluated in this analysis.

First, the results of the F-test (see Table 5) indicate 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

Next, Table 6 shows that the Hausman test failed to reject the null hypothesis of random effects for three of the four regressions at $p \leq 0.15$.[8] It is concluded that the random effects model is the preferred choice for interpreting the results from three of the regressions and the fixed effects model is more appropriate for SAIFI (with major events included).[9]

---

8 A significant 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, a Hausman (1978) test was conducted on model specifications that do not include the following time-invariant explanatory variable:investor-owned utility. Future improvements 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.

9 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, two procedures were implemented to ensure that the findings were not biased: (1) increase 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) report in the technical appendix the findings from both the random and fixed effects models. Interestingly, the Hausman test fails to reject the null

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?***
Log of SAIDI—without major events	8.3	7	0.30	No
Log of SAIDI—with major events	5.7	9	0.77	No
Log of SAIFI—without major events	9.2	8	0.33	No
Log of SAIFI—with major events	14.3	9	0.11	Yes

1.7.5 Base Model

Accordingly, the following regression specification was used (see Equation 8) to analyze the effect of the following regressors on the total annual number of minutes of electric utility interruptions: annual positive deviation in heating and cooling degree-days; annual positive deviation in lightning strikes; annual positive and negative deviation in precipitation; annual positive deviation in wind speed (and wind speed squared); lagged T&D O&M expenditures; delivered electricity; number of customers per line mile of T&D extent; the share of T&D line miles underground; and the presence of outage management systems (OMS).

$$\begin{aligned}\ln(\mathrm{SAIDI}_{it}) = {} & \beta_1 + \beta_2\mathrm{Sales} + \beta_3\mathrm{Expenditures} + \beta_4\mathrm{PostOMS} + \beta_5\mathrm{OMS} + \beta_6\mathrm{Cold} + \beta_7\mathrm{Warm} \\ & + \beta_8\mathrm{Lightning} + \beta_9\mathrm{Windy} + \beta_{10}\mathrm{Windy}^2 + \beta_{11}\mathrm{Wet} + \beta_{12}\mathrm{Dry} + \beta_{13}\mathrm{Year} \\ & + \beta_{14}\mathrm{Customers} + \beta_{15}\mathrm{Underground} + \upsilon_{it}\end{aligned} \tag{8}$$

Three of the four regressions were configured as a one-way random effects model, where the error term, υ_{it}, is specified as $\upsilon_{it} = \alpha_i + \varepsilon_{it}$ and α_i are the utility effects. In these models, the variance components for the one-way random effects are obtained using a specialization (Baltagi and Chang 1994) of the approach used by Wansbeek and Kapteyn (1989) for unbalanced two-way models (SAS Institute 2014).[10] In the

hypothesis for the SAIDI regressions indicating that the random effects model is the preferred model for regressions related to the duration of interruptions.

[10] According to the SAS Institute's PROC PANEL documentation, the "estimation of the variance components is performed by using a quadratic unbiased estimation (QUE) method. This involves

case of the lone fixed effects model, the error term, υ_{it}, is specified as $\upsilon_{it} = \gamma_i + \varepsilon_{it}$ where γ_i are the nonrandom parameters to be estimated (SAS Institute 2015a).

The following regression specification was used (see Equation 9) to analyze the effect of the following regressors on the *frequency* of electric utility interruptions: annual positive deviation in heating and cooling degree-days; annual positive deviation in lightning strikes; annual positive and negative deviation in precipitation; annual positive deviation in wind speed (and wind speed squared); lagged T&D O&M expenditures; delivered electricity; number of customers per line mile of T&D extent; the share of T&D line miles underground; and the presence of outage management systems (OMS).

$$\begin{aligned}\ln(\text{SAIFI}_{it}) = {} & \beta_1 + \beta_2\text{Sales} + \beta_3\text{Expenditures} + \beta_4\text{PostOMS} + \beta_5\text{OMS} + \beta_6\text{Cold} + \beta_7\text{Warm} \\ & + \beta_8\text{Lightning} + \beta_9\text{Windy} + \beta_{10}\text{Windy}^2 + \beta_{11}\text{Wet} + \beta_{12}\text{Dry} + \beta_{13}\text{Year} \\ & + \beta_{14}\text{Customers} + \beta_{15}\text{Underground} + \upsilon_{it}\end{aligned} \tag{9}$$

1.7.6 Base Model Robustness and Performance of Alternative Models

A series of robustness tests and analyses are conducted of alternative model configurations to confirm the base model findings. Hoen et al. (2009) evaluated the impact of wind power projects on residential property values by evaluating base model robustness considering a number of criteria including model: (1) performance (i.e., fit); (2) parsimony (i.e., smallest number of covariates); and (3) coefficient stability. Accordingly, this process follows the lead of Hoen et al. (2009) and evaluates base and alternative model performance, parsimony, and coefficient stability.

The additive modeling approach started with the Eto et al. (2012) model configuration ("Model A") and sequentially incorporated groupings of regressors that were of interest. This sequential modeling approach allows for an evaluation of whether the incorporation of abnormal weather, non-linear weather metrics, ownership type,

focusing on quadratic forms of the centered residuals, equating their expected values to the realized quadratic forms, and solving for the variance components" (SAS Institute 2014).

and/or expenditures improve model performance, while not violating the preference of econometricians to use “simpler, more parsimonious statistical models” (Hoen et al. 2009; Newman 1956). Table 7 shows the regressors included in the base models (Model F) as well as six alternative model configurations.

Table 7. Parameters for base model and six alternatives

		Base model specification:						
		A	B	C	D	E	F	G
Reliability metric:	**SAIDI (without major events)**						✓	
	SAIDI (with major events)						✓	
	SAIFI (without major events)						✓	
	SAIFI (with major events)						✓	
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							●	●

As discussed earlier, Model A, which is a close proxy[11] to the Eto et al. (2012) configuration, includes the following independent 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. Model B extends Model A by replacing the basic temperature metrics with abnormal measures of temperature, precipitation, wind speed, and lightning. Model C also incorporates non-linear weather terms and Model D builds on Model C by also including previous year transmission and distribution O&M expenditures. Model E removes non-linear weather terms with the exception of wind speed and it also includes customers per line mile. Model F is similar to model E, but it also includes share of underground T&D line miles. Model G includes all regressors with the exception of absolute heating and cooling degree-days.

Table 7 shows that sequentially adding groupings of regressors related to abnormal weather, non-linear weather metrics, and expenditures generally increases model performance as measured by both increased adjusted/generalized r-squared and decreased root mean square error (RMSE). 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 relatively lower BIC statistic indicates that the subsequent model configuration is relatively more parsimonious than the previous configuration.

As shown in Table 8, the BIC statistic both increases and decreases from Model A through Model C, but then consistently decreases as the previous year expenditures, customers per line mile, and share of underground miles regressors are incorporated into the model. Technical Appendix A contains full regression results for all seven models for each of the four reliability metrics. The technical appendix also shows that the coefficients remain stable—that is, the same regressors generally remain

[11] There are relatively minor differences between Eto et al. (2012) and Model A. In Model A, sales are normalized by number of customers and utility-specific annual heating/cooling degree-days are used. In contrast, 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.

significant at $p \leq 0.10$ and the signs on the coefficients do not switch from positive to negative (or vice versa).

Table 8. Performance statistics for base model (model A) and six alternatives

		Model specification:						
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 (RMSE)	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
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
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
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

For the SAIDI regressions, 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 has less parsimony. For these reasons, Model F is the preferred choice for interpreting the results from the SAIDI regressions.

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. Given its higher performance and that the coefficients are stable for all models under consideration; Model F is the preferred choice for the SAIFI regressions.

Comment on sample size decrease from Model E to Model F

It is observed that the number of utilities represented in the empirical findings significantly decreased as the share of underground line miles is incorporated as a regressor into the model specification. Technical Appendix A shows that the number of utilities modeled drops by ~50% between Models E and F. Not surprisingly, a relatively large number of utilities did not report information on underground T&D line coverage. This under-reporting of undergrounded line miles significantly impacted the final number of utilities used in the Model F and G regressions.

Despite this decrease in the number of utilities modeled, the U.S. Department of Energy has indicated that widespread power outages, which are often caused by severe storms, "inevitably lead to discussions about burying electric utility transmission and distribution (T&D) infrastructure" (USDOE 2012). For this reason, it is important to include the share of underground line miles variable in the base model as a potential correlate with long-term electric utility reliability.

1.8 Principal Findings

This section describes the principal findings from this analysis. Table 9 and Table 10 show results for the SAIDI and SAIFI panel regressions with and without the effect of major events for the *base* models (see previous sections). Results for all model specifications (pooled OLS, fixed, random) and reliability metrics (SAIDI and SAIFI—with and without major events) are presented in the Technical Appendix.

1.8.1 Increasing Outage Frequency and Total Number of Minutes Customers are Without Power

If major events are included in SAIDI and SAIFI, reliability events are increasing in frequency and the total minutes customers are without power is also increasing. The total outage minutes and frequency of reliability events have increased approximately 10% (Table 9) and 1% (Table 10) per year since 2000, respectively. However, only the time trend within the duration regression is statistically significant. This time trend associated with major events suggests that severe weather-related impacts (or how they are being defined and/or reported) are becoming slightly more frequent, but this increase in weather-related events is strongly correlated with relatively longer total amounts of time customers are without power.

Table 9. Results for SAIDI regressions

	Dependent variable:	
Explanatory variables:	**Log of SAIDI (without major events)**	**Log of SAIDI (with major events)**
Intercept	-21.218 (13.53)	-185.236*** (49.627)
Electricity delivered (MWh per customer)	0.002 (0.002)	0.004 (0.015)
Abnormally cold weather (% above average HDDs)	0.001 (0.001)	0.004 (0.013)
Abnormally warm weather (% above average CDDs)	0 (0.001)	-0.008* (0.004)
Abnormally high # of lightning strikes (% above average	0.001 (0)	0.001 (0.002)
Abnormally windy (% above average wind speed)	0.021** (0.009)	0.121*** (0.031)
Abnormally windy squared	-0.002** (0.001)	-0.007*** (0.002)
Abnormally wet (% above average total precipitation)	0.002 (0.002)	0.01* (0.005)
Abnormally dry (% below average total precipitation)	0.001 (0.002)	0.001 (0.005)
Outage management system?	0.037 (0.049)	0.128 (0.136)
Years since outage management system installation	-0.007 (0.009)	-0.02 (0.025)
Year	0.013* (0.007)	0.095*** (0.025)
Lagged T&D O&M expenditures ($2012 per customer)	-0.005 (0.026)	0 (0.07)

Explanatory variables:	Dependent variable: Log of SAIDI (without major events)	Log of SAIDI (with major events)
Number of customers per line mile	-0.003 (0.003)	0.006 (0.007)
Share of underground T&D miles to total T&D miles	-0.002 (0.004)	-0.014** (0.007)
Degrees of freedom:	523	335
Number of utilities:	63	46
Generalized R^2 (Buse 1973)	0.05	0.14
Root mean square error	0.26	0.73
Utility effects:	Random	Random

Notes:

Standard errors are presented in parentheses underneath coefficient.
*** 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

If major events are not included in SAIDI and SAIFI, total minutes customers are without power is increasing and these events are becoming slightly more frequent. However, there is no statistically significant trend in the frequency of events, while there is a statistically significant increase in the total minutes customers are without power when major events are not included (~1% increase per year).

Table 10. Results for SAIFI regressions

Explanatory variables:	Dependent variable: Log of SAIFI (without major events)	Log of SAIFI (with major events)
Intercept	-8.622 (15.225)	-23.488 (20.295)
Electricity delivered (MWh per customer)	0.002 (0.002)	-0.005 (0.011)
Abnormally cold weather (% above average HDDs)	-0.001 (0.001)	0.002 (0.005)
Abnormally warm weather (% above average CDDs)	0 (0.001)	0 (0.001)
Abnormally high # of lightning strikes (% above average	0 (0.001)	0.002** (0.001)
Abnormally windy (% above average wind speed)	0.023** (0.011)	0.04*** (0.012)
Abnormally windy squared	-0.002** (0.001)	-0.003*** (0.001)
Abnormally wet (% above average total precipitation)	-0.001 (0.001)	0.002 (0.001)

Explanatory variables:	Dependent variable: Log of SAIFI (without major events)	Log of SAIFI (with major events)
Abnormally dry (% below average total precipitation)	0.001 (0.001)	0.003* (0.002)
Outage management system?	0.003 (0.038)	-0.02 (0.051)
Years since outage management system installation	-0.003 (0.006)	0 (0.012)
Year	0.004 (0.008)	0.012 (0.01)
Lagged T&D O&M expenditures ($2012 per customer)	-0.02 (0.021)	-0.069 (0.184)
Number of customers per line mile	-0.004** (0.002)	0.008 (0.005)
Share of underground T&D miles to total T&D miles	0.001 (0.002)	-0.001 (0.004)
Degrees of freedom:	522	292
Number of utilities:	63	46
Generalized R^2 (Random); Adjusted R^2 (Fixed)	0.03	0.71
Root mean square error	0.24	0.26
Utility effects:	Random	Fixed

Notes:

Standard errors are presented in parentheses underneath coefficient.
*** 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% leve

1.8.2 Differences between Utilities that have Consistently Reported Reliability Information and Those that Have Not

This analysis evaluates whether electric utility reliability performance—when major events are included—continues to decline regardless of whether utilities reported all thirteen years of reliability metrics (2000–2012), or an incomplete panel of reliability information (i.e. no more than two years of missing reliability metrics). The hypothesis is that utilities which have relatively weaker reliability performance may be inclined to avoid reporting SAIDI and/or SAIFI information consistently over time.

Interestingly, both the annual total minutes and frequency of outages increases even further if the analysis dataset is restricted to only include utilities that provide the full thirteen years of reliability data. Figure 7 shows that the duration of outages is increasing, with strong statistical significance, by approximately 10% per year for the full panel data set and 10% per year for the panel dataset that contains utilities who have consistently reported SAIDI every year. Furthermore, the frequency of outages is increasing, again with strong statistical significance, by approximately 1% per year for the full panel data set and ~3% per year for the panel dataset that only contains utilities who have consistently reported SAIFI every year. Technical Appendix C contains the full results from this analysis.

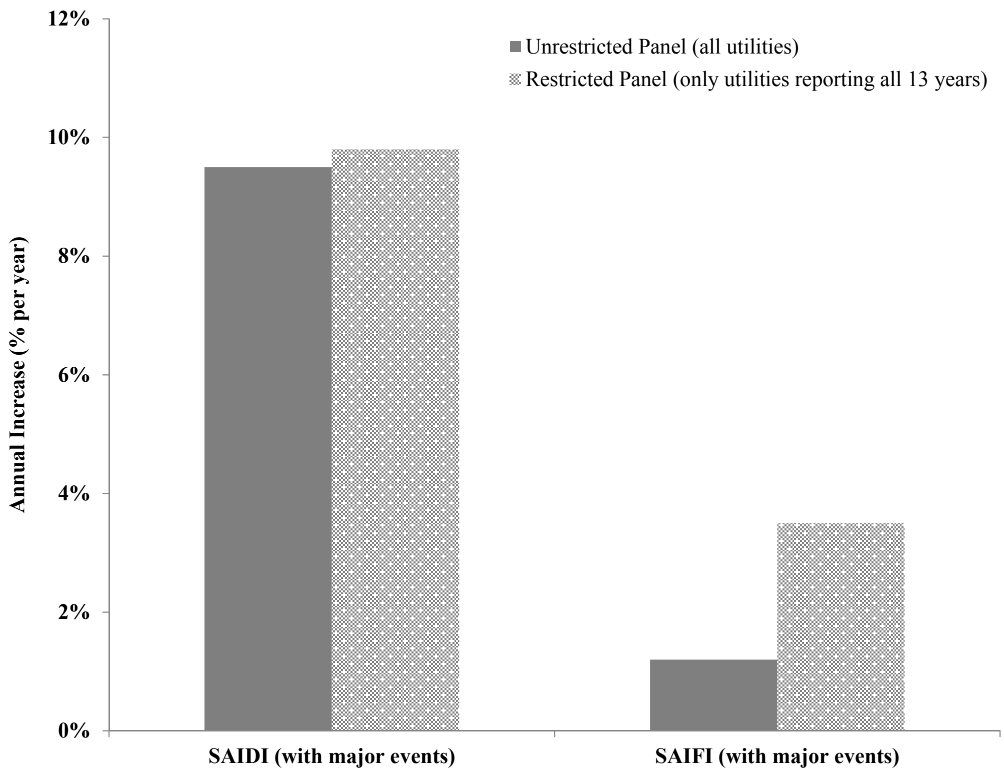

Figure 7. Restricted and unrestricted panel regression results for annual trend (YEAR)

1.8.3 Factors that are Correlated with the Total Number of Minutes of Reliability Events

If major events are included, the following are observed for the random effects model (Model F):

- 10% increase in annual precipitation—above the thirteen-year average—is correlated with a 10% increase in the total annual duration of reliability events
- 10% increase in the number of cooling degree-days (i.e., warmer weather) is correlated with a 8% decrease in the total annual duration of interruptions
- 5% increase in annual average wind speed is correlated with a 56% increase in the total annual duration of reliability events (see Figure 8); 10% increase in annual average wind speed is correlated with a 75% increase in the total annual duration of reliability events
- 10% increase in the percentage share of underground line miles is correlated with a 14% reduction in the total annual duration of interruptions

Above-average precipitation and wind speed are correlated with longer total annual minutes of interruptions, and warmer than average temperatures and increased line miles undergrounded are correlated with shorter total annual minutes of interruptions; however, no other potential factors, except for the time trend, are statistically significant in the random effects model (when major events are included).

If major events are not included, the following statistically significant results are observed for the random effects model (Model F):

- 5% increase in annual average wind speed is correlated with a 5% increase in the total annual duration of reliability events (see Figure 8); 10% increase in annual average wind speed is correlated with a 2% decrease in the total annual duration of reliability events

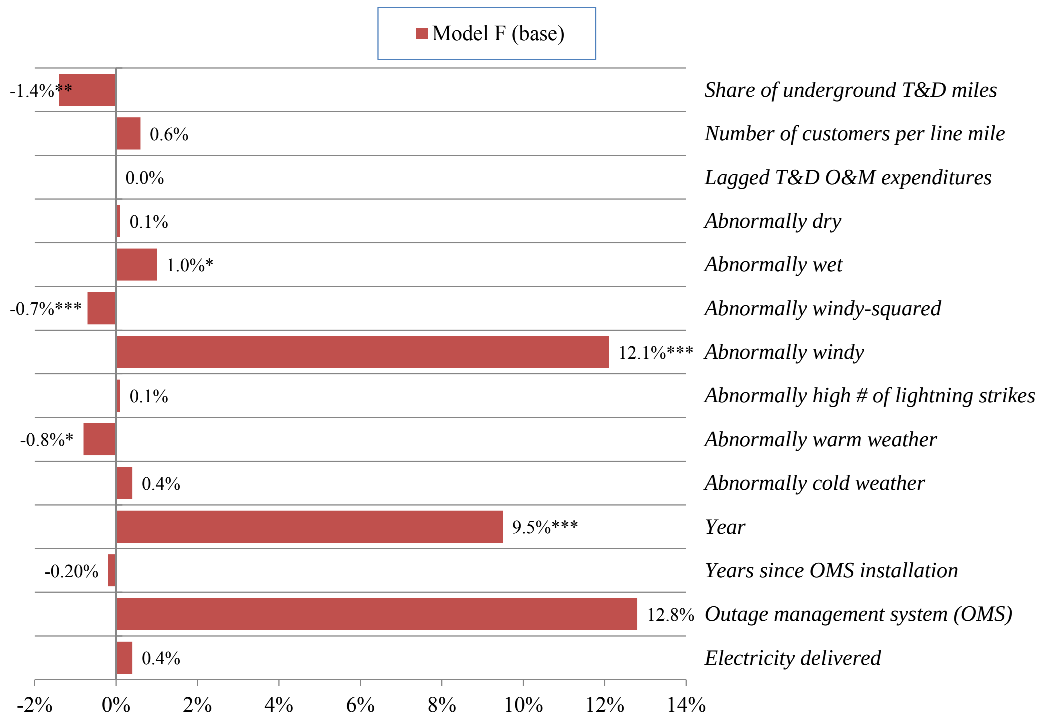

Figure 8. Percentage change in SAIDI (with major events included)

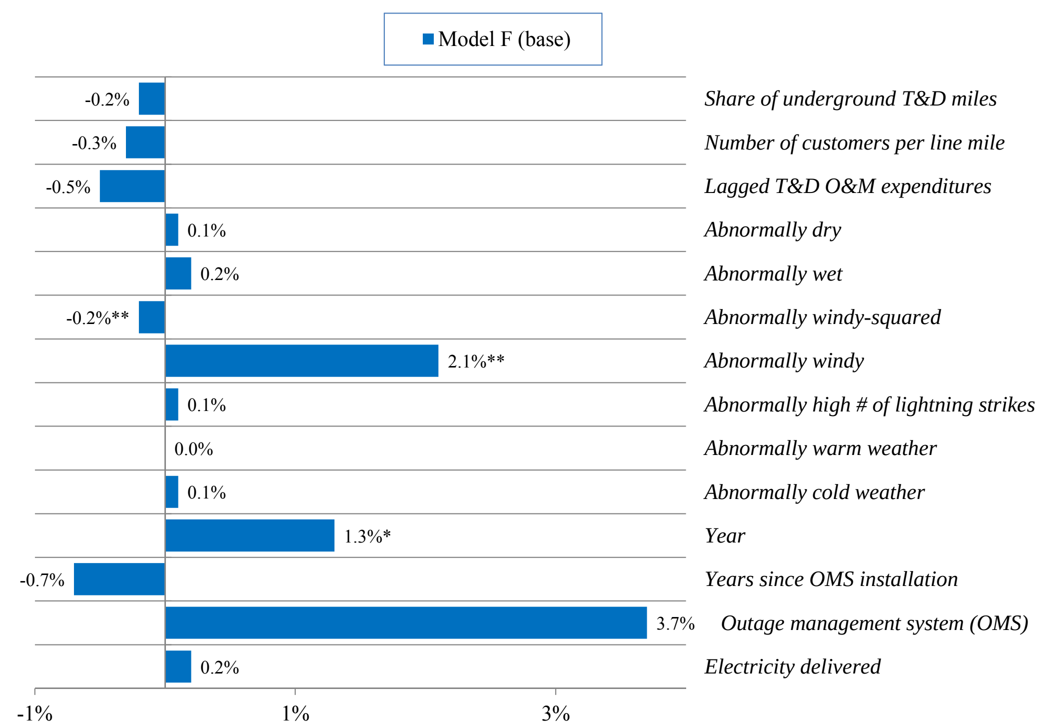

Figure 9. Percentage change in SAIDI (without major events included)

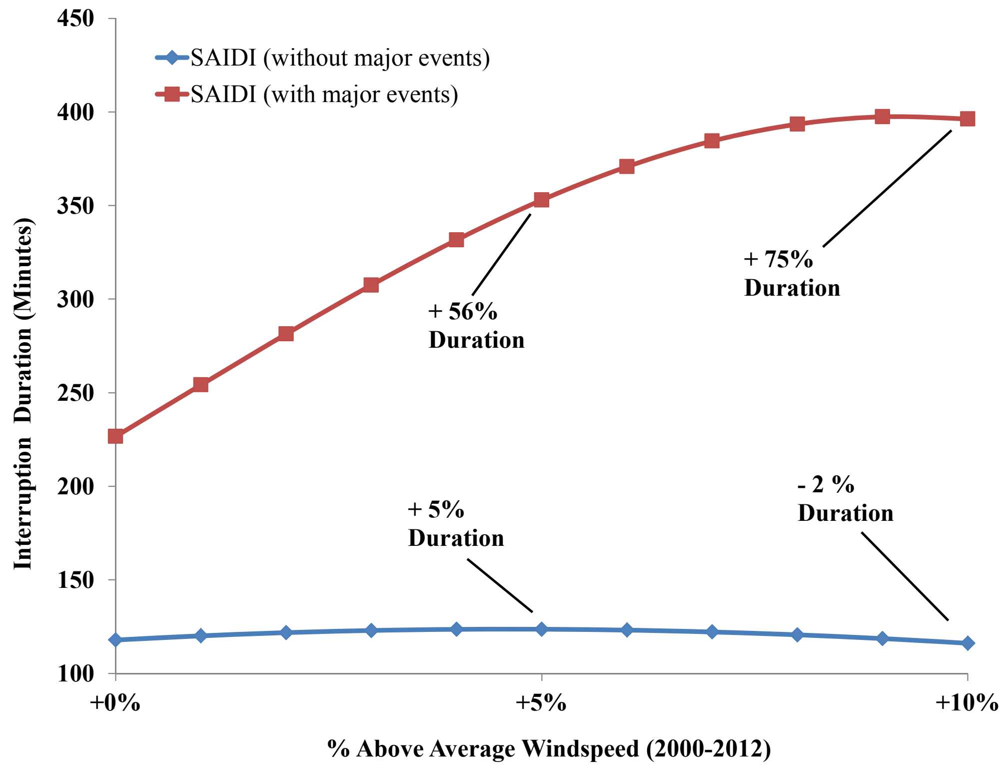

Figure 10. Above-average wind speed and duration of interruptions (SAIDI)

1.8.4 Factors Correlated with the Frequency of Reliability Events

If major events are included, the following is observed:

- 10% increase in annual lightning strikes is correlated with a 2% increase in the frequency of reliability events
- 5% increase in annual average wind speed is correlated with a 14% increase in the frequency of interruptions (see Figure 10); 10% increase in annual average wind speed is correlated with a 15% increase in the frequency of interruptions
- 10% decrease in average total precipitation is correlated with a 3% increase in the frequency of interruptions

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).

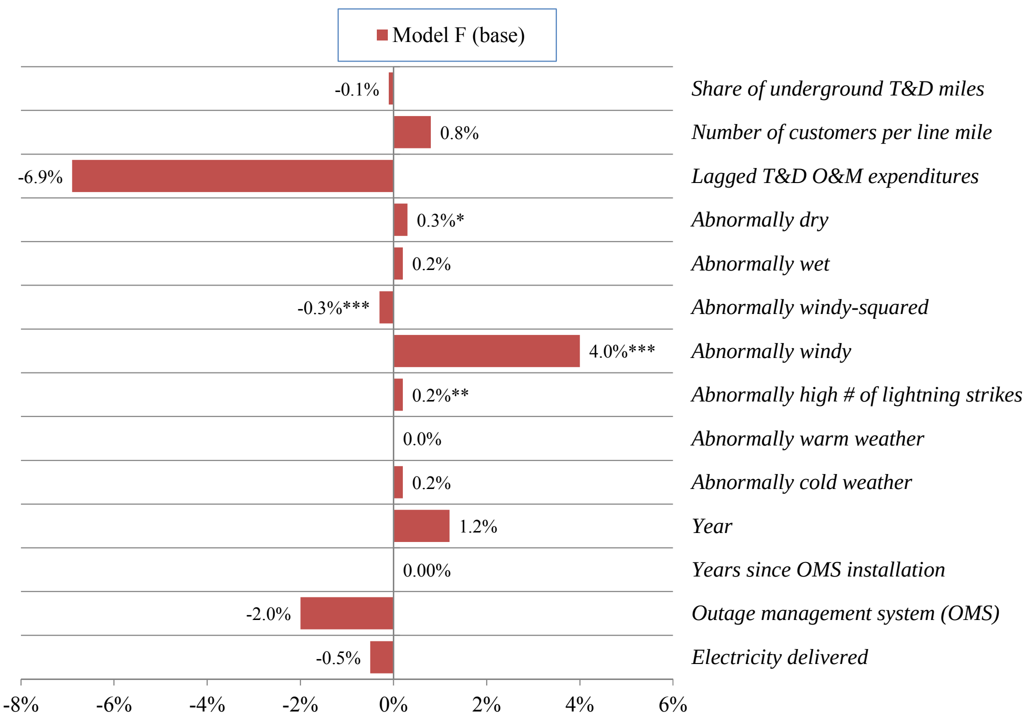

Figure 11. Percentage change in SAIFI (with major events included)

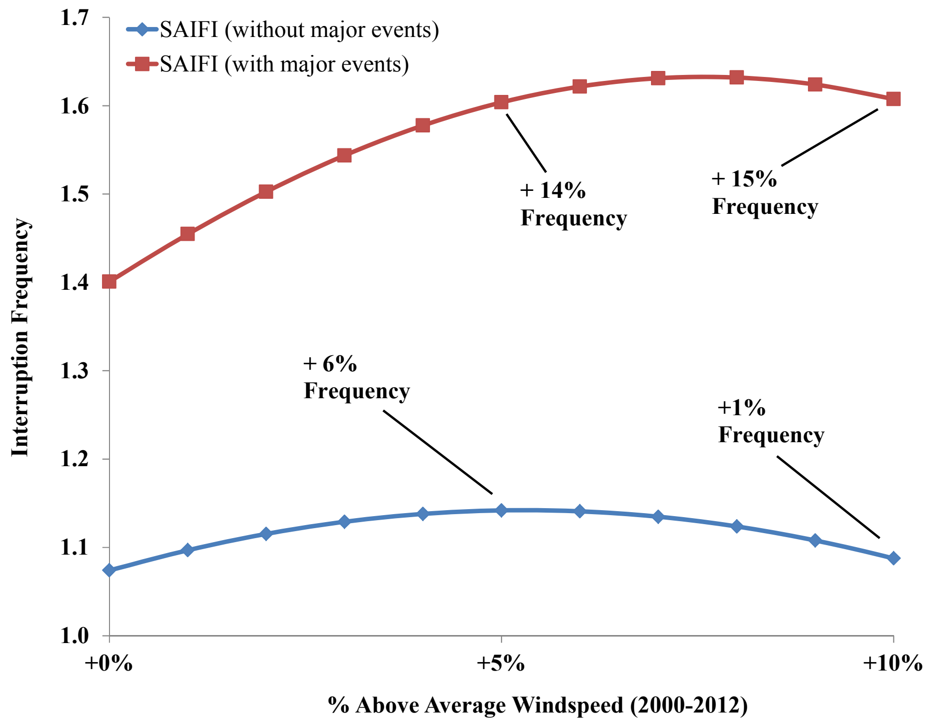

Figure 12. Above average wind speed and frequency of interruptions (SAIFI)

If major events are not included, the following statistically significant results are observed for the random effects model (Model F):

- 10% increase in the number of customers per line mile is correlated with a 4% decrease in the frequency of interruptions

- 5% increase in annual average wind speed is correlated with a 6% increase in the frequency of reliability events (see Figure 12); 10% increase in annual average wind speed is correlated with a 1% increase in the frequency of reliability events

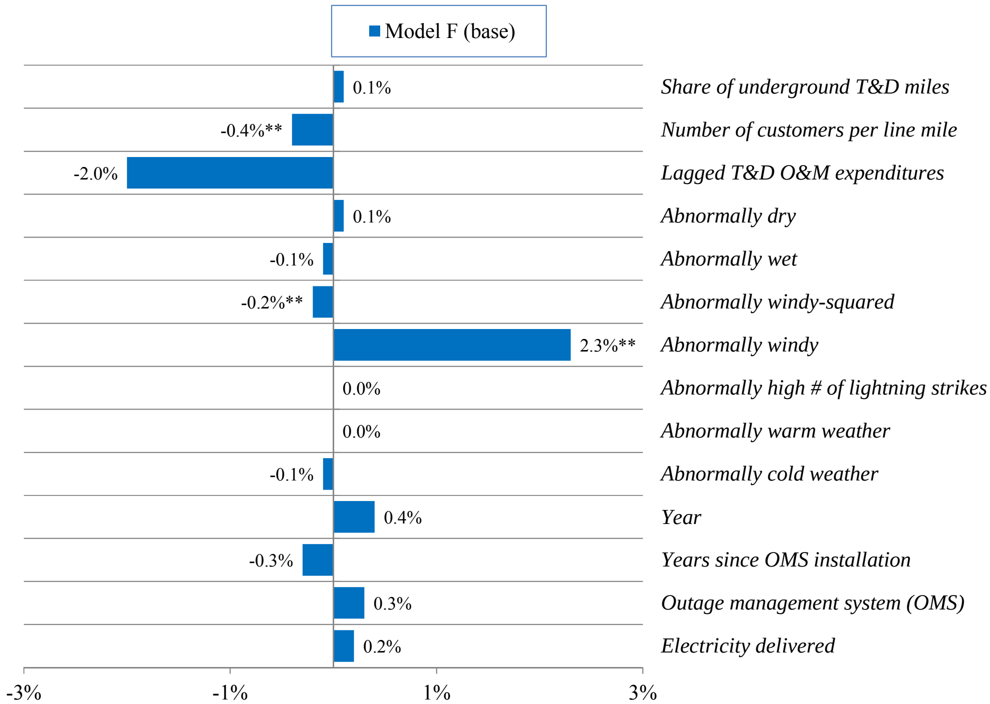

Figure 13. Percentage change in SAIFI (without major events included)

Above-average wind is correlated with more frequent interruptions. Higher population density is correlated with less 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, there is no statistically significant correlation between the installation of OMS (or years since the installation) and the frequency of interruptions.

1.9 Assessment, Discussion, and Caveats

This section compares these findings to the Eto et al. (2012) study. In addition, considerations are discussed in this effort to seek statistically significant correlations for (1) the annual reliability time trend when performance information is inconsistently reported by utilities; and (2) observed reliability and utility transmission and distribution spending. This section concludes with a short discussion of the limitations of the present study.

1.9.1 Comparison to Previous Findings

Overall, the results show that electric utility reliability is generally getting worse over time, but the annual increase in three of the four reliability metrics is not as pronounced as was first reported in Eto et al. (2012). However, SAIDI—when major events are included—is increasing 9.5% each year in this study compared to 2.6% annually in Eto et al. (2012). In summary, when major events are included, it appears that the frequency of these events are decreasing—when compared to Eto et al. (2012) —but the total annual duration of time that customers are without power is significantly increasing. Table 11 summarizes the difference between the Eto et al. (2012) study and the current study.

Table 11. Comparison of annual trend in reliability metrics (% per year)

Reliability metric:	Eto et al. (2012)	Current study
SAIDI (with major events)	2.6%***	9.5%***
SAIDI (without major events)	6.5%***	1.3%*
SAIFI (with major events)	2.1%***	1.2%
SAIFI (without major events)	3.3%***	0.4%

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

1.9.2 Discussion of Findings for Utility Transmission and Distribution O&M Spending

The a priori expectation was that increased O&M spending in the previous year would be correlated (and statistically significant) with improvements in reliability. The regression output tables in the Technical Appendix show that the coefficients on lagged transmission and distribution O&M expenses per customer were negative for ten of the twelve regressions, which implies that reliability improvements are correlated with increased utility O&M spending on T&D in the previous year—but these results were not significant at the 90th percentile or above. It was surprising to find that utility T&D O&M expenditures were not significantly correlated with interruption frequency or duration in the base model specifications. It is important to note that only the pooled SAIDI and SAIFI regressions (i.e., no fixed or random effects included) contained statistically significant results for lagged utility T&D O&M expenditures.

Furthermore, counter-intuitive results were observed within the four base models. For example, the O&M expenditures variable coefficient in the base SAIDI models had a negative and positive sign without and with major events included, respectively. Although none of these expenditure regressors were statistically significant, the base model results imply that increased O&M spending may be correlated with less frequent and less total minutes of interruptions—if major events are not included in the performance metrics. If major events are included, increased spending may be correlated with less frequent, but more total minutes of interruptions. Consequently, the models were re-run to confirm if these counter-intuitive findings persisted under alternative expenditures metrics and normalization criteria (e.g., O&M expenses per line mile, O&M expenses per MWh delivered, O&M expenses per customer, O&M expenses from previous two years, distribution-only O&M expenses, transmission-only O&M expenses; % deviation in annual O&M expenses compared to thirteen-year average). Some of the expenditures variables became statistically significant under the alternative normalization method, but many still showed a mix of both positive and negative signs depending on the metric (SAIDI or SAIFI) and whether or not major events were included.

Unfortunately, more detailed breakdowns were not collected for annual utility O&M expenditures related to T&D. It is likely 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 expenditure 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 T&D expenses and a relatively lower SAIDI (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 T&D O&M expenses and a relatively higher SAIDI (SAIFI). It follows that these competing proactive versus reactive utility expenditure strategies could explain the aforementioned inconsistencies in the expenditure coefficient signs. And this analysis did not include information detailing annual utility capital spending, which may impact reliability in other ways.

1.9.3 Inconsistent Reporting of Reliability Performance

This analysis also evaluated whether electric utility reliability performance—when major events are included—continues to decline if the analysis had: (1) an incomplete panel of reliability information ("unrestricted panel"); (2) all thirteen years of reliability information ("partially restricted panel"); or (3) for utilities that reported all thirteen years of reliability information and reported performance metrics for both with and without major events ("fully restricted panel"). The hypothesis of interest was whether utilities consistently under-reported information when reliability tended to be worse. The analysis was conducted for the base model (Model F) and an alternative model that had a larger sample size to draw from (Model E).

Interestingly, both the annual total interruption minutes and frequency of interruptions consistently increases when the analysis dataset is restricted to only include utilities for which all thirteen years of reliability data had been obtained, or for those utilities that reported all thirteen years and the reliability metrics including and excluding major events.

Table 12. Fully restricted, partially restricted, and unrestricted panel regression results for annual trend (YEAR) for base model and model E

	Model F (base model)			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 included	9.5%***	9.8%***	9.3%***	5.5%**	4.8%**	3.9%*
SAIFI annual trend—with major events included	1.2%	2.8%**	2.4%*	0.5%	1.1%	0.9%

Table 12 shows that the duration of interruptions is increasing, with strong statistical significance, by approximately 5.5–9.5% per year for the full, unrestricted panel data set, 4.8–9.8% per year for the panel dataset that contains utilities that had reported SAIDI for all thirteen years, and 3.9–9.3% for the dataset that contains SAIDI data for all years, reported both with and without major events information. Furthermore, the frequency of interruptions is increasing, without statistical significance, by approximately 0.5–1.2% per year for the full panel data set. The frequency of interruptions is increasing 1.1–2.8% per year, with statistical significance, for the panel dataset that only contains utilities that had reported SAIFI for all years—and 0.9%–2.4% for the fully restricted panel. Technical Appendix C contains the full results from this analysis.

1.9.4 Trends in the Total Interruption Minutes and Frequency of Interruptions

Regardless of model specification, both the total annual duration and frequency of interruptions is increasing over time. Figure 14 and Figure 15 show the year coefficient for each of the four reliability metrics and for all models under consideration in this study.

If major events are excluded, the frequency and total annual duration of interruptions has increased—on average—each year by 0.2–0.9% and 0.4–1.3%, respectively. If major events are included in the reliability performance metric, the frequency and total annual duration of interruptions has increased—on average—each year by 0.5–1.8% and 2.8–9.5%, respectively.

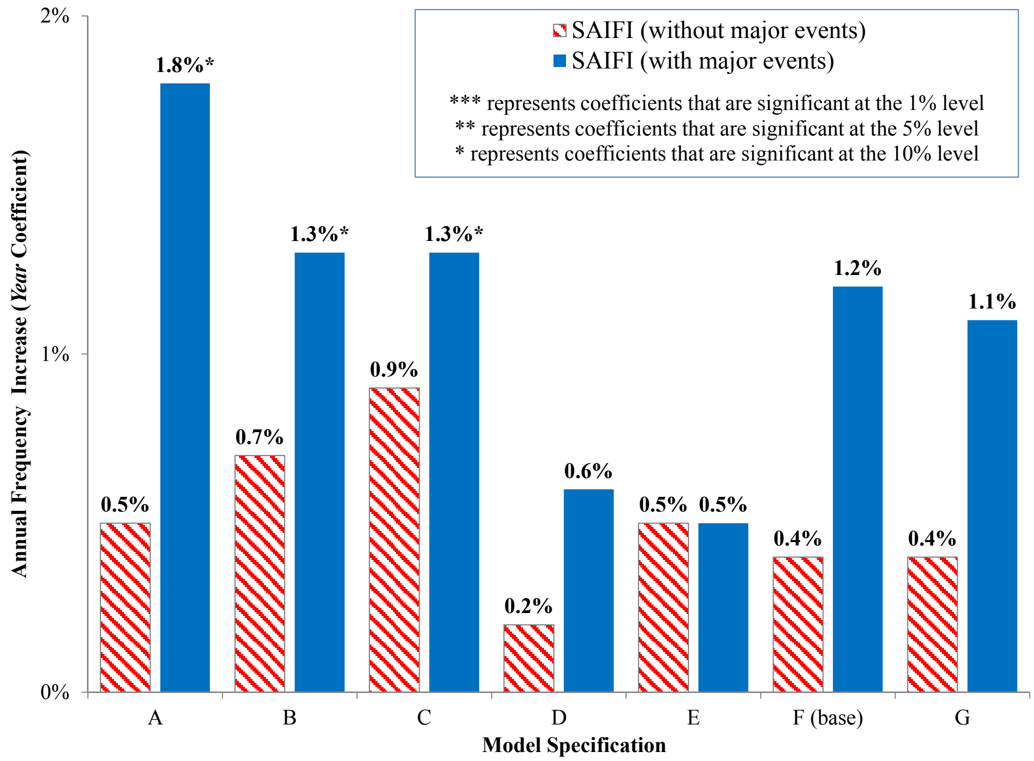

Figure 14. Annual increase in frequency of interruptions: all models considered

The better performing models (i.e., Models E–G) indicate that the annual increase in the frequency of interruptions is relatively smaller when compared to the worst performing models (i.e., Models A–D). Alternatively, the better performing models show that the annual increase in the total minutes of interruptions is relatively larger when compared to the worst performing models.

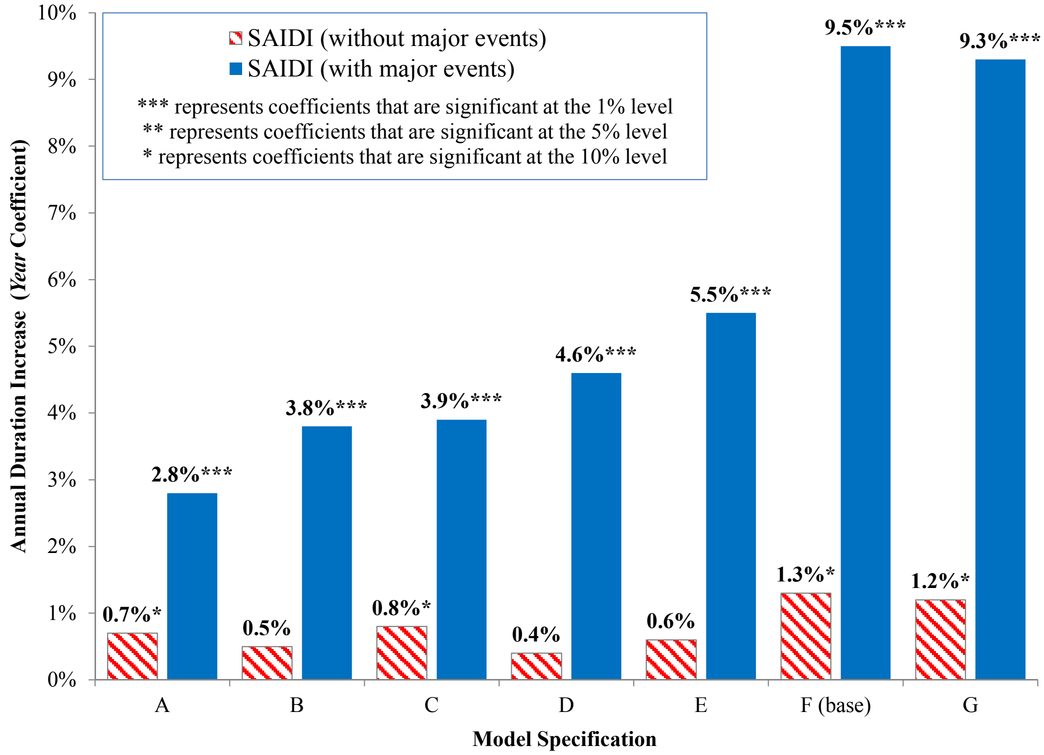

Figure 15. Annual increase in duration of interruptions: all models considered

In summary, power system interruptions—with or without major events included—are slightly increasing over time, but with little or no statistical significance. The total minutes customers are without power is slightly increasing—with marginal statistical significance—when major events are excluded. However, if major events are included, the total minutes of power interruptions are substantially increasing and with very strong statistical significance.

1.9.5 Major Events are Increasing the Frequency and Total Number of Minutes of Power System Interruptions

As shown in the preceding graphics, a key finding from this analysis is that the time trend (i.e., coefficient on YEAR regressor) —in *every* model evaluated—increases when comparing SAIDI and SAIFI (without major events) to SAIDI and SAIFI (with major events). In short, when major events are included, both the frequency and total annual duration of power interruptions are increasing at a more pronounced rate than when major events are not included. This finding implies that a typical U.S. utility may be having a more difficult time preventing and responding to power outages as weather becomes more frequent and/or severe.

1.9.6 Model Limitations

There are a number of limitations with this study that should be considered when evaluating the results. First, it was shown that the regression results were significantly different depending on whether major events were included in the SAIFI and SAIDI calculations. Utilities are using inconsistent criteria to define a "major event" (Eto and LaCommare 2008; Eto et al. 2012). For this reason, it follows that this inconsistency may bias the results in a pooled regression. However, the effects models (random or fixed) which were used in this study were implemented to fully (or partially) mitigate the effect of these types of utility-by-utility differences. Furthermore, the causes of reliability interruptions are inconsistently reported across utilities—and this makes it challenging to identify consistent regressors that can explain reliability across the United States.

As noted above, T&D O&M expenditures did not have a statistically significant correlation with improvements in reliability. This finding (or lack thereof) is counter-intuitive, because it was expected that increased utility T&D O&M expenditures would be significantly correlated with improved reliability. Unfortunately, it is not immediately possible to collect detailed breakdowns on annual utility capital or O&M expenditures related to T&D. It is suspected that reliability is affected differently depending on whether utilities spend relatively more on preventative maintenance when compared to reactive maintenance.

Although 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 regressors. Multicollinearity does not create bias, but it can lead to inflated standard errors and p-values (e.g., see Greene 2000 and Wooldridge 2002).

There are a number of other unobservable or intangible factors that could significantly affect utility reliability. One example of an intangible factor might include the effect of a company's "culture" (PA Consulting 2014) on reliability. One example of an unobservable factor is the share of utility customers who have installed Smart Grid technologies. It is suspected that these technologies could improve reliability, but penetration rates of Smart Grid technologies are not currently reported for a significant number of utilities.

Despite its limitations, this model provides a convenient and consistent framework to evaluate how past (or future) changes in weather, utility O&M spending, share of underground line miles, and other factors are correlated with changes in reliability. The following sections explore how reliable electric service has economic value to society and that this value can be readily incorporated into analyses that estimate the costs and benefits of decisions to improve reliability.

Part 2:
A Review of Value-based Reliability Planning

2.1 Value-based Reliability Planning

For nearly sixty years, researchers have acknowledged that reliable electric service (or lack thereof) has economic benefits (costs) to society. As the electric industry evolved over this time period, so have the methods used by researchers to value reliability. Part Two is organized as follows: Section 2.2 discusses a technique to visualize how research into reliability and value has evolved over time. Sections 2.3 and 2.4 provide examples of early and recent research, respectively, into the value of reliability and value-based reliability planning. The section concludes with a discussion of an expert elicitation exercise that was conducted to test whether utility customer surveys of the value of lost load may be inaccurate.

2.2 Word Clouds: A Technique to Visualize Evolution of Research

As part of this review, thirty-one relevant papers published between 1957 and 1995 and nearly fifty manuscripts published from 1996–2015 were collected. Next, all of the abstracts were compiled and the text was entered into a software tool that creates "word clouds."[12] Word clouds were created to compare and contrast how early

[12] Word clouds are a technique used to visualize the relative importance of qualitative information (e.g, see Nguyen et al. 2011).

research and more recent research into value-based reliability planning has evolved over time. Figure 16 is a word cloud based on abstracts published from 1957–1995. The earliest studies typically focused on (1) identifying the need for research into new methods to determine the cost of unserved energy (typically expressed in kWh); (2) estimating the cost of unserved energy on commercial and industrial facilities; (3) and the cost of unserved energy from outages caused by electricity generation.

Figure 16. Word cloud for abstracts: 1957-1995 (n=31)

More recent studies, however, focus on determining the value of outage "events" including both retrospective and hypothetical power interruptions that impact regional and national economies as well as outages that are experienced by households (see Figure 17).

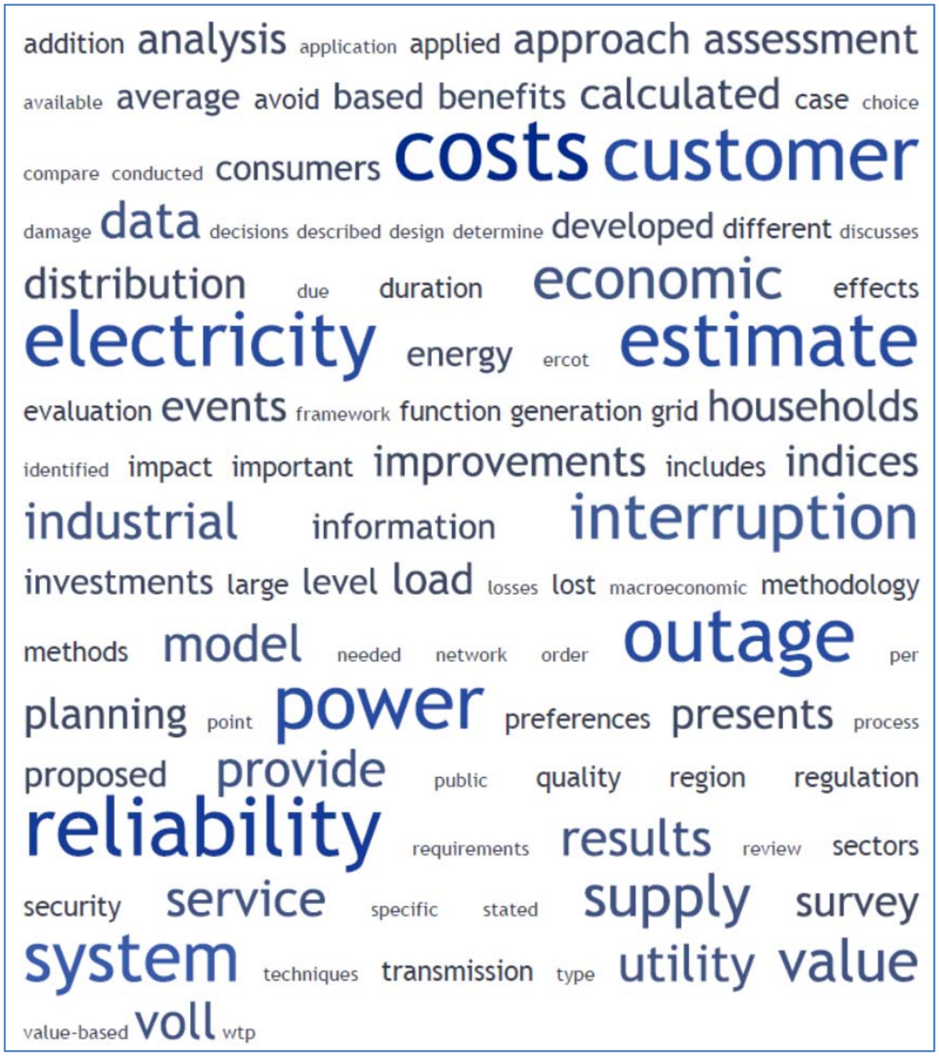

Figure 17. Word cloud for abstracts: 1996-2015 (n=49)

2.3 Early History of Value-based Reliability Planning: 1957-1995

The earliest studies into the value of reliability focused on the need to design methods to quantify the costs of power interruptions or, conversely, the cost of improved reliability. In one of the earliest published studies, Dickinson (1957) describes a technique to evaluate the economics from an improvement in reliability under alternative types of industrial power systems. Gaver et al. (1964) note that "no definite economic value can be assigned to degree of reliability in utility systems, utilities are for the most part forced to rely on history and experience to establish acceptable levels of system reliability." Shipley et al. (1972) conducted one of the first known methods to determine the economic optimum of power system reliability. The authors indicated that the primary motivation for this research was to "provoke discussion and further research into the cost of power interruptions…" Telson (1975) constructed an early cost-benefit analysis to determine the point at which the costs of adding generation capacity exceed the benefits of improved reliability. This study found that the present "1-day-in-10-year" loss of load probability target may be uneconomically high and suggested that the target could be relaxed to at least a "5-day-in-10-year" level. Krohm (1978) conducted one of, if not the, the earliest survey(s) of residential electricity customer attitudes following a weeklong power outage over a holiday. Krohm (1978) found that the outage costs to Springfield, Illinois residents were ~$1.26/kWh. Corwin and Miles (1978) evaluate the impacts of a large blackout affecting New York City in 1977. Munasinghe and Gellerson (1979) follow the lead of Shipley et al. (1972) and develop a model to optimize reliability by balancing social benefits and costs of changes in reliability. More specifically, these researchers developed outage cost functions for both residential and industrial consumers located in Cascavel, Brazil. Other researchers (e.g., Shipley et al. 1972; Bental and Ravid 1982) investigated the costs of interruptions with a focus on industrial customers. As more studies focused on quantifying costs of interruptions, researchers began conducting thorough literature reviews of studies conducted for the United States (e.g., Sanghvi 1982; Billinton et al. 1983) and abroad (e.g., Sanghvi 1982). Sanghvi (1982) was one of the first studies to make a key distinction by separately reporting costs by outage duration for residential, commercial, and industrial customers.

The term *value of service reliability* (VOS) may have been formally introduced around the time that papers by Hall et al. (1988) and Burns and Gross (1990) were published, but was informally referred to in earlier presentations, lectures, and tutorials by Billinton (Billinton 2015). VOS is defined as a "reliability evaluation that explicitly incorporates into the planning process customer choices regarding reliability 'worth' and service costs" (Burns and Gross 1990). In the optimum, additional costs of any resource employed to improve reliability should equal the benefits associated with reducing outages by "explicitly incorporating customer outage cost information"

(Burns and Gross 1990). Burns and Gross (1990) also describe four general methods used to quantify customer outage costs including (1) proxy methods; (2) market-based methods; (3) after-the-fact-measurement; and (4) survey-based methods. It was noted that electric utilities have concentrated their efforts on conducting four different customer surveying techniques, which include: direct costs ("what cost would the customer incur due to an outage of specified duration with a specified warning time?"); willingness to pay ("how much would the customer be willing to pay to avoid an outage of specified duration with a specified warning time?"); willingness to accept ("how much would the utility have to pay the customer to accept an outage of specified duration with a specified warning time?"); and revealed preference ("would the customer prefer [various] levels of service reliability…at [various] prices?") (Burns and Gross 1990).

In the early 1990s, researchers developed more sophisticated methods to value service reliability (e.g., Chen et al. 1995). New techniques were published that demonstrated direct costs of outages, willingness to pay, and/or willingness to accept approaches (EPRI 1990; Sanghvi et al. 1991; Tishler 1993; Lehtonen and Lemstrom 1995) as well as revealed preference techniques (e.g., Beenstock 1991; Caves et al. 1992). It is important to note that a significant number of the earliest studies tended to focus estimation techniques on commercial and industrial processes (e.g., Shipley et al. 1972; Tishler 1993; Bental and Ravid 1982; Pasha et al. 1989; Beenstock 1991), because it was assumed, at the time, that the largest costs would be incurred in these sectors of the economy. Table 13 contains examples of customer outage cost estimates from the earliest studies.

Table 13. Examples of early estimates of customer outage costs[13]

Outage cost ($2013)	Original Units	Description	Study
$56	$/kWh (1972)	Highly automated, low electricity demand (USA)	Cited by Shipley et al. (1972)
$8	$/kWh (1972)	Less automated, high electricity demand (USA)	Cited by Shipley et al. (1972)
$5	$/kWh (1972)	Industrial plants in general (USA)	Cited by Shipley et al. (1972)
$3	$/kWh (1972)	Average U.S. cost of interruption	Derived by Shipley et al. (1972)
$3	$/kWh (1981)	Residential response after blackout in Springfield, Illinois (USA)	Krohm (1978)
$0-$1	$/kWh (1981)	WTP to avoid household "cost of inconvenience" under different duration lengths (1,2,4,8,12 hours) and timing scenarios (8am,12pm,4pm)	Sanghvi (1982)
$0-$12	$/kWh (1981)	Industrial idle resource costs, material losses, equipment damage, additional fuel costs under different duration lengths (15 min.,25 min.,400 min.,660 min.) and for different types of plants	Sanghvi (1982)
$1	$/kWh (1986)	$0.38/kWh for planned outages and $0.67 for unplanned outages in the industrial sector of Pakistan.	Pasha et al. (1989)
$8	$/kWh (1988)	Average residential outage cost during summer afternoon with one hour notice: Pacific Gas & Electric, California.	Burns and Gross (1990)
$78	$/kWh (1988)	Average commercial outage cost during summer afternoon with one hour notice: Pacific Gas & Electric, California.	Burns and Gross (1990)
$13	$/kWh (1988)	Average industrial outage cost during summer afternoon with one hour notice: Pacific Gas & Electric, California.	Burns and Gross (1990)
$7	$/kWh (1988)	Average agricultural outage cost during summer afternoon with one hour notice: Pacific Gas & Electric, California.	Burns and Gross (1990)
$3-$45	$/kWh (1987)	Range of expected outage costs for a number of industrial processes in Israel.	Tishler (1993)

[13] Outage cost estimates were inflated to 2013 dollars using the U.S. Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) Inflation Calculator (BLS 2015) and rounded to the nearest dollar.

2.4 Recent History of Value-based Reliability Planning: 1996–2015

In more recent years, research efforts focused on delineating customer outage costs for different durations of planned and unplanned interruptions; whether the outage was related to transmission, distribution, or generation; and under other circumstances (Sullivan et al. 1996; Sullivan et al. 1997). Sullivan et al. (1996), which contains results from an outage cost study conducted by Duke Power Company and the Electric Power Research Institute (EPRI), is the first known study to estimate interruption costs for voltage disturbances and momentary outages. Other researchers (e.g., Dalton et al. 1996; Chowdhury and Koval 1998; Chowdhury and Koval 1999) continued to explore the concept of value-based reliability planning, which included, among other things, employing probabilistic techniques and the development of a "customer outage costs data base" (Dalton et al. 1996; Lawton et al. 2003). For the first time, Goel (1998) acknowledges that the:

> "…basic concepts associated with quantitative reliability assessment of electric power systems are reasonably well established and well accepted by the power industry…the evaluation of the costs and benefits of competing investments is now becoming a standard practice in power system planning."

Despite this proclamation by Goel (1998), new valuation techniques continued to be proposed for (1) "composite systems" (i.e., power systems that have interacting generation and T&D components) using macroeconomic indicators (Choi et al. 2000); and (2) a wider variety of electricity end-uses and by using insurance industry perspectives (Eto et al. 2001). Lawton et al. (2003) use sophisticated economic analysis techniques (e.g., Tobit models) to estimate customer damage functions for a "given outage scenario and customer class as a function of location, time of day, consumption, and business type". The authors indicate that this approach can be used to estimate outage costs for a wide range of customer types and circumstances. Sullivan et al. (2009, 2010) build on Lawton et al. (2003) by describing how over-simplified assumptions in economic models can "substantially impact" the estimated value of service. Sullivan et al. (2009, 2010) propose a "simple, but robust" cost estimation method that does not rely on these over-simplifying assumptions. Table 14 contains examples of customer outage cost estimates from more recent studies.

Table 14. Examples of more recent estimates of customer outage costs[14]

Outage cost ($2013)	Original units	Description	Study
$3-$4 (generation); $8-$9 (T&D)	$ per peak kWh (1992); $ per event (1992)	Duke Power residential customer outage costs per peak kWh and event	Sullivan et al. (1996)
$35-$76 (generation); $1,003-$2,187 (T&D)	$ per peak kWh (1992); $ per event (1992)	Duke Power commercial customer outage costs per peak kWh and event	Sullivan et al. (1996)
$6-$13 (generation); $7,356-$15,614 (T&D)	$ per peak kWh (1992); $ per event (1992)	Duke Power industrial customer outage costs per peak kWh and event	Sullivan et al. (1996)
$12,775-$124,258	$ per event (1992)	Average total costs per event to large commercial and industrial customers ranging from voltage sag to four hour outage without notice	Sullivan et al. (1997)
$0-$1	$ per monthly kWh (1992)	Average total costs per monthly kWh to large commercial and industrial customers ranging from voltage sag to four hour outage without notice	Sullivan et al. (1997)
$0-$188	Canadian $ per kWh (1987)	Range of interruption costs for various sectors (large, small, commercial, farm, residential, government, office) and durations (1 min, 20 min, 60 min, four hours, 8 hours)	Goel (1998)
$0-$1	$ per annual kWh (2002)	Range of interruption costs (per kWh) for wide range of firms and durations (voltage sag, momentary, 1 min, 15 min, 20 min, 30 min, 1 hour, 4 hour, 8 hour, and 12 hour)	Lawton et al. (2003)
$16,762-$155,022	$ per event (2002)	Range of interruption costs (per event) for wide range of firms and durations (voltage sag, momentary, 1 min, 15 min, 20 min, 30 min, 1 hour, 4 hour, 8 hour, and 12 hour)	Lawton et al. (2003)
$2-$11	$ per event (2008)	Average residential customer costs per event for range of durations (momentary, 30 minutes, 1 hour, 4	Sullivan et al. (2010)

[14] Outage cost estimates were inflated to 2013 dollars using the U.S. Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) Inflation Calculator (BLS 2015) and rounded to the nearest dollar. Canadian dollars were converted to U.S. dollars using an average annual exchange rate of 0.77 U.S. dollars for 1 Canadian dollar.

Outage cost ($2013)	Original units	Description	Study
		hours, 8 hours)	
$317-$5,621	$ per event (2008)	Average small commercial and industrial customer costs per event for range of durations (momentary, 30 minutes, 1 hour, 4 hours, 8 hours)	Sullivan et al. (2010)
$7,096-$74,965	$ per event (2008)	Average large and medium commercial and industrial customer costs per event for range of durations (momentary, 30 minutes, 1 hour, 4 hours, 8 hours)	Sullivan et al. (2010)

The most recent studies involve quantifying regional and macroeconomic effects of outages, refining value of lost load (VoLL) estimation techniques—especially for households, and compiling utility outage cost surveys into accessible meta-datasets and applied software tools.

Regional and national VoLL studies

LaCommare and Eto (2005, 2006) published the first known bottom-up, national estimate of how much annual power interruptions cost U.S. electricity consumers. The authors indicate that sensitivity analyses suggest that the total annual cost of power interruptions could range from "less than $30 billion to more than $130 billion". Sun et al. (2009) quantify the Gross Domestic Product (GDP) impact of power system outages on a region in China (Shanghai) using a Cobb-Douglas production function. Leahy and Tol (2011) also use a macroeconomic production function technique to estimate the value of short-term lost load across Ireland. The aforementioned paper finds that the VoLL is highest in the residential sector for both the Republic of Ireland and Northern Ireland. London Economics (2013) employs a number of techniques to quantify the value of lost load for Great Britain. In this study, willingness-to-pay to avoid an outage, willingness-to-accept payment for an outage, and a stated preference choice experiment are used to determine the residential and small business (SMEs) value of lost load (expressed in £/MWh). Interesting, these authors indicated that the stated choice method is "preferred to the contingent valuation method as it allows us to examine outages that are multi-dimensional, reduces the possibility of 'strategic responses' and allows us to examine preferences for attributes over a range of price/payment levels" (London Economics 2013). In addition, value-at-risk (VAR), real options, and other econometric techniques—based on sectoral level gross value-added statistics—were used to determine the value of lost load for commercial, industrial, and other large electricity using customers (London Economics 2013). More specifically, London Economics (2013) found that:

> "The VoLLs for [industrial and commercial] customers are significantly lower than for SMEs. This is intuitive as a) large users use more electricity per unit of [gross value-added] than small business, and this impacts the VoLL/MWh. In essence, large industry tends to be more intensive on energy use, and less intensive on labour use, with the former driving up the denominator in the VAR VoLL calculation and the later driving down the numerator. Further, large customers may engage in action to limit the impacts of outages or manage security of supply, such as self-supply, engaging in demand-side response, or have onsite back-up equipment when production is load-critical, and this will limit the VoLL for large customers. Finally, when assessing various policy parameters and the impacts of VoLL, the importance of industry would in some cases be best weighted by load, so larger users, although having lower VoLLs, would get a larger weight in calculations such as estimating efficient levels of aggregate capacity."

Growitsch et al. (2014) use information on households and industry to estimate sector-specific and regional VoLL, which is defined as "the loss in output resulting from failing to supply one unit of electricity"—expressed in Euros per kilowatt-hour (€/KWh). It was noted that, on average, aggregate outage costs were split equally across German commercial, industrial, and residential electricity customers.

Disaster-induced VoLL studies

A number of researchers transitioned away from conducting general estimates of VoLL and into evaluating regional economic impacts under specific disaster scenarios. Sanstad (2015) conducted a literature review of outage cost studies that have employed input-output modeling, computable general equilibrium (CGE) modeling, and other macroeconomic analysis techniques to evaluate economic impacts from both hypothetical (Greenberg et al. 2007; Rose et al. 1997) and recently observed (Rose et al. 2005) regional power system conditions. Greenberg et al. (2007) evaluate impacts from a hypothetical terrorist attack on New Jersey's power system. Power system restoration times, employment effects, and overall impact on Gross State Product (GSP) were evaluated in this study. It was noted that the state economy would likely take a year to recover, but if the attack on the power system causes firms to close or relocate, then the economy would not fully recover in five years. A key takeaway from this study is that the "policy implication is that the costs and benefits of making the power system more resilient to plausible attacks should be weighed" (Greenberg et al. 2007). Rose et al. (1997) estimated losses to the Memphis, Tennessee regional economy from a hypothetical earthquake damaging the power system. This study found that regional economic output was reduced by ~7% over a four-month restoration period, but that impacts could be reduced substantially by strategically reallocating "scarce" electricity across economic sectors. Rose et al. (2005) use a CGE model to estimate total regional economic impacts from four rolling blackouts that occurred in Los Angeles, California, in 2001. Regional direct economic losses were estimated at 5–10%—without adaptive responses (Rose et al. 2005).

Advances in VoLL estimation for private households

In parallel, a number of studies conducted outside of the United States made advances in how to best estimate outage costs at the household-level. Ozbafli and Jenkins (2015) and Abdullah and Mariel (2010) estimate household willingness to pay to avoid outages using a stated choice method in Cyprus and Kenya, respectively. The stated choice method allowed Ozbafli and Jenkins (2015) to "break down the service improvement concerned into different attributes at different levels and estimate the marginal willingness to pay (MWTP) for each service attribute". Cyprus residential customers were willing to incur 4–14% increases in their monthly electricity bill to avoid outages in summer and winter, respectively (Ozbafli and Jenkins 2015). Some researchers are addressing the uncertainties present in estimating VoLL at the household-level by conducting Monte Carlo simulations to present a distribution of results. Praktiknjo et al. (2011) adapted a macroeconomic model and introduced Monte Carlo simulations to account for the "high degrees of uncertainties" when valuing lost load for private households in Germany. Praktiknjo (2014) used a combination of the stated-preference WTP approach and Monte Carlo simulations to "increase the representativeness of the estimations" of VoLL for German residential customers.

Development of VoLL estimation tools and meta-datasets

Perhaps the most significant advances in estimating VoLL involve research and development activities to create meta-datasets and outage cost calculators. As discussed earlier, Lawton et al. (2003) built the first known meta-database of outage characteristics and VoLL. In this database, each "outage scenario (e.g., the loss of electric service for one hour on a weekday summer afternoon) is treated as an independent case or record both to permit comparisons between outage characteristics and to increase the statistical power of analysis results" (Lawton et al. 2003). Sullivan et al. (2009) collect and organize information from nearly thirty VOS reliability studies undertaken by ten U.S. electric utilities from 1989 to 2005. Sullivan et al. (2009) indicate that:

> "…because these studies used nearly identical interruption cost estimation or willingness-to-pay/accept methods it was possible to integrate their results into a single meta-database describing the value of electric service reliability observed in all of them. Once the datasets from the various studies were combined, a two-part regression model was used to estimate customer damage functions that can be generally applied to calculate customer interruption costs per event by season, time of day, day of week, and geographical regions within the U.S. for industrial, commercial, and residential customers."

The U.S. Department of Energy then built on the research by Sullivan et al. (2009, 2010) and sponsored Lawrence Berkeley National Laboratory (LBNL) and Nexant to develop the Interruption Cost Estimate (ICE) Calculator—an online tool for "planners at utilities, government organizations or other entities that are interested in estimating interruption costs and/or the benefits associated with reliability improvements in the United States" (LBNL/Nexant 2015). Sullivan et al. (2015) is an update to earlier work to compile a U.S. outage cost meta-database containing utility VoLL survey data (Sullivan et al. 2009). This update increased the number of utility studies from twentynine to thirty-four, and expands the analysis time period by seven years (from 1989–2005 to 1989–2012). It is anticipated that updates will be made to the ICE Calculator based on this revised information (Sullivan et al. 2015).

Possible disadvantages of relying on aggregated customer survey data

Despite these advances, a number of researchers have indicated that utility surveys that rely on a contingent valuation framework (i.e., willingness to pay, willingness to accept) may be inaccurate in their assessment of the aggregate value of lost load (see, e.g., London Economics 2013; Growitsch et al. 2014; Rose et al. 2005). For example, Growitsch et al. (2014) notes that "consumers may both under- and overstate their willingness to pay either due to a lack of information or as a result of strategic response behavior." Rose et al. (2005) indicate that "nearly every estimate of outages has omitted resilience and general equilibrium effects, and therefore could significantly misstate true outage costs." Furthermore, Sullivan et al. (2010) indicate that most, but not all, utility-sponsored surveys ask residential customers about their willingness to pay to avoid outages. Sullivan et al. (2015), in an effort to create a single meta-dataset of value of electric service reliability, note that it was possible to integrate thirty-four different surveys because "these studies used nearly identical interruption cost estimation or willingness to pay/accept methods". There has been extensive research conducted into the divergence between results from willingness to accept and willingness to pay survey methods (see, e.g., Kolstad and Guzman 1999, Horowitz and McConnell 2002). Unfortunately, Sullivan et al. (2015) do not specifically state how residential customer willingness to pay estimates were integrated with willingness to accept estimates in this meta-dataset —and whether the known divergence between these two techniques was addressed in some fashion.

2.5 Expert Elicitation of Value of Lost Load

To test this hypothesis, a series of structured Delphi[15] exercises were conducted at a pair of ninety-minute workshops that took place during the 2014 and 2015 Power Grid Resilience Conferences (Larsen 2014, 2015). Power Grid Resilience Conference (PGRC) attendees include power system experts from private companies, government agencies, academia, nonprofits, and other institutions. Workshop participants were asked to answer fifteen questions, including questions used to determine the costs of power system interruptions for residential, small C&I, and larger C&I customers.

PGRC workshop participants were given three empty, gridded worksheets: (1) "Cost of Residential Interruption ($2013)"; (2) "Cost of Small C&I Interruption ($2013)"; and (3) "Cost of Large C&I Interruption ($2013)". The worksheets had the following x-axis labels: "Momentary", "30 minutes", "1 hour", "4 hours", "8 hours", "24 hours", and "72 hours". In the 2014 workshop, the worksheet y-axes had a pre-determined range of dollar values: $0–100 for residential; $0–50,000 for small C&I; and $0–500,000 for larger C&I.[16] In both years, workshop participants were given background information about the typical annual electricity usage and costs for each of the three categories of customers. Next, workshop participants were asked to draw, with precision, an interruption cost curve based on their expert judgement and the basic information provided on each of the three worksheets describing a typical customer's annual electricity consumption and costs in 2013.

It is important to note that including a pre-defined range of y-axis (dollar) values may have introduced a downward bias on the range of possible interruption costs reported by the workshop participants. For that reason, the 2015 worksheet was modified by

[15] A Delphi estimation technique relies on a small group of industry experts to reach consensus on a set of predefined questions relevant to their areas of expertise (Linstone and Turoff 1975; Satchwell et al. 2010).

[16] The range of y-axis values (dollars) was determined by (1) reviewing the range of costs reported through utility surveys as reported by Sullivan et al. (2010); and (2) increasing this range by at least one order of magnitude to account for the possibility that experts believed there was a greater range of costs.

removing the pre-defined y-axis labels. Figure 18 is an example of an empty worksheet and instructions provided to each 2015 workshop participant.

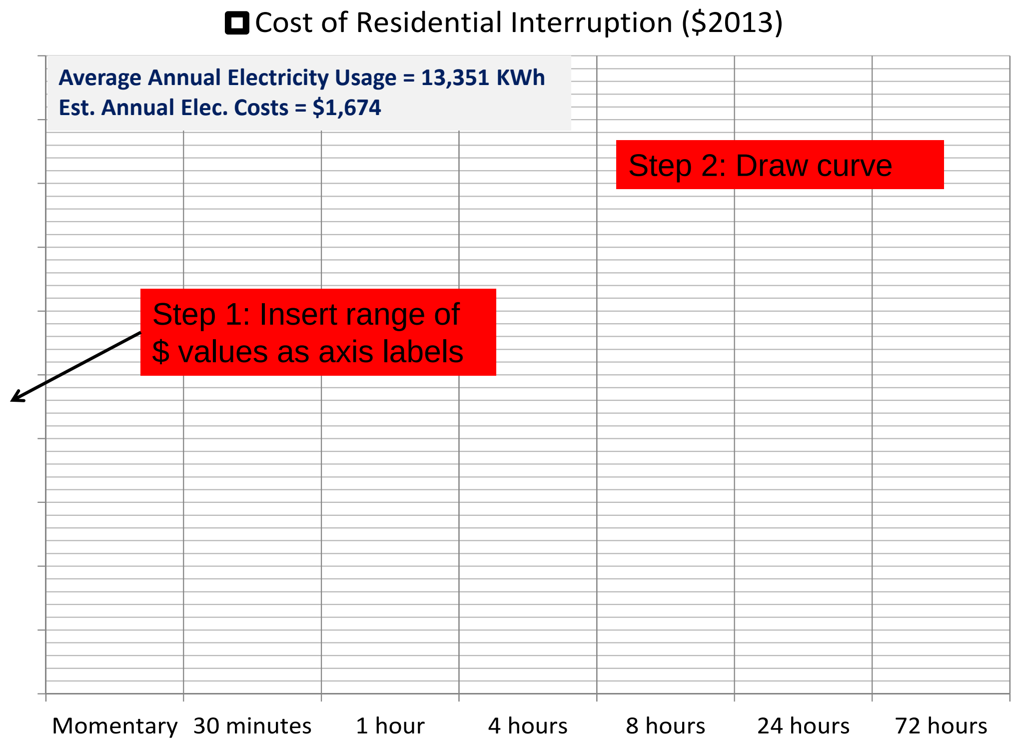

Figure 18. Example of empty worksheet distributed to each 2015 workshop participant

Nearly all 2014 workshop participants chose to draw the cost curves, but only about half of the participants in the 2015 workshop completed the worksheets. The curves drawn by each participant were digitized and compared to the latest survey results from Sullivan at al. (2015). It is important to note that workshop participants were not given any information about the Sullivan et al. (2010, 2015) estimates prior to completing the worksheets. Figures 19, 20, and 21 contain results for the residential, small C&I, and large C&I Delphi exercises, respectively.[17]

[17] Light gray-colored lines represent individual responses from the 2014 workshop. Charcoal-colored lines represent individual responses from the 2015 workshop. Gray or charcoal-colored hash marks at the top of lines indicate that the range of values was constrained by the predefined range of values (2014) or the range specified by the participant (2015). For example, a 2014 interruption cost curve with a $100 hash mark at a sixty-minute outage duration means that the respondent's curve extended beyond the highest predefined value ($100) starting at 60 minutes. In 2015, some participants cost curves extended beyond their own supplied range of axes labels. For display purposes, a few 2015 responses were not presented above $500.

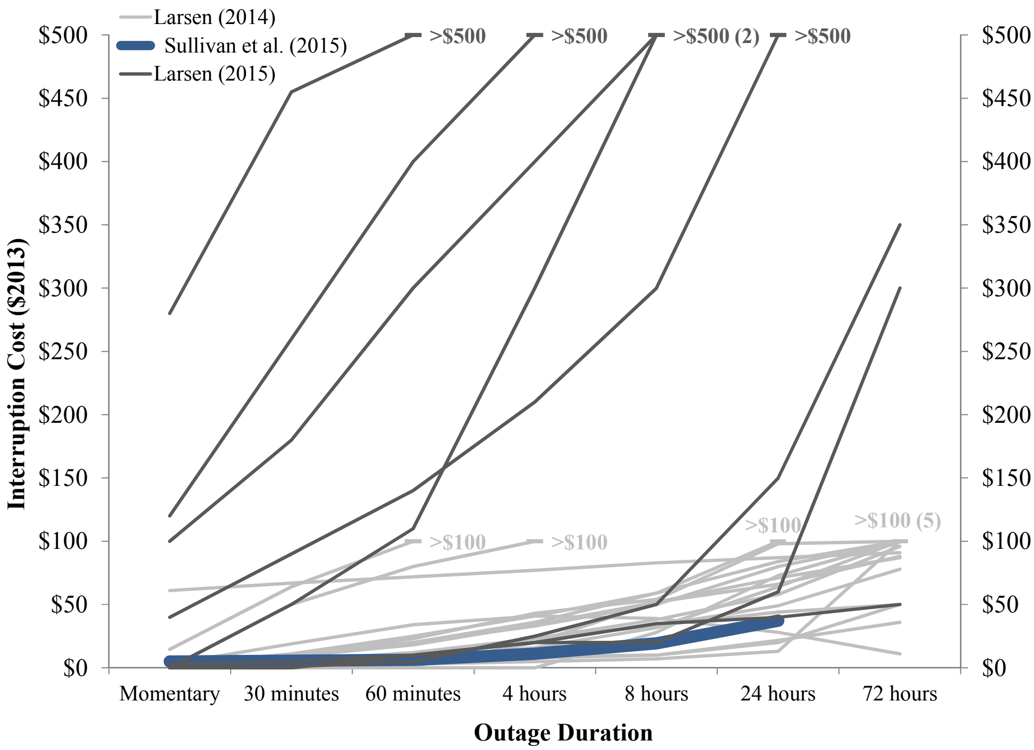

Figure 19. Residential customer interruption cost

Interestingly, the vast majority of workshop participants' interruption cost curves—in both 2014 and 2015—were significantly higher than the utility survey data compiled by Sullivan et al. (2015).

The substantial discrepancies between what was reported by Sullivan et al. (2015) and this set of workshop exercises hint at some of the potential disadvantages with using contingent valuation survey data to inform long-term value-based reliability planning.

In other words, the results from this simple Delphi exercise, when compared to information reported by Sullivan et al. (2015), are consistent with some of the disadvantages (e.g., under-statement of willingness to pay to avoid outages) first identified by other researchers (Growitsch et al. 2014; London Economics 2013).

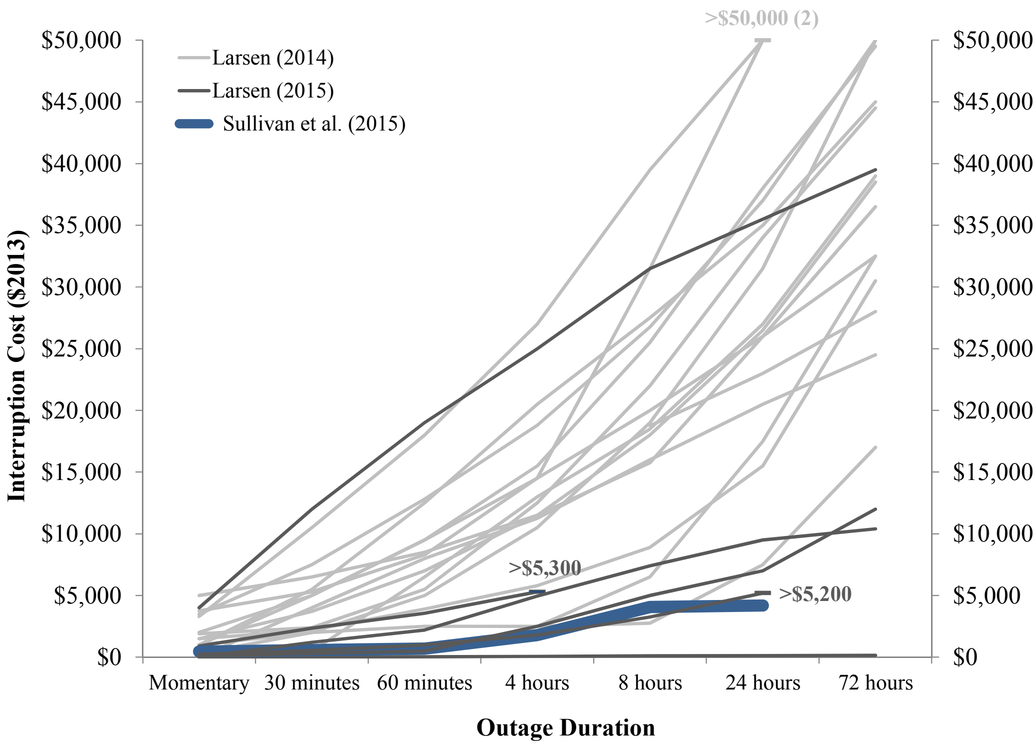

Figure 20. Small commercial and industrial customer interruption cost

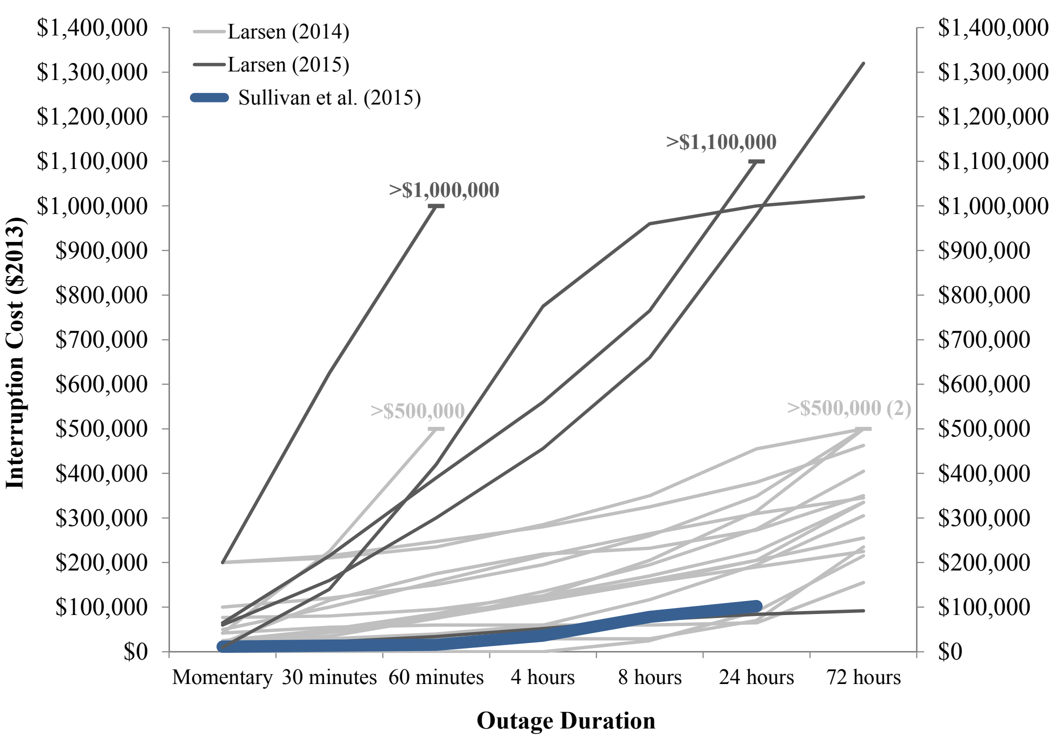

Figure 21. Medium and large commercial and industrial customer interruption cost

Are outage cost assumptions important in value-based transmission and distribution system planning scenarios?

Despite decades of research into determining the VoLL under a variety of conditions and customer types, there is a general lack of published research evaluating the relative importance of outage costs/value of lost load assumptions within the context of transmission and distribution planning scenarios. Take, for example, the idea that undergrounding power lines will lead to improved reliability. In this case, there are a number of assumptions that must be made to consider all of the costs (e.g., increased capital costs, increased operations and maintenance costs, increased risk to worker safety during conversion from overhead to underground) and benefits (e.g., improved aesthetics, avoided outage costs) of this strategy intended to improve power system resiliency. It is unclear how important these assumptions are, including the VoLL estimates, within the decision of whether or not to underground T&D lines.

Part 3:
A Method to Estimate the Costs and Benefits of Undergrounding Power Lines

3.1 Introduction

Despite the high costs attributed to power outages, there has been little or no research to quantify both the benefits and costs of improving electric utility reliability—especially within the context of decisions to underground T&D lines (e.g., EEI 2013; Nooij 2011; Brown 2009; Navrud et al. 2008). Brown (2009) found that the costs—in general—of undergrounding Texas electric utility transmission and distribution (T&D) infrastructure were "far in excess of the quantifiable storm benefits". However, Brown (2009) also noted that targeted storm-hardening activities may be cost-effective. Transparent assessments of the costs and benefits of undergrounding and other grid-hardening activities are useful to policymakers interested in enabling the long-term resilience of critical electricity system infrastructure (Executive Office of the President 2013a).

3.1.1 Research Questions

The purpose of this study is to expand on research by Larsen et al. (2015) by systematically evaluating a policy that requires investor-owned utilities (IOUs) to bury all existing and future T&D lines underground. More specifically, this analysis will attempt to address the following questions:

- What are the lifecycle costs of undergrounding all existing and new T&D lines at the end of their useful lifespan?
- Could increasing the share of underground T&D lines lead to fewer power interruptions—and are there corresponding monetary benefits from this reduction?
- Are there aesthetic benefits from reducing the number of overhead T&D lines?
- How much might health and safety costs change if there is an extensive conversion of overhead-to-underground lines?
- How much might undergrounding T&D lines affect ecosystem restoration costs?
- How important are assumptions, including VoLL estimates, relative to one another within a decision to underground power lines?
- What are the minimum conditions necessary for a targeted undergrounding initiative to have net social benefits?

Part Three is organized as follows: Section 3.2 provides background on the causes of power outages, how electric system reliability is measured, and undergrounding. Section 3.3 contains a discussion of the over-arching analysis framework including study perspective and standing. Section 3.4 introduces the empirical methods and identifies key data sources. General results and a sensitivity analysis are presented in Sections 3.5 and 3.6, respectively. Section 3.7 evaluates the minimum conditions necessary for a targeted undergrounding initiative to have net social benefits. Section 3.8 concludes with a policy recommendation, discussion of the analysis shortcomings, and highlights potential areas for future research.

3.2 Background

Revisiting how electric utility reliability is measured

The IEEE (1366-2012) formally defines a number of metrics to track electric utility reliability. The System Average Interruption Frequency Index (SAIFI) is one of the most commonly used metrics to assess electric utility reliability (Eto et al. 2012). Equation 10 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 all events in year t is Affected_t and the total number of customers served by the utility in a given year is Customers_t.

$$\text{SAIFI}_t = \frac{\sum \text{Affected}_t}{\text{Customers}_t} \tag{10}$$

An IEEE survey of 106 utilities found that the median 2012 SAIFI value is 1.5 interruption events for a typical customer (IEEE 2013). Figure 22 shows the average SAIFI values for all Texas utilities used in the Larsen et al. (2015) study without and with major events included. The pronounced effect of major events (i.e., storms) on the frequency of outages can be seen in this figure. The figures show a fairly flat time trend for the reliability data without major events, but a slightly increasing trend for the frequency of outages with the inclusion of major events.

Definition of undergrounding

It follows that burying power lines (i.e., “undergrounding”) would mitigate some of the risk associated with weather-related events (EEI 2013). In 2012, the Department of Energy reported that “calls for undergrounding are common from customers, elected officials, and sometimes state utility commissions. However, undergrounding is costly and the decisions are complex” (USDOE 2012).

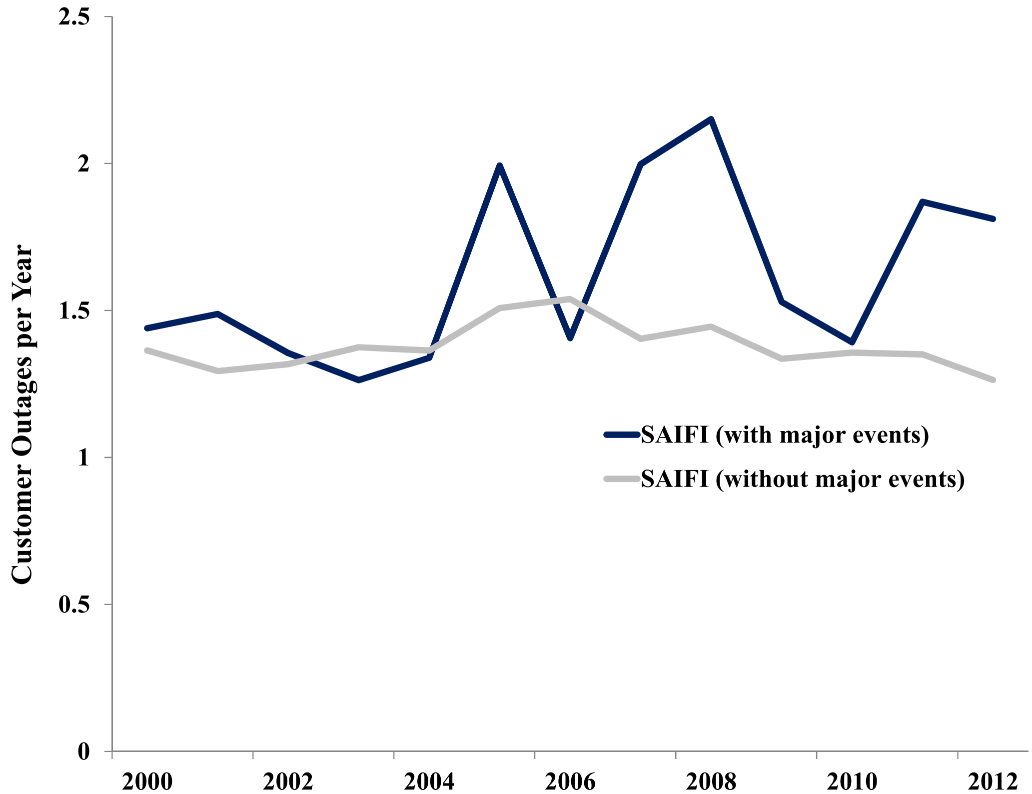

Figure 22. System average interruption frequency index over time—annual average of all Texas utilities

According to a U.S. Department of Energy press release, widespread power outages, which are often caused by severe storms, "inevitably lead to discussions about burying electric utility transmission and distribution (T&D) infrastructure" (USDOE 2012). Coincidentally, just three months after this press release, "Superstorm Sandy"—a large hurricane affecting the U.S. Eastern Seaboard—caused power outages for tens of millions of people with damages estimated in excess of $50 billion dollars (NOAA 2013). Not surprisingly, the New York Department of Public Service's electric reliability performance report for that year noted that "2012 was by far the worst year ever for storm effects in the twenty-four years of staff recordkeeping, taking that distinction from last year"(NYDPS 2013). According to the NYDPS, Hurricane Sandy caused most, but not all storm-related system outages in New York during 2012. There were ~170 million hours of customer interruptions (about a quarter of the total number of hourly interruptions since 1989) attributed to Hurricane Sandy (NYDPS 2013). It was reported that over two million customers were affected by this specific storm, but other storms also significantly affected system reliability including a major blizzard in January and severe thunderstorms in the summer (NYDPS 2013).

Is undergrounding T&D lines more costly?

Brown (2009) conducted a narrow cost-benefit analysis of storm hardening strategies on behalf of the Public Utility Commission of Texas. This study indicated that undergrounding T&D lines is significantly more expensive when compared to traditional overhead installations.

Brown (2009) assumed that converting existing overhead transmission lines to underground lines would cost approximately $5 million per mile.[18] For comparison, Brown (2009) indicates that it costs ~$180,000/mile to replace single, wood pole transmission lines and ~$459,000/mile to replace state-of-the-art, overhead transmission lines that meet current National Electric Safety Code (NESC) standards.[19]

Brown (2009) estimated that undergrounding local overhead distribution lines would cost ~$1 million per mile. For comparison, the minimum replacement costs for existing overhead distribution lines ranged from $86,700 to $126,900/mile with maximum replacement costs ranging from $903,000 to $1,000,000 (EEI 2013).

---

[18] The Edison Electric Institute (EEI) (2013) reported a minimum overhead-to-underground transmission line conversion cost of $536,760–1,100,000/mile and a maximum conversion cost of $6,000,000–12,000,000. EEI (2013) reported a minimum overhead-to-underground distribution line conversion cost range of $158,100–1,000,000/mile and a maximum conversion cost range of $1,960,000–5,000,000. EEI estimates that the minimum replacement costs for overhead transmission lines range from $174,000 per mile (rural) to $377,000 (urban). The maximum replacement costs for existing overhead transmission lines ranges from $4.5 million/mile (suburban) to $11 million/mile for urban customers (EEI 2013). EEI (2013) also reported that installing new underground distribution lines costs from $297,200-1,141,300/mile (minimum) to $1,840,000–4,500,000/mile (maximum). EEI noted that installing new underground transmission lines costs from $1,400,000–3,500,000/mile (minimum) to $27,000,000-30,000,000/mile (maximum).

[19] Brown (2009) assumes that future costs and benefits are discounted 10% annually. In addition, underground and overhead T&D infrastructure have forty- and sixty-year lifespans, respectively.

Additional health and safety costs for utility crews

It is unfortunate, but likely, that replacing a large amount of overhead infrastructure with underground infrastructure will lead to relative increases in risk to utility operational staff working in the field. EEI (2013) indicates that undergrounding infrastructure has “created a significant safety hazard for crews attempting to locate and repair failed equipment.” For this reason, it was assumed that worker health and safety costs will increase—above levels observed with the status quo—as the share of underground lines increases.

Aesthetic benefits of undergrounding

Reducing risk of power outages from severe storms is not the only reason given by stakeholders during discussions about burying T&D lines. Aesthetic improvements are a commonly listed benefit of undergrounding electric utility infrastructure (Brown 2009; EEI 2013; Navrud et al. 2008; Headwaters Economics 2012). EEI (2013) notes that utility customers “prefer underground construction” with “customer satisfaction” and “community relations” being the primary benefit of undergrounding. For example, the community of Easthampton, New York issued a stop-work order and threatened to sue the local utility, PSEG Long Island, over their plan to build new high-voltage transmission lines (Gralla 2014). This community and others are advocating for the undergrounding of future high-voltage transmission lines.

Des Rosiers (2002) found that a direct view of a transmission system pylon or conductors had a significantly negative impact on property prices with lost values ranging from -5% to -20% depending on the distance from the overhead infrastructure to the residence. Sims and Dent (2005) also evaluated how property prices changed based on proximity to high-voltage overhead transmission lines. Sims and Dent studied four different types of property and found that the relationship is not linear, but that there was a ~10–18% reduction in value for semi-detached properties and a ~6–13% reduction for detached properties. Furthermore, properties having a rear view of a pylon were found to have their value reduced by ~7%. By comparison, the negative impact on value for property having a frontal view was found to be greater (14.4% loss).

Electricity infrastructure interactions with ecosystems

Both overhead and underground electric utility infrastructure affects the natural environment and the services that these ecosystems provide. As discussed earlier, wildlife (e.g., squirrels, birds) die prematurely because of the presence of overhead electric utility infrastructure, and in doing so, cause reliability problems. The U.S. Fish and Wildlife Service estimates that collisions with power transmission and distribution lines "may kill anywhere from hundreds of thousands to 175 million birds annually, and power lines electrocute tens to hundreds of thousands more birds annually" (Manville 2005). Undergrounding lines may reduce mortality rates of birds and squirrels, but the process of installing underground power delivery infrastructure could significantly disturb sensitive wetlands (Jones and Pejchar 2013), forests (Most and Weissman 2012), or other valuable ecosystems within the T&D corridor. It is likely that undergrounding infrastructure will *increase* the area of environmental disturbance—when compared to traditional overhead line replacement (Public Service Commission of Wisconsin 2013). Measurement of the total economic value of an ecosystem is a controversial and difficult undertaking (e.g., Loomis et al. 2000). Goulder and Kennedy (2009) discuss the value of ecosystem services within a benefit-cost analysis framework. It is noted that:

> "…when a portion of the ecosystem is threatened with conversion, it may be more important to know the change or loss of ecosystem value associated with such conversion than to know the total value of the entire original ecosystem….*willingness to pay* offers a measure of the change in well-being to humans generated by a given policy change to protect nature or environmental quality. No comparable measure is currently available for assessing changes in satisfaction to other species or communities of them" (Goulder and Kennedy 2009).

The purchase of conservation easements (i.e., the willingness to pay to conserve land) is one way that developers are able to mitigate some or all of the lost value of an ecosystem affected by specific development projects (The Nature Conservancy 2014).

Developers often purchase conservation easements in locations with similar habitats to the corridor that was affected by the development activity. For example, if new power lines were installed across a prairie habitat in Texas, a developer would be allowed to purchase a conservation easement for comparable land somewhere else.

3.3 Analysis Framework

Study perspective and standing

This analysis is conducted from the perspective of any individual who cares about maximizing net social benefit. There are a number of stakeholders in this type of analysis including the state government, electric utility ratepayers, electric utilities, developers of T&D infrastructure, and society (i.e., all state residents). Given resource constraints, this preliminary analysis assumes that all additional costs to utilities associated with undergrounding will be passed along to ratepayers—including additional administrative, permitting, and siting expenses. Given this key assumption, the stakeholders with standing in this analysis are investor-owned utilities (IOUs), utility ratepayers, and all residents within the service territory.

Policy alternatives

This analysis evaluates impacts of a policy ("require undergrounding") against a baseline ("status quo"). In the following sections, the benefits and costs were evaluated for a policy that requires independently-owned Texas electric utilities to underground (1) existing T&D lines at the end of their useful life; and (2) when new infrastructure is needed to meet projected growth.

Impact categories

Table 15 describes a range of possible impacts (costs and benefits) for each alternative and group with standing (see above). It is expected that utility ratepayers will bear the cost burden as utilities pass-through all of the costs to install and maintain underground power lines. The largest beneficiaries of policies to encourage undergrounding of power lines would be the state's residents.

Table 15. Potential impacts from a policy requiring the undergrounding of T&D lines

Key Stakeholders	**Undergrounding Mandate**	
	Selected Costs	**Selected Benefits**[20]
IOUs	• Increased worker fatalities and accidents	
Utility ratepayers	• Higher installation cost of underground lines • Additional administrative, siting, and permitting costs associated with undergrounding • Increased ecosystem restoration/right-of-way costs	• Lower operations and maintenance costs for undergrounding[21]
All residents within service area		• Avoided costs due to less frequent power outages • Avoided aesthetic costs

3.4 Predicting, Monetizing, and Discounting Impacts

In general, this analysis involved predicting and monetizing impacts for five distinct categories: (1) lifecycle infrastructure costs including administrative, permitting, and siting costs; (2) benefits from less frequent power interruptions; (3) reduced aesthetic costs; (4) increased health and safety costs; and (5) increased ecosystem restoration costs. The stream of benefits and costs were evaluated from 2013 through 2050—the approximate lifespan of an underground T&D line installed in 2012. All future benefits and costs were discounted back to the present using a typical utility weighted average cost of capital (Brown 2009; Public Utilities Fortnightly 2013).

3.4.1 Lifecycle Infrastructure Costs

In this section, an empirical method is introduced to estimate the “status quo” and undergrounding-related costs associated with replacing and maintaining existing

[20] Other potential impacts not evaluated in this study include societal benefits from improved local/regional/national security, and changes to the likelihood of electrocution to the general public.
[21] Anecdotal evidence suggests that O&M expenses are lower for undergrounded systems (e.g., significant savings accrue from reduced vegetation management expenditures). However, there is little or no published information describing annual O&M cost differences between underground and overhead T&D systems. For the Texas analysis, it is assumed that the percentage share of replacement costs that represent operations and maintenance costs are the same between overhead and underground systems.

overhead T&D infrastructure, installing new overhead (underground) T&D infrastructure, and converting existing overhead infrastructure to underground lines. Determining the lifecycle costs of infrastructure involved a number of important steps including (1) collecting basic information on the total line mileage and replacement (i.e., conversion) and operations and maintenance (O&M) costs of T&D infrastructure that is currently overhead and underground for IOUs operating in Texas (Brown 2009; EEI 2013); (2) randomly determining the age and length of each segment (i.e., circuit) of existing overhead and underground infrastructure; (3) and calculating the net present replacement and O&M costs of T&D infrastructure through 2050 for a status quo and undergrounding mandate.

As discussed earlier, Brown (2009) and EEI (2013) report the costs of replacing and converting both overhead and underground T&D infrastructure. In addition, Brown (2009) provides useful summary statistics that describe the total number of T&D miles currently overhead and underground for the following Texas IOUs: TNMP, Oncor, Entergy Texas, Centerpoint, SWEPCO, AEP TX North, and AEP TX Central. Table A - 1 in the Technical Appendix shows the existing number of T&D miles assumed for this study, the assumed costs for the T&D lines, and a number of other key assumptions.

Unfortunately, there are no publicly available sources of information identifying the current age, location, or length of overhead and underground T&D line segments across Texas.[22] The timing of when these T&D costs materialize and any associated benefits accrue will determine how much future costs and benefits will need to be discounted back to the present. Therefore, the next step in estimating the lifecycle costs of infrastructure involved randomly generating the current age and length of each line circuit up to the total mileage for all IOUs operating in Texas.[23] Equations

[22] In this analysis, it is assumed that a line segment is analogous to a "circuit". However, it is likely that what is referred to as a segment may be much longer than a typical T&D line circuit. For this preliminary analysis, it is assumed that electric utilities will replace or convert each circuit (segment) independently.

[23] It is assumed that the total T&D line mileage grows at 2% per year.

11–13 describe how each segment (i) of existing infrastructure was randomly assigned an age using a statistical technique to approximate a bounded, normal distribution (StackExchange 2015). Unfortunately, the average age of overhead and underground transmission and distribution lines located in Texas could not be easily determined. For this reason, publicly accessible information was used to describe average ages ($\overline{\text{Age}_x}$) for underground and overhead T&D systems located in other Western states (Northwestern Energy 2011; Southern California Edison 2013). Northwestern Energy recently filed a report with the Montana Public Service Commission that contained an overhead distribution system "age profile" (i.e., histogram of electricity infrastructure ages) (Northwestern Energy 2011). The shape of this distribution was approximately normal with a slight skew to the right. Accordingly, the shape of this 2012 age profile was estimated for Texas using the average age for underground and overhead T&D line circuits and repeatedly drawing from a gamma distribution (SAS Institute 2015b) that is scaled (Equation 11), shaped (Equation 12), and lower-bounded at zero (StackExchange 2015). Throughout this section, the subscript *x* refers to overhead transmission (x=1) and distribution (x=2) lines and underground transmission (x=3) and distribution (x=4) lines.

$$\text{Scale}_x^{\text{Age}} = \frac{\left(\dfrac{\overline{\text{Age}_x}}{2}\right)^2}{\overline{\text{Age}_x}} \tag{11}$$

$$\text{Shape}_x^{\text{Age}} = \frac{\overline{\text{Age}_x}}{\left(\dfrac{\overline{\text{Age}_x}}{2}\right)^2} \tag{12}$$

Equation 13 denotes the randomly determined circuit age (in 2012) where z is a positive observation generated from the gamma probability distribution (SAS Institute 2015b).

$$\text{Age2012}_i \sim \text{Scale}_x^{\text{Age}} \left(\frac{1}{\Gamma\left(\text{Shape}_x^{\text{Age}}\right)} \right) z^{\text{Shape}_x^{\text{Age}}\text{-1}} e^{\text{-z}},\ z > 0 \tag{13}$$

For example, Figure 23 is a histogram of existing overhead distribution line circuit ages that were simulated using this technique.

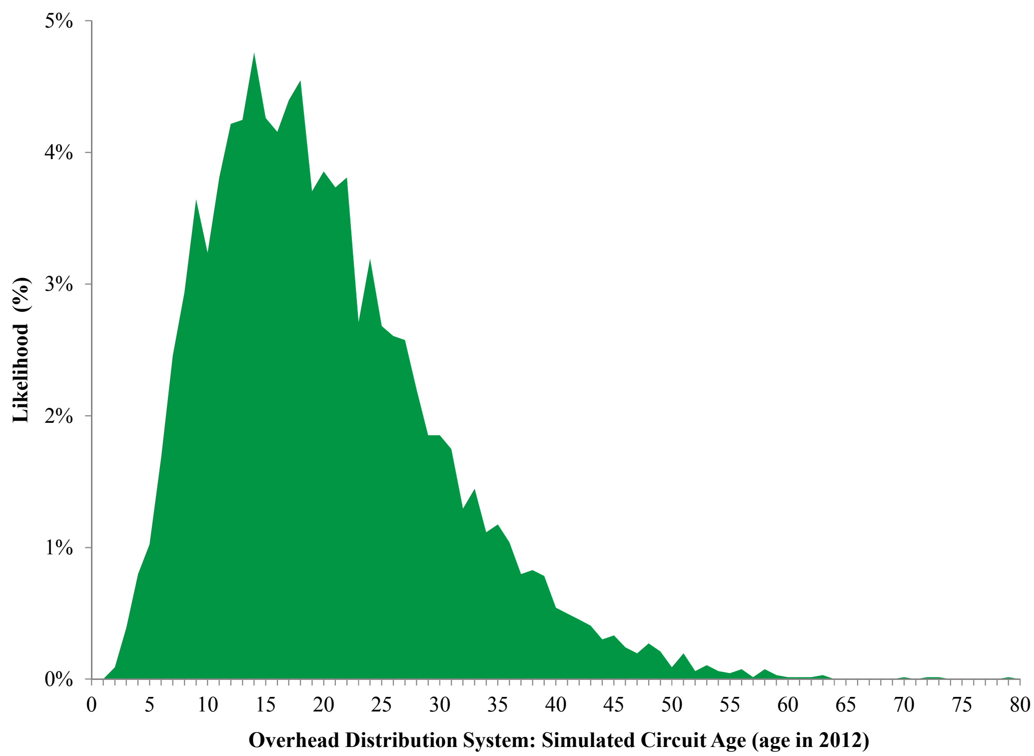

Figure 23. Simulated age profile of Texas IOU overhead distribution lines

Individual circuit length was determined following a similar process to what is described above for generating circuit ages (see Equations 14–16). In this case, an assumption was made about the average circuit length ($\overline{\text{Length}}_x$), in miles, for underground and overhead T&D systems.

$$\text{Scale}_x^{\text{Length}} = \frac{\left(\frac{\overline{\text{Length}}_x}{2} \right)^2}{\overline{\text{Length}}_x} \tag{14}$$

$$\text{Shape}_x^{\text{Length}} = \frac{\overline{\text{Length}_x}}{\left(\frac{\overline{\text{Length}_x}}{2}\right)^2} \tag{15}$$

$$\text{Length}_i \sim \text{Scale}_x^{\text{Length}} \left(\frac{1}{\Gamma\left(\text{Shape}_x^{\text{Length}}\right)}\right) z^{\text{Shape}_x^{\text{Length}}-1} e^{-z},\ z > 0 \tag{16}$$

Figure 24 is a histogram of existing overhead distribution line circuit lengths that were simulated using this technique. Note that the integral of this distribution is an estimate of the total mileage of overhead distribution lines operated by Texas IOUs in 2012 (i.e., 165,141 miles simulated versus 165,158 actual overhead distribution lines).

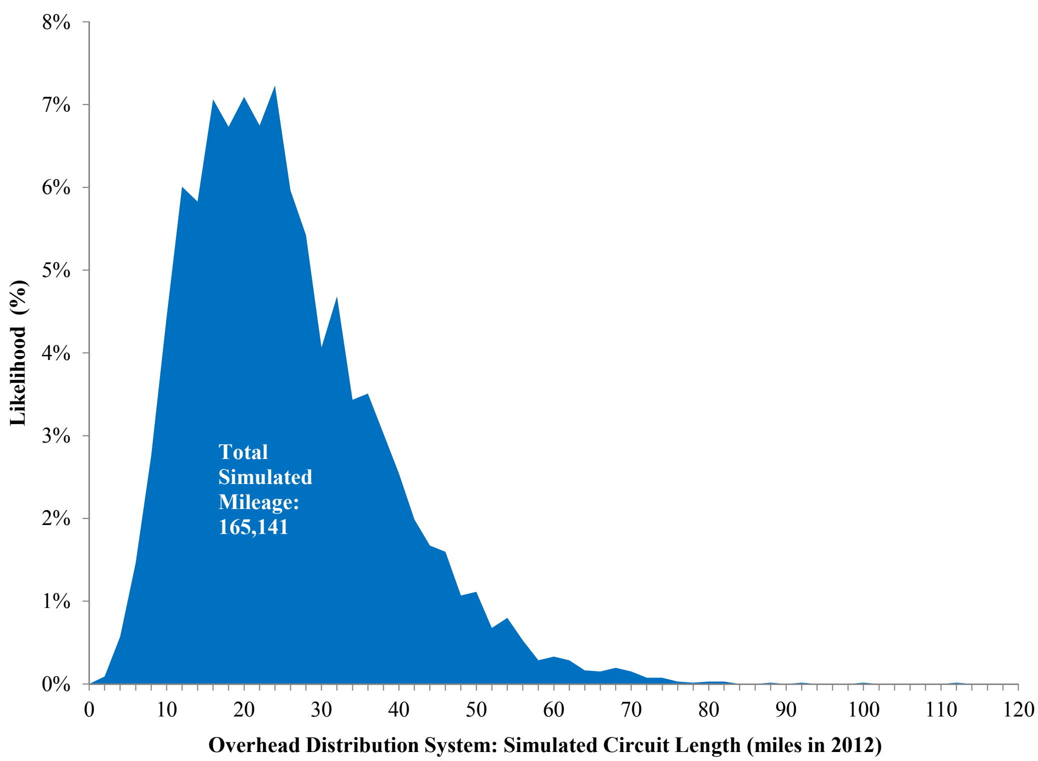

Figure 24. Simulated mileage profile of Texas IOU overhead distribution lines

A lifecycle analysis of T&D line costs through 2050 can be conducted with information on the circuit age in 2012, the length, expected useful lifespan, and replacement and O&M costs for all underground and overhead infrastructure. Equations 17–21 describe a technique to calculate the "true economic depreciation" of infrastructure (Samuelson 1964; Larsen et al. 2008; Heal 2012).[24] Under the status quo, it is assumed that overhead (underground) infrastructure is replaced at the end of its useful lifespan with the same type of infrastructure (overhead is replaced with overhead, underground is replaced with underground). Equation 17 denotes how the age of each circuit into the future was determined given the age of the circuit in the base year (2012), its expected lifespan, and whether or not it was replaced in any given future year.

$$\mathrm{Age}_{it} = \begin{cases} \mathrm{Age2012}_i + (t - 2012),\ \text{if } \mathrm{Age}_{it} \le \mathrm{Lifespan}_x \\ 1,\ \text{if } \mathrm{Age}_{it} - \mathrm{Lifespan}_x = 1 \\ \mathrm{Age}_{it\text{-}1} + 1,\ \text{if } \mathrm{Age}_{it} - \mathrm{Lifespan}_x > 1 \end{cases} \quad : \forall\ i,t,x \qquad (17)$$

It is possible that overhead and underground T&D line replacement costs may increase (decrease) from the initial replacement cost assumption for the base year (i.e., 2012). Equation 18 depicts how line replacement costs could increase (decrease) linearly in time at an annual growth (decay) rate expressed as Ψ_x.

$$\mathrm{ReplCost}_{xt} = \begin{cases} \mathrm{ReplCost}_x,\ \text{if } t = 2012 \\ \mathrm{ReplCost}_x + \Psi_x (t\text{-}2012)(\mathrm{ReplCost}_x),\ \text{if } t > 2012 \end{cases} \quad : \forall\ i,t,x$$

(18)

Equation 19 denotes status quo capital expenses (CAPEX) occurring in future years (t) when the age (Age_i) of the circuit exceeds the expected useful lifespan. All capital expenses incurred for each circuit (i) are then discounted t-2012 years back to the present—every time a replacement occurs—using discount rate () and summed over the entire analysis period (2013–2050).

---

[24] A variation of this method was used to estimate the additional costs to Alaska's infrastructure from the impacts of rapid climate change (Larsen et al. 2008).

$$\text{CAPEX}_i^{\text{StatusQuo}} = \begin{cases} \sum_{t=2013}^{2050} \dfrac{\text{ReplCost}_{xt}(\text{Length}_i)}{(1+r)^{t\text{-}2012}}, \text{if Age}_{it} = 1 \\ 0, \text{if Age}_{it} \neq 1 \end{cases} \quad : \forall \text{ i,t,x} \tag{19}$$

Equation 20 describes how annual O&M expenses (OPEX) for each type of T&D line are assumed to be a fraction (Θ_x) of the overall replacement costs—and that these O&M expenses increase at a constant amount each year as the circuit approaches its expected useful lifespan.[25]

$$\text{OPEX}_{xt} = \begin{cases} \Theta_x(\text{ReplCost}_{xt}), \text{ if Age}_{it} = 1 \text{ and x} = [1,2] \\ \text{OPEX}_{xt\text{-}1} + \Theta_x(\text{ReplCost}_{xt}), \text{ if Age}_{it} > 1 \text{ and x} = [1,2] \\ \Theta_x(\text{ReplCost}_{xt}), \text{ if Age}_{it} = 1 \text{ and x} = [3,4] \\ \text{OPEX}_{xt\text{-}1} + \Theta_x(\text{ReplCost}_{xt}), \text{ if Age}_{it} > 1 \text{ and x} = [3,4] \end{cases} \quad : \forall \text{ i,t} \tag{20}$$

Annual O&M expenses incurred for each circuit (i) are then discounted back to the present using discount rate () and then summed for all future years in the analysis (see Equation 21).

$$\text{OPEX}_i^{\text{StatusQuo}} = \sum_{t=2013}^{2050} \frac{(\text{OPEX}_{xt})(\text{Length}_i)}{(1+r)^{t-2012}} \quad : \forall \text{ i,t} \tag{21}$$

Total lifecycle costs, under the status quo, can then be estimated by summing both recurring capital and ongoing O&M expenditures for all circuits (see Equation 22).

$$\text{LifecycleCost}^{\text{StatusQuo}} = \sum_i \text{CAPEX}_i^{\text{StatusQuo}} + \sum_i \text{OPEX}_i^{\text{StatusQuo}} \quad : \forall \text{ i} \tag{22}$$

---

[25] It is likely that actual infrastructure O&M expenses increase (decrease) over time in a non-linear fashion. Future research should be undertaken to determine a more appropriate functional form. For the purposes of this initial analysis, however, a linear increase is more accurate than the assumption that O&M expenditures are constant regardless of circuit age.

Under the undergrounding alternative, however, the model replaces existing overhead infrastructure with underground infrastructure in the first retirement year. Equation 23 describes how the first retirement year is determined using the expected useful lifespan and age of circuit in 2012.

$$\text{FirstRetire}_i = \text{Lifespan}_x \text{-Age2012}_i + 2012 \qquad : \forall \ i,x \tag{23}$$

Equation 24 describes how at a specific point in time (FirstRetire_i) and in all future retirement years, the overhead lines are replaced with underground lines that have a relatively shorter lifespan and higher capital costs (CAPEX).

$$\text{CAPEX}_i^{\text{Under}} = \begin{cases} \sum_{t=2013}^{2050} \frac{\text{ReplCost}_{(x+2)t}(\text{Length}_i)}{(1+r)^{t\text{-}2012}}, \text{if Age}_{it} = 1 \text{ and x=[1,2]} \\ \sum_{t=2013}^{2050} \frac{\text{ReplCost}_{xt}(\text{Length}_i)}{(1+r)^{t\text{-}2012}}, \text{if Age}_{it} = 1 \text{ and x=[3,4]} \\ 0, \text{if Age}_{it} \neq 1 \end{cases} \qquad : \forall \ i,t \tag{24}$$

Administrative, permitting, and siting costs

For the purposes of this analysis, it is assumed that an administrative, permitting, and siting fee (% share of the total circuit replacement cost) is levied by the government against the utilities in the year before the first conversion decision. For example, if a utility converts an overhead transmission line to an underground transmission line in 2020, a proportional fee (e.g., 2%) is assessed in 2019 and discounted back to the present. In this analysis, this government fee (i.e., tax) is considered a deadweight loss to society, because this form of government revenue is not recycled back into the economy (Boardman et al. 2011). It is assumed that utilities will include this fee in the cost of line replacement or conversion.

Figure 25 illustrates this capital replacement method graphically for a hypothetical transmission line. The overhead transmission line begins to depreciate in year t and has no remaining value at year t'—the first retirement year ($FirstRetire_i$). Under the status quo, the overhead transmission line is replaced with another overhead line at year t'. Under the underground alternative, the overhead transmission line is replaced with a more expensive and shorter lasting underground line at year t'.

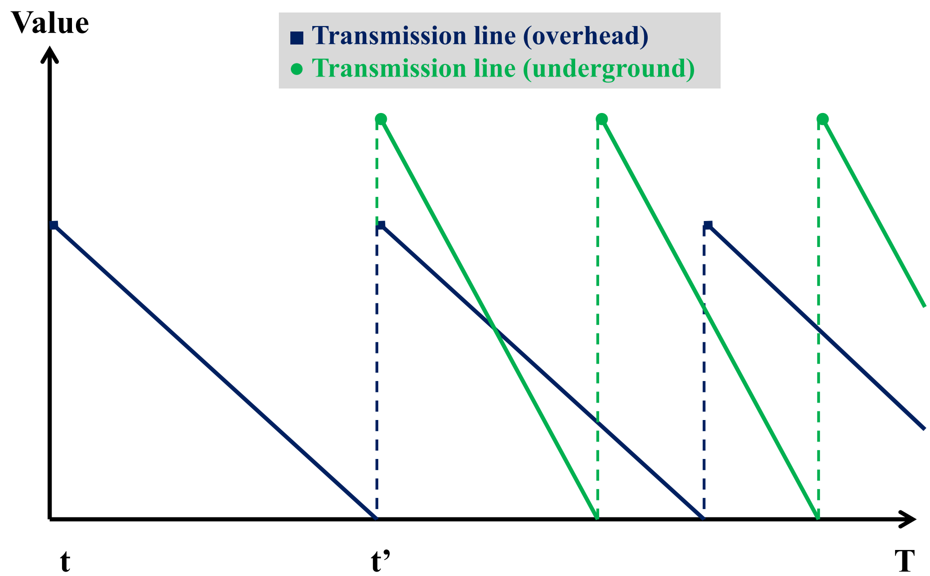

Figure 25. Depiction of capital replacement for a hypothetical line segment

For the undergrounding scenario and prior to the first retirement, annual overhead O&M expenses are estimated in the same fashion as described in Equation 20. However, after an overhead circuit is first converted to an underground circuit, then annual O&M expenses are re-estimated for the new underground line and these costs increase each year according to the amount specified in Equation 20. Equation 25, below, describes how circuit O&M costs reset as overhead lines are converted to underground lines.

$$OPEX_i^{Under} = \begin{cases} \sum_{t=2013}^{2050} \frac{(OPEX_{xt})(Length_i)}{(1+r)^{t-2012}}, \text{ if } x=[3,4] \\ \sum_{t=2013}^{2050} \frac{(OPEX_{xt})(Length_i)}{(1+r)^{t-2012}}, \text{ if } t < FirstRetire_i \text{ and } x=[1,2] \\ \sum_{t=2013}^{2050} \frac{(OPEX_{(x+2)t})(Length_i)}{(1+r)^{t-2012}}, \text{ if } t \geq FirstRetire_i \text{ and } x=[1,2] \end{cases} \quad : \forall\ i,t \tag{25}$$

Total lifecycle costs, under the undergrounding scenario, can then be estimated by summing both the recurring capital and ongoing O&M expenditures for all circuits (see Equation 26).

$$LifecycleCost^{Under} = \sum_i CAPEX_i^{Under} + \sum_i OPEX_i^{Under} \quad : \forall\ i \tag{26}$$

Equation 27 shows that future annual underground line mileage ($Underground_t$) can be determined based on the existing amount of underground line miles in 2012 ($Underground_{2012}$) and the ongoing conversion from overhead to underground T&D lines described above.

$$Underground_t = \begin{cases} \left(Underground_{2012}\right) + \sum_i Length_i, \text{ if } t \geq FirstRetire_i \\ \left(Underground_{2012}\right), \text{ if } t < FirstRetire_i \end{cases} \quad : \forall\ i,t,x \tag{27}$$

Finally, the net present value of costs associated with the status quo case are subtracted from the undergrounding alternative to estimate the additional lifecycle costs due to undergrounding (see Equation 28).

$$LifecycleCost^{Net} = LifecycleCost^{Under} - LifecycleCost^{StatusQuo} \tag{28}$$

3.4.2 Benefits from Less Frequent Outages

All residents and businesses living and operating, respectively, within the IOU service territories will avoid costs if undergrounding leads to less frequent power outages. The avoided costs from a more reliable electrical grid were derived by: (1) applying an econometric model (see previous section) to estimate the total number of outages—under the status quo—from now until 2050; (2) estimating the total number of outages—for the undergrounding alternative—by gradually removing the effect of weather on this same econometric model as the share of undergrounded line miles increases each year; (3) assigning a dollar value for the total number of annual customer-outages for both alternatives; and (4) subtracting the outage-related costs for the undergrounding alternative from the outage costs for the status quo to determine the dollar value of reduced outages.

In the preceding sections, an electric utility reliability model was developed that correlates annual measures of weather (heating degree-days, cooling degree-days, lightning strikes, wind speed, and precipitation), utility T&D expenditures, delivered electricity, presence of outage management systems, number of customers per line mile, and share of underground miles to the frequency of power outages across the United States (see Equation 29).[26]

$$\text{Outages}_t^{\text{StatusQuo}} = \exp\begin{pmatrix}\beta_1+\beta_2\text{Sales}+\beta_3\text{Expenditures}+\beta_4\text{PostOMS}+\beta_5\text{OMS}+\beta_6\text{Cold}+\beta_7\text{Warm}\\ +\beta_8\text{Lightning}+\beta_9\text{Windy}+\beta_{10}\text{Windy}^2+\beta_{11}\text{Wet}+\beta_{12}\text{Dry}+\beta_{13}\text{Year}\\ +\beta_{14}\text{Customers}+\beta_{15}\text{Underground}\end{pmatrix} \tag{29}$$

The model coefficients (and intercept) from the previous section were used along with average values of historical weather and other model inputs that are relevant for Texas

[26] Electric utility and reporting year are represented by subscript i and t, respectively. Please see the Technical Appendix for the values of the coefficients used in this analysis.

(see Technical Appendix) to estimate the future number of outages for Texas IOUs for the status quo[27].

Next, the total number of outages were estimated—for the undergrounding alternative—by gradually removing the effect of weather on this same econometric model as the share of undergrounded line miles increases each year. Again, the coefficients and intercept were used from Larsen et al. (2015). However, instead of using a fixed ~20% value for the share of T&D miles underground, the share of underground miles was increased based on annual overhead-to-underground conversion decisions from the lifecycle replacement analysis. In addition, a weather impact mitigation factor, phi, was used to decrease the impact of the weather on utility reliability—as the share of underground miles increased. Equation 30 represents the weather impact mitigation factor.

$$\phi_t = 1 - (\text{Underground}_t - \text{Underground}_{2012}) \tag{30}$$

Equation 31 depicts how the frequency of power outages was re-estimated using both the weather impact mitigation factor and the increasing share of underground miles.

$$\text{Outages}_t^{\text{Under}} = \exp\begin{pmatrix} \beta_1 + \beta_2\text{Sales} + \beta_3\text{Expenditures} + \beta_4\text{PostOMS} + \beta_5\text{OMS} \\ +\phi_t\left(\beta_6\text{Cold} + \beta_7\text{Warm} + \beta_8\text{Lightning} + \beta_9\text{Windy} + \beta_{10}\text{Windy}^2 + \beta_{11}\text{Wet} + \beta_{12}\text{Dry}\right) \\ +\beta_{13}\text{Year} + \beta_{14}\text{Customers} + \beta_{15}\text{Underground} \end{pmatrix} \tag{31}$$

The total value of lost load under the status quo (Equation 32) and undergrounding (Equation 33) alternative can be estimated using (1) the number of outages from

---

[27] This extrapolation technique is a preliminary attempt to project future outages using the model described in the previous section. Given that this projection is being made "far from the known data" (National Research Council 2007), future research should be conducted to ensure that this model is both appropriate and able to accommodate a wide range of input assumptions (i.e., sensitivities).

Equations 32 and 33, respectively; (2) the number of customers for each class of service (i.e., commercial and industrial, residential, other), *c*; and (3) and assumptions about the lost economic value, by customer class, for each power outage.

$$\mathrm{VLL}^{\mathrm{StatusQuo}} = \sum_{t=2013}^{2050} \frac{\left(\sum_{c=1}^{3} \mathrm{Outages}_{t}^{\mathrm{StatusQuo}} (\mathrm{Customers}_{c})(\mathrm{VLL}_{c}) \right)}{(1+r)^{t-2012}} \tag{32}$$

Sullivan et al. (2010) report a range of values of lost load per outage—by duration—for residential, commercial and industrial customers. For the base case analysis, it is assumed that the value of lost load per customer is based on a 30-minute power outage, and that other and small commercial and industrial customers have equivalent VoLLs.

$$\mathrm{VoLL}^{\mathrm{Under}} = \sum_{t=2013}^{2050} \frac{\left(\sum_{c=1}^{3} \mathrm{Outages}_{t}^{\mathrm{Under}} (\mathrm{Customers}_{c})(\mathrm{VoLL}_{c}) \right)}{(1+r)^{t-2012}} \tag{33}$$

Finally, the benefits of avoided outages were calculated by subtracting the status quo total value of lost load from the total value of lost load from the undergrounding alternative (Equation 34).

$$\mathrm{VoLL}^{\mathrm{Avoided}} = \mathrm{VoLL}^{\mathrm{StatusQuo}} - \mathrm{VoLL}^{\mathrm{Under}} \tag{34}$$

3.4.3 Avoided Aesthetic Costs as a Proxy for Property Value Improvements

For this analysis, it is assumed that Texas property owners will receive no aesthetic benefit from undergrounding *distribution* lines, because it is likely that poles with television cable and internet cables will continue to stay in place for the foreseeable future (Most and Weissman 2012). However, as discussed earlier, hedonic studies (Des Rosiers 2005; Sims and Dent 2002; Headwaters Economics 2012; Navrud et al. 2008) have shown that the presence of overhead high-voltage transmission lines negatively affect the value of real estate (e.g., ~ -5% to -20%). It is assumed that avoided aesthetic costs serve as a proxy for improved property values. Calculating the net aesthetic benefit of undergrounding these transmission lines involves the following: (1) estimating the number of residential, commercial and industrial, and other properties within an "overhead transmission corridor" (e.g., 300 feet on either side of overhead transmission line or 600 feet wide) which is decreasing in size over time; (2) multiplying the number of affected properties against the median real estate value for each property class and lost property value associated with overhead high-voltage transmission lines (e.g., 12.5% for the base case); and (3) discounting the stream of avoided aesthetic costs back to the present using a 10% discount rate (see Equation 35).

$$\text{Aesthetic}^{\text{Under}} = \sum_{t=2013}^{2050} \frac{\left(\dfrac{\left(\dfrac{\text{Corridor}}{5280}\right)\left(\text{Underground}_t - \text{Underground}_{t-1}\right)}{\text{ServiceArea}} \right)(\text{Customers}_c)(\text{PropertyValue}_c)(\text{PriceImpact})}{(1+r)^{t-2012}} \tag{35}$$

3.4.4 Ecosystem-related Restoration Costs

For this analysis, it is assumed that habitat restoration activities took place when the existing overhead and underground lines were sited, but that fewer restoration activities will need to take place as new lines are added and/or converted to underground infrastructure. It is also assumed that undergrounding T&D lines will affect a larger area than overhead lines (Public Service Commission of Wisconsin 2013). The monetization of ecosystem restoration costs involved (1) estimating the number of acres affected by T&D line growth in the future (using development corridor width and total line miles); (2) multiplying total T&D line corridor acreage against a conservation easement price; and (3) discounting this cost back to the present.

Equation 36 describes initial assumptions about the width, in feet, of the T&D line corridor for the overhead transmission (x=1) and distribution (x=2) lines and underground transmission (x=3) and distribution (x=4) lines.

$$\text{Corridor}^{\text{Eco}} = \begin{cases} 60 : x = [1,2] \\ 120 : x = [3,4] \end{cases} \tag{36}$$

The total ecosystem restoration cost of the status quo alternative was calculated by multiplying the additional overhead line miles (built after 2012) against the relevant corridor width ($\text{Corridor}^{\text{Eco}}$), converting square miles to acres, and multiplying the impacted ecosystem acreage against the per-acre price of a conservation easement in Texas in year t (see Equation 37).

$$\text{Restoration}^{\text{StatusQuo}} = \sum_{t=2013}^{2050} \frac{\left(\sum_{x=1}^{2}\sum_{i}\text{Length}_{it} - \sum_{x=1}^{2}\sum_{i}\text{Length}_{it-1}\right)\left(\frac{\text{Corridor}^{\text{Eco}}(640)}{5280}\right)(\text{EasementValue})}{(1+r)^{t-2012}} \tag{37}$$

The total ecosystem restoration cost of the undergrounding alternative was calculated by multiplying the additional underground line miles (built after 2012) against the relevant corridor width ($\text{Corridor}^{\text{Eco}}$), converting square miles to acres, and multiplying the impacted ecosystem acreage against the per-acre price of a conservation easement in Texas in year t (see Equation 38).

$$\text{Restoration}^{\text{Under}} = \sum_{t=2013}^{2050} \frac{\left(\text{Underground}_{t} - \text{Underground}_{t-1}\right)\left(\frac{\text{Corridor}^{\text{Eco}}(640)}{5280}\right)(\text{EasementValue})}{(1+r)^{t-2012}} \tag{38}$$

It is assumed in the initial base case analysis that an unlimited amount of Texas conservation easements can be purchased for $3,000/acre in any year (Nature Conservancy 2014) and that future easement purchases were discounted back to the present using a 10% discount rate. It follows that the additional (net) restoration costs—due to undergrounding—can be calculated by subtracting the status quo restoration costs from the undergrounding alternative restoration costs (see Equation 39).

$$\text{Restoration}^{\text{Net}} = \text{Restoration}^{\text{Under}} - \text{Restoration}^{\text{StatusQuo}} \tag{39}$$

3.4.5 Construction-related Morbidity and Mortality Costs

It is unfortunate, but likely, that replacing a large amount of overhead infrastructure with underground infrastructure will lead to relative increases in risk to utility operational staff working in the field. For that reason, it is assumed that health and safety costs will increase—above levels observed with the status quo—as the share of underground lines increases. Quantifying the additional costs associated with increases in worker morbidity and mortality involved a number of steps.

First, publicly accessible information was used from the utilities to estimate the total number of employees working for all Texas IOUs represented in this study. Next, information was collected on the existing incidence rates and costs of relevant injuries (e.g., electrocution, broken bones, burns, sprains, mass trauma) for electric utility workers from the U.S. Occupational Safety and Health Administration (OSHA 2014). In addition, information is collected on existing fatality rates for the electric utility sector from BLS (2014a) and the value of a statistical life ($6.9 million) from a recent document published by the Executive Office of the President (2013b). The following equations describe how non-fatal costs (Equation 40) and fatality-related economic losses (Equation 41) were calculated by multiplying the corresponding incidence rates by the number of IOU employees, a randomly determined annual injury cost, and the value of statistical life, and discounting the future annual morbidity and mortality costs back to the present using an appropriate discount rate.

$$\text{NonFatal}^{\text{StatusQuo}} = \sum_{t=2013}^{2050} \frac{\left((\text{NFIR}) \left(\frac{\text{Employees}}{100000} \right) (\text{InjuryCost}) \right)}{\left(1+r\right)^{t-2012}} \tag{40}$$

Where *NFIR* and *FIR* represents non-fatality and fatality incidence rates, respectively; *Employees* are the total number of employees working for the Texas IOUs, *InjuryCost* is the total direct and indirect cost of an injury that is likely to occur for workers in the electric utility sector; and VSL is the value of a statistical life.

$$\text{Fatal}^{\text{StatusQuo}} = \sum_{t=2013}^{2050} \frac{\left((\text{FIR}) \left(\frac{\text{Employees}}{100000} \right) (\text{VSL}) \right)}{\left(1+r\right)^{t-2012}} \tag{41}$$

The fatal and non-fatal incidence rates were increased proportionally as the share of underground line miles increases each year (see Equation 42).

$$\psi_t = \left(\frac{\text{Underground}_t}{\text{Underground}_{t-1}} \right) \tag{42}$$

Next, the increased incidence rates by the number of employees, injury costs, and value of statistical life for the undergrounding alternative; and discounted the future annual morbidity and mortality costs back to the present using an appropriate discount rate (see Equations 43 and 44).

$$\text{NonFatal}^{\text{Under}} = \sum_{t=2013}^{2050} \frac{\left((\psi_t)(\text{NFIR}) \left(\frac{\text{Employees}}{100000} \right) (\text{InjuryCost}) \right)}{\left(1+r\right)^{t-2012}} \tag{43}$$

$$\text{Fatal}^{\text{Under}} = \sum_{t=2013}^{2050} \frac{\left((\psi_t)(\text{FIR}) \left(\frac{\text{Employees}}{100000} \right) (\text{VSL}) \right)}{(1+\text{r})^{\text{t-2012}}} \tag{44}$$

Finally, the NPV of status quo fatal and non-fatal costs is subtracted from the NPV of fatal and non-fatal costs (undergrounding alternative) to determine the NPV of morbidity and mortality costs due to undergrounding (see Equation 45).

$$\text{HealthSafety}^{\text{Net}} = \left(\text{NonFatal}^{\text{Under}} + \text{Fatal}^{\text{Under}} \right) - \left(\text{NonFatal}^{\text{StatusQuo}} + \text{Fatal}^{\text{StatusQuo}} \right) \tag{45}$$

3.4.6 Sensitivity Analysis

A sensitivity analysis was conducted by varying several of the key inputs to this cost-benefit analysis—independently and together—including the: (1) replacement cost of undergrounding lines; (2) impact of undergrounding on reliability; (3) purchase price of conservation easements; (4) increased chance of construction-related accidents and fatalities; (5) discount rate; (6) alternative lost real estate value assumptions; (7) alternative lifespan assumptions for overhead infrastructure; (8) assumptions related to the value of mortality and morbidity; (9) alternative value of lost load assumptions; (10) the number of customers per line mile; and (11) O&M costs of undergrounding lines. Table 16 shows which sensitivity analyses apply to each of the selected impact categories.

Table 16. Sensitivity analyses and impact categories

		Range			Impact Category				
#	**Sensitivity/scenario analysis**	**Minimum value (10th %)**	**Base case value (50th %)**	**Maximum value (90th %)**	**Lifecycle assessment (cost)**	**Avoided outages (benefit)**	**Aesthetics (benefit)**	**Health and safety (cost)**	**Ecosystem restoration (cost)**
1	Alternative replacement cost of undergrounding T&D lines ($ per mile)	$71,400 (dist.) $336,000 (trans.)	$357,000 (dist.) $1,680,000 (trans.)	$642,600 (dist.) $3,024,000 (trans.)	*	*			
2	Alternative values of lost load for each customer class ($ per event)	$0.5 (residential) $87 (other) $1,843.4 (C&I)	$2.7 (residential) $435 (other) $9,217 (C&I)	$4.9 (residential) $783 (other) $16,590.6 (C&I)		*			
3	Alternative discount rates (%)	2%	10%	18%	*	*	*	*	*
4	Alternative aesthetic-related property loss factors (% of property value)	2.5%	12.5%	22.5%			*		
5	Alternative incidence rates for accidents and fatalities (per 100,000 employees)	420 (non-fatal) 3 (fatal)	2,100 (non-fatal) 15 (fatal)	3,780 (non-fatal) 27 (fatal)				*	
6	Alternative accident costs and VSL ($ per accident/$ per life)	$26,131.6 $1,380,000 (VSL)	$130,658 $6,900,000 (VSL)	$235,184.4 $12,420,000 (VSL)				*	
7	Alternative conservation easement prices ($/acre)	$600	$3,000	$5,400					*

		Range			Impact Category				
#	**Sensitivity/scenario analysis**	**Minimum value (10th %)**	**Base case value (50th %)**	**Maximum value (90th %)**	**Lifecycle assessment (cost)**	**Avoided outages (benefit)**	**Aesthetics (benefit)**	**Health and safety (cost)**	**Ecosystem restoration (cost)**
8	Alternative lifespan assumptions for overhead T&D infrastructure (years)	45	60	75	*	*	*	*	*
9	Share of underground line miles impact on reliability	-0.0002	-0.001	-0.0018		*			
10	Number of customers per line mile	15	75.0	135		*			
11	Annual O&M cost expressed as % of replacement cost: underground T&D lines	1% (trans.) 0.1% (dist.)	5% (trans.) 0.5% (dist.)	9% (trans.) 0.9% (dist.)	*				

3.5 Results and Discussion

3.5.1 Estimated Costs

Figure 26 shows the impact of varying the assumed lifespan of overhead T&D lines. Not surprisingly, as the assumed lifespan is decreased from seventy-five to sixty to forty-five years, the lifecycle algorithm replaces overhead lines with underground lines earlier in time—leading to a larger share of underground line miles by 2050. For example, the entire Texas IOU T&D system could be 50% underground by 2028 if the lifespan of existing overhead lines is assumed to be forty-five years instead of sixty years. The share of underground line miles has important economic implications throughout this analysis. Accordingly, a sensitivity analysis is conducted on the assumed lifespan of existing overhead T&D infrastructure.

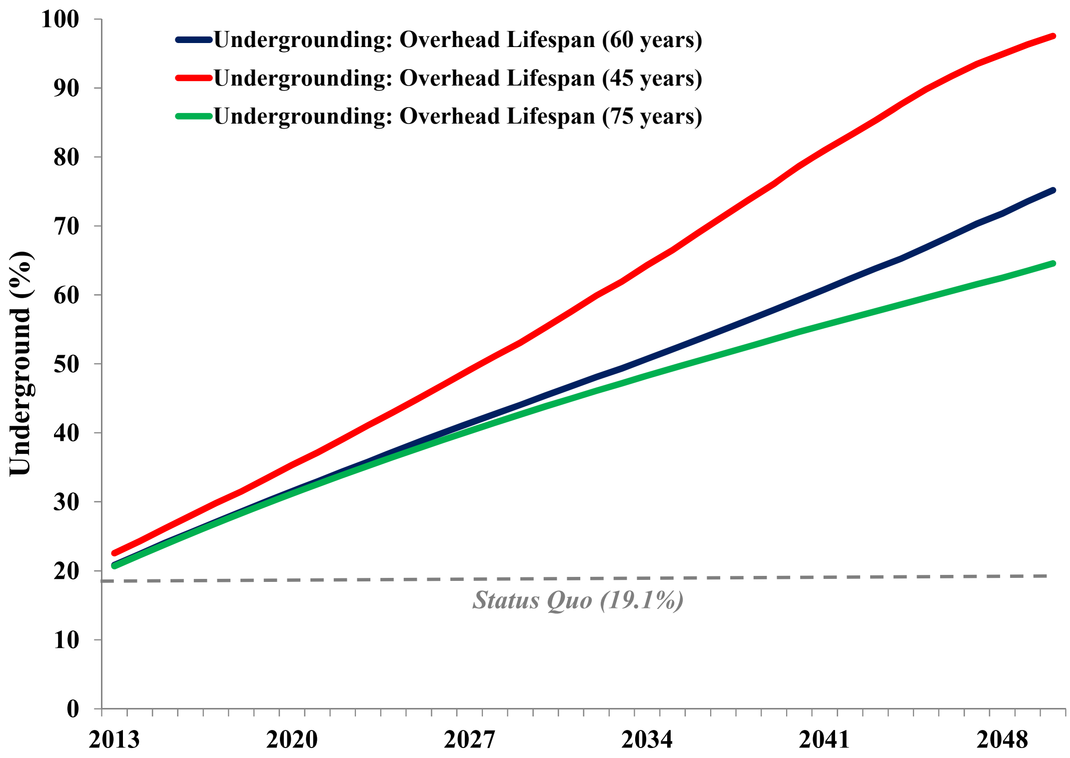

Figure 26. Share of underground line miles using alternative useful lifespans of overhead T&D lines

Figure 27 shows that the lifecycle replacement costs ranged from ~$26.0 billion (status quo) to $52.3 billion (undergrounding). Net increased NPV replacement costs were ~$26.3 billion. The net present value of ecosystem restoration costs were ~$1.0 billion for the status quo and ~$2.8 billion for the undergrounding alternative. Additional ecosystem restoration costs due to undergrounding were ~$1.8 billion. Base case health and safety costs were ~$313 million and $560 million for the status quo and undergrounding alternative, respectively. It follows that additional health and safety costs due to undergrounding are ~$245 million.

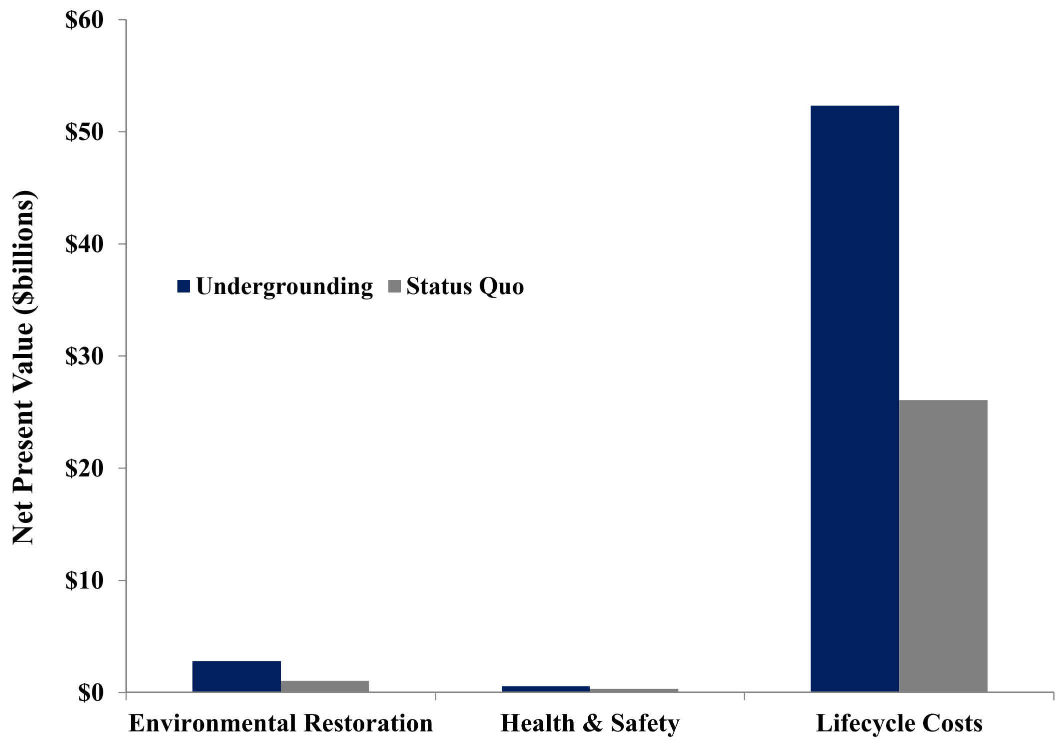

Figure 27. Net present value of costs for status quo and undergrounding alternative

3.5.2 Estimated Benefits

In the previous section, it was demonstrated that as the share of underground line miles increases, customers will experience less frequent power outages over time relative to the status quo (see Figure 28).

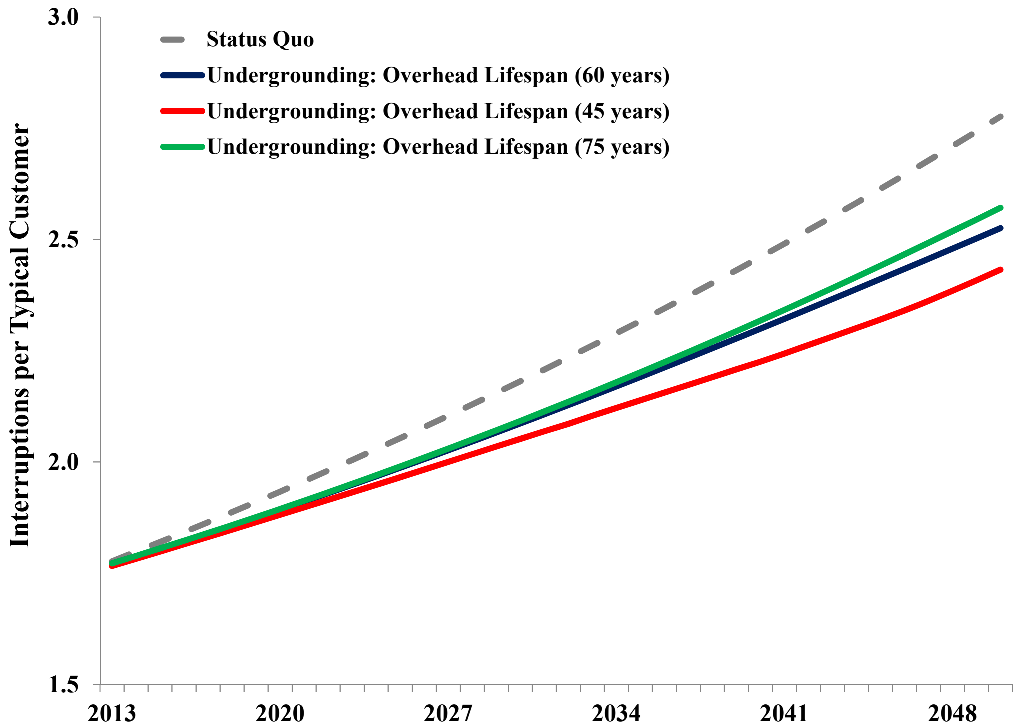

Figure 28. Typical number of interruptions per customer for status quo and alternative assumptions about useful lifespan of overhead T&D lines

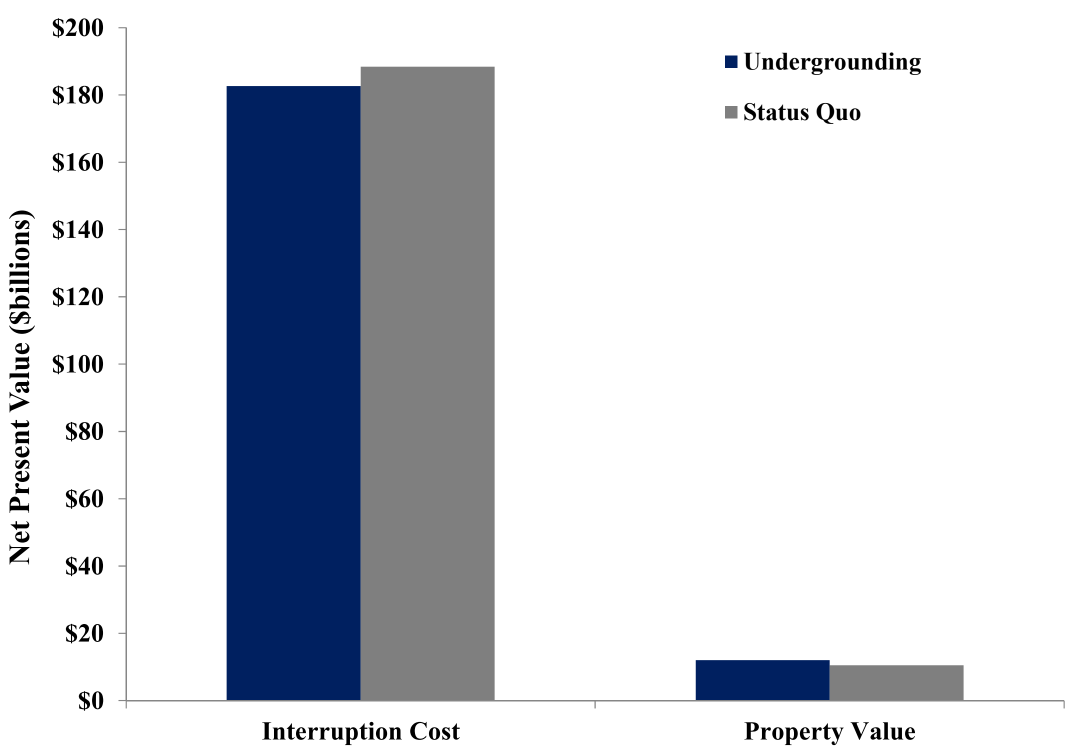

Figure 29. Net present value of benefits for status quo and undergrounding alternative

Figure 29 shows the value of lost load for the status quo (~$188 billion) and undergrounding alternative (~$183 billion). Accordingly, the *avoided* value of lost load due to undergrounding is estimated at approximately $5.8 billion. Figure 29 also shows that the total avoided aesthetic costs for the status quo is estimated at $10.5 billion with the avoided aesthetic costs increasing to $12.0 billion for the undergrounding alternative. Net increased avoided aesthetic costs, which is a proxy for the property value benefits of undergrounding, is estimated at ~$2 billion.

Figure 30 shows a breakdown of the net benefits of avoided outage costs by the three customer classes. Commercial/industrial customers are projected to receive the largest share of net benefits ($5.7 billion) primarily due to the relatively higher value of lost load assumption for this customer class when compared to the other customer classes.

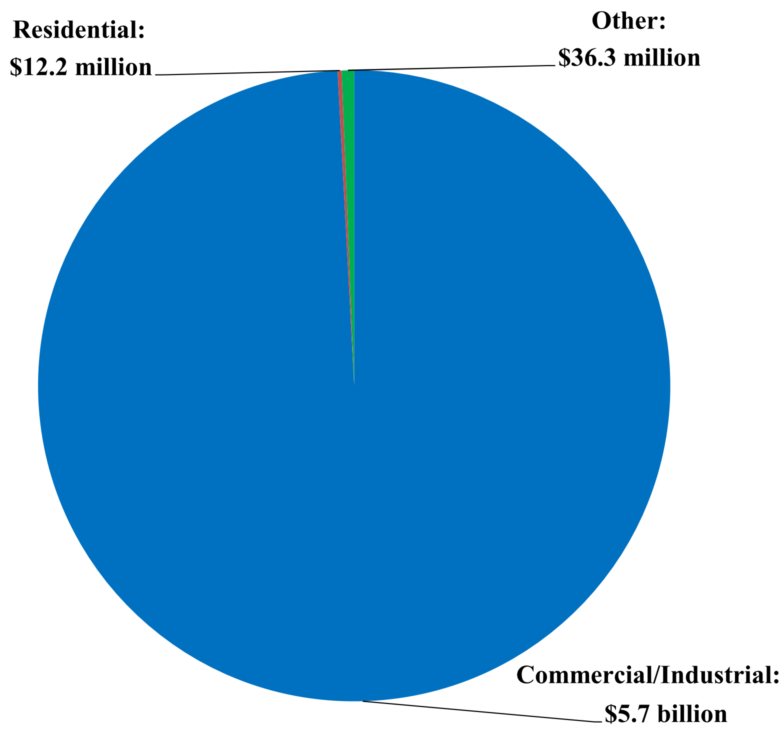

Figure 30. Net present value of net avoided interruption costs by customer type

Figure 31 shows a breakdown of the net increase in avoided aesthetic costs by the three customer classes. Commercial/industrial and residential customers are projected to benefit from an approximately equal share of the avoided aesthetic cost gains.

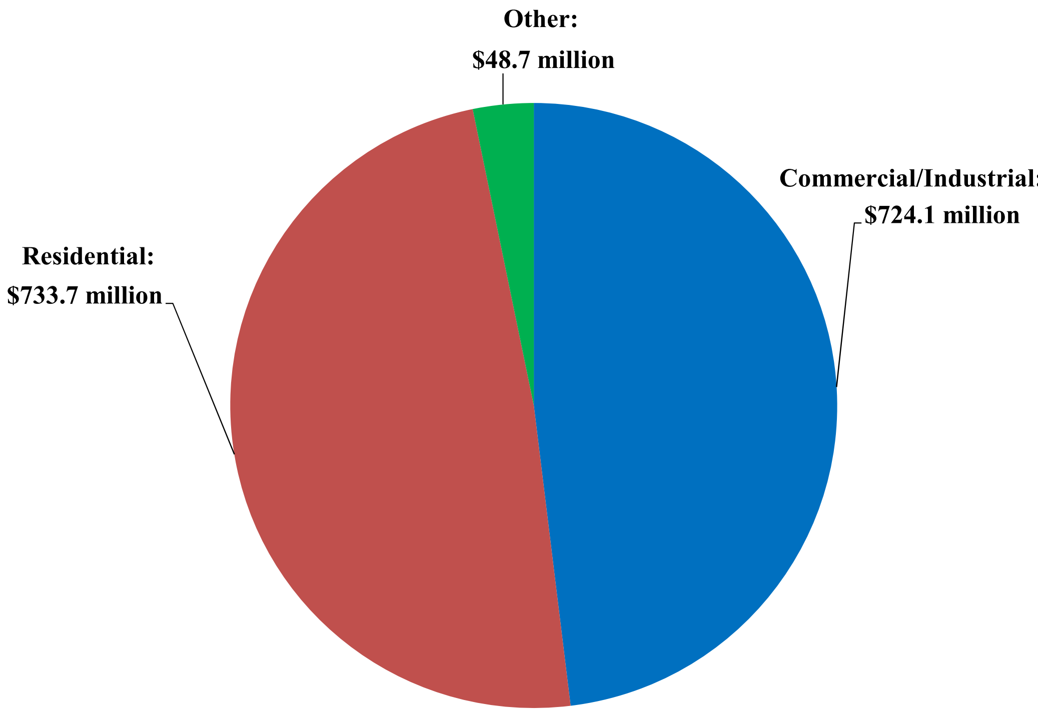

Figure 31. Net present value of *net* avoided aesthetic costs by customer type

3.6 Net Social Loss and Sensitivity Analysis

3.6.1 Net Social Loss

Under the base case, the net costs from undergrounding are estimated at ~$28.3 billion with net benefits of ~$7.3 billion (see Table 17). It follows that the base-case net social loss from undergrounding all Texas IOU T&D lines is ~$21 billion, which is equivalent to a 0.3 benefit-cost ratio. Interestingly, the external benefits (avoided aesthetic costs) are a relatively minor share of the total benefits when compared to the private benefits (avoided interruption costs).

Table 17. Summary of base case costs and benefits

Impact Category	Undergrounding	Status Quo	Net Cost ($billions)
Environmental restoration	$2.8	$1.0	$1.8
Health & safety	$0.56	$0.31	$0.2
Lifecycle costs	$52.3	$26.1	$26.3

Total net costs (Undergrounding)			$28.3
Impact Category	**Undergrounding**	**Status Quo**	**Net Benefit ($billions)**
Interruption cost	$182.7	$188.4	$5.8
Avoided aesthetic costs	$12.1	$10.6	$1.5
Total net benefits (Undergrounding)			$7.3
Net Social Loss (Undergrounding)			
Net social loss (billions of $2012)			**-$21.0**
Benefit-cost ratio			**0.3**

3.6.2 Sensitivity Analysis Results

Figure 32 is a tornado diagram (Howard 1988) created by varying each of the eleven key input assumptions, separately, to evaluate the overall effect on the total net benefit calculation.[28] This type of sensitivity analysis shows that the net benefit (loss) calculation is most sensitive to the choice of (1) discount rates; (2) replacement cost of undergrounding lines; (3) overhead T&D line lifespan; (4) value of lost load; and (5) customers per line mile. For example, the minimum costs for replacing underground T&D lines leads to net benefits of ~$5 billion whereas assuming the maximum replacement cost yields net losses of ~$47 billion—all else being equal.

A Monte Carlo simulation was conducted by sampling all of the key input assumptions from uniform distributions—bounded by the minimum and maximum values reported in Table 16— *simultaneously*. The resulting distributions, which are based on repeated sampling (n=500), show the full range of net benefits possible if all key parameters vary simultaneously and independently of one another. Figure 33 shows the likelihood of total net losses for an assumed overhead T&D line lifespan of forty-five years (red), sixty years (dark blue), and seventy-five years (green). As discussed earlier, if overhead lifespans are assumed to be shorter, a larger share of lines are undergrounded—with corresponding relative increases in net losses. The results of the Monte Carlo simulations show average net losses of ~$21.6 billion.

[28] The results were generated by running the individual parameter minimum and maximum values as shown in Table 16. There are disadvantages to using tornado diagrams including the assumption that there is independence among the parameters being compared (Reilly 2000).

Interestingly, varying all of the key parameters simultaneously leads to consistently negative average net losses. In addition, net losses may be the highest in places where the typical lifespan of overhead lines is the shortest. In this case, the net present value (NPV) lifecycle costs of replacing the shorter lifespan overhead lines with underground lines—in the near term—far exceed the NPV lifecycle costs of replacing longer lifespan overhead lines many decades into the future. For this reason, the net losses are lower under the seventy-five-year lifespan sensitivity assumptions.

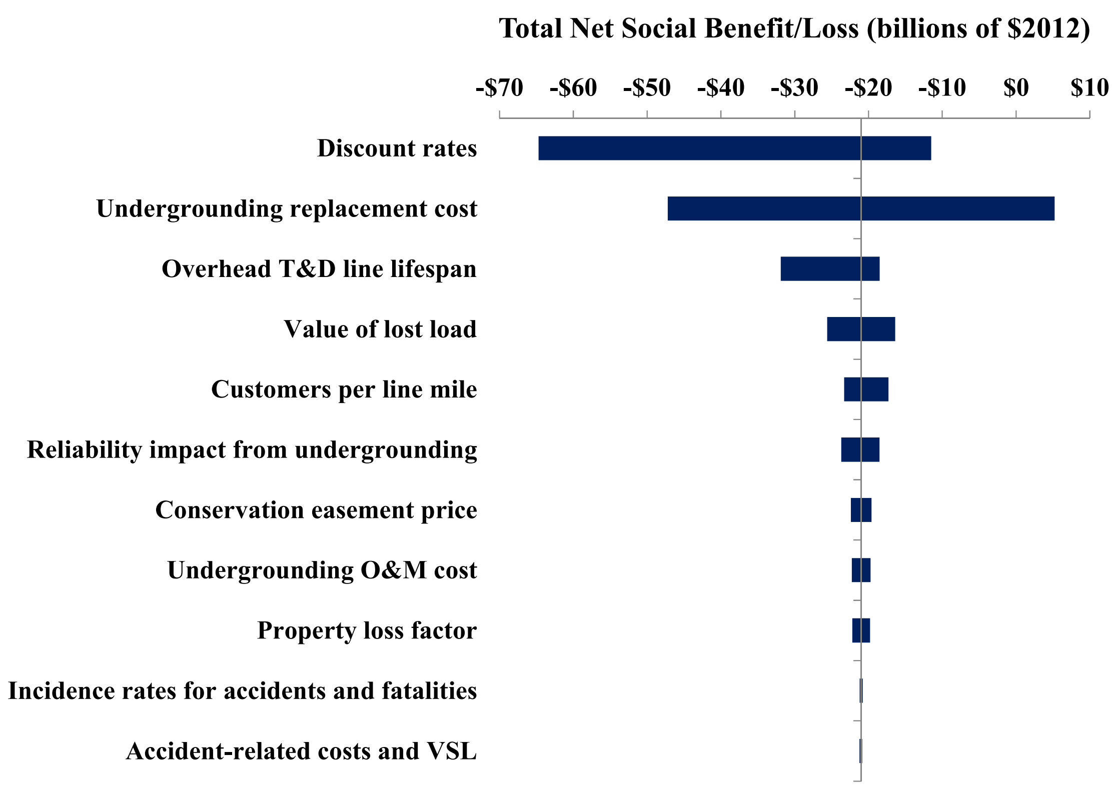

Figure 32. Sensitivity analysis of net social benefit (loss) using alternative model parameters

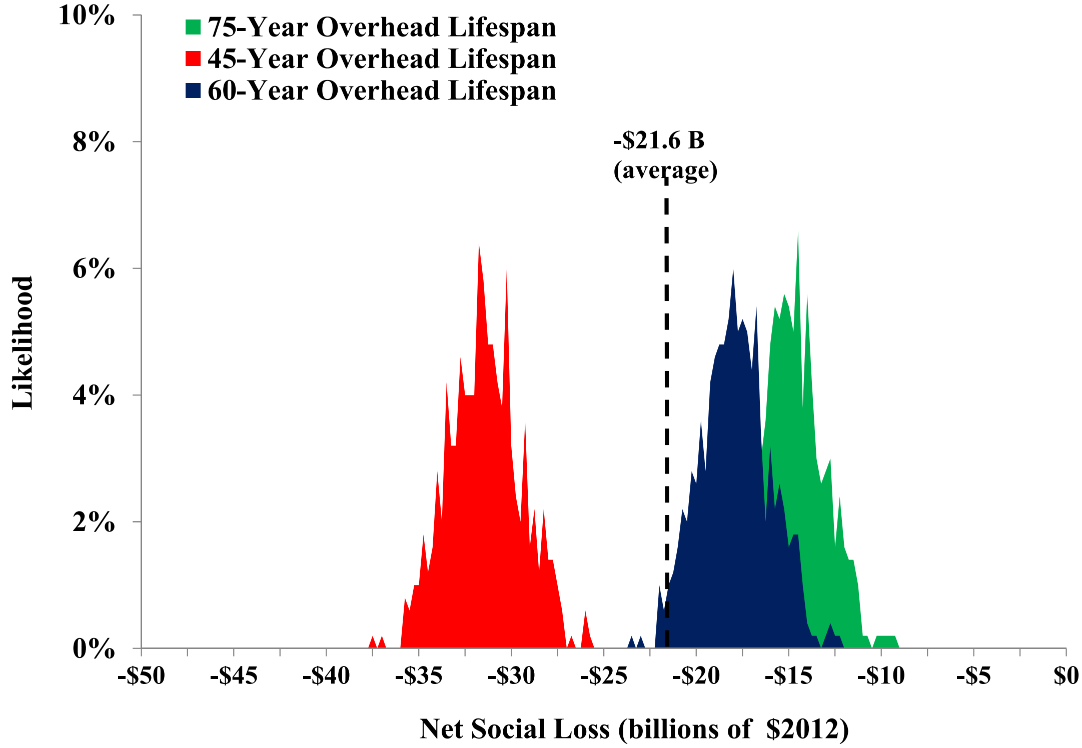

Figure 33. Monte Carlo simulation of net social loss for 45/60/75-year lifespan for overhead T&D lines (billions of $2012)

3.7 Minimum Conditions Necessary for Net Social Benefits

To date, widespread undergrounding initiatives have been most prevalent in urban areas including Washington D.C., San Diego, New York City, and London (Washington D.C. Power Line Undergrounding Task Force 2014; City Council of San Diego 2002; NYC Office of Long-Term Planning and Sustainability 2013; National Grid-UK 2016). It is possible that there may be localized net benefits in places where (1) there are a large number of customers per line mile (i.e., urban areas)—thus allowing IOUs to achieve economies of scale during the installation of underground lines; and (2) undergrounding is expected to lead to substantial reliability improvements in urban areas vulnerable to frequent and intense storms.

This subsection evaluates the possibility that strategically focusing undergrounding efforts on urban areas within Texas IOU service territories could lead to net benefits.

3.7.1 Method and Key Assumptions

The goal of this analysis is to identify the minimum conditions that would need to be met in order for a targeted undergrounding initiative to have a net social benefit (i.e., benefit-cost ratio greater than or equal to one). To achieve this, the undergrounding model was solved through a backward induction technique where:

- only T&D lines passing within one mile of an urban area are considered in the analysis
- the reliability impact from undergrounding falls within the range of the base case and maximum values reported in Table 16
- the right-of-way (i.e., easement area) is assumed to be larger for overhead lines than underground lines
- the initial underground T&D line capital costs vary within the range of the minimum and base case values (see Table 16) and in subsequent years are decreased until the resulting benefit-cost ratio is approximately equal to one.

These conditions and the assumptions used in this analysis are described in greater detail below.

Target urban areas within Texas IOU service territories

First, the extent of overhead and underground T&D line miles was reduced to reflect the subset of lines located near urban areas. Table 18 shows the assumed line miles and number of customers from the original, unrestricted analysis (rural and urban) and the restricted analysis (urban only) described in this subsection. As shown in Table 18, the customers per line mile more than doubles when only urban areas are considered. In addition to justifying undergrounding cost economies-of-scale (see below), customers per line mile is an explanatory variable in the model component used to project future outages (see section 3.4.2)—and the associated benefits from reductions in outages dues to undergrounding. It is assumed that the number of customers per line mile randomly varies from 63.5 (see Table 2218) to 135 (the maximum value reported in Table 16).

Table 18. Summary of Texas IOU line mileage and number of customers

Overhead or underground	Type	Urban + Rural Line Miles (Brown 2009)	Urban Line Miles
Overhead	Distribution	165,158	75,250 [a]
Overhead	Transmission	33,060	15,063 [b]
Underground	Distribution	46,669	2,881 [a]
Underground	Transmission	81	5 [b]
Total line mileage:		**244,968**	**93,199**
Number of customers:		**6,983,069**	**5,914,659** [c]
Customers per line mile:		**28.5**	**63.5**

Sources:
[a] Author estimates based on extrapolation using Brown (2009) and ABB-Ventyx (2015) sources
[b] ABB-Ventyx (2015)
[c] Author estimated by multiplying Census (2010) share of Texas residents living in urban areas (84.7%) against estimate of all Texas IOU customers from Brown (2009)

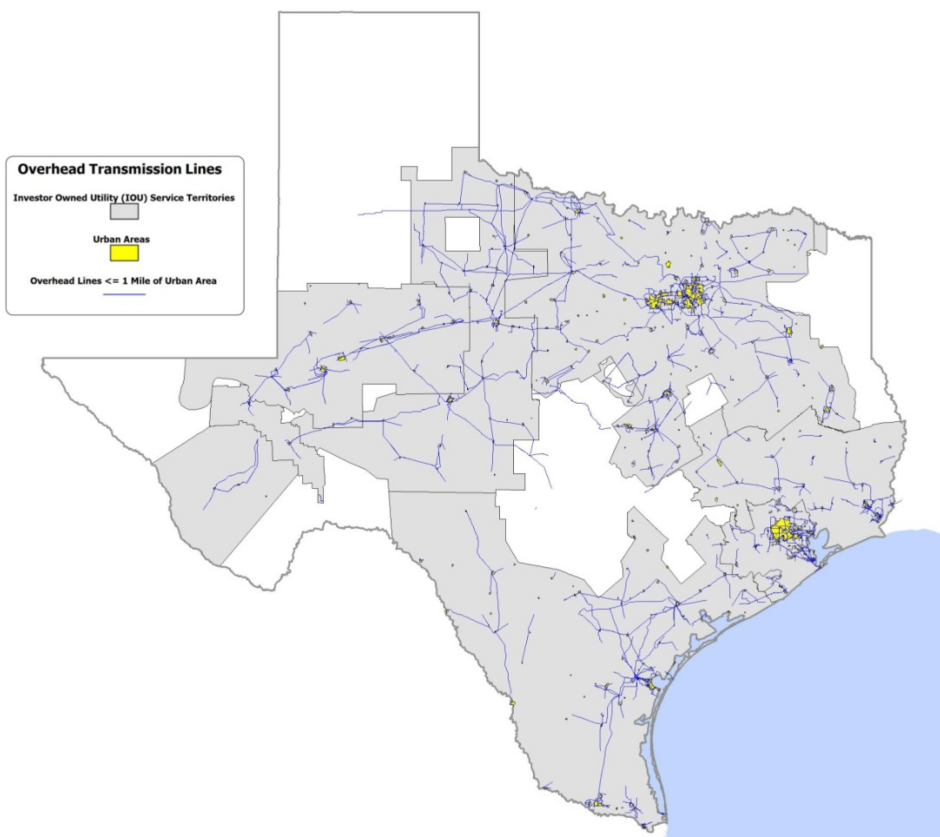

Figure 34. Overhead transmission lines near urban areas within investor-owned utility service territories

Figure 34 is a map depicting the location of all overhead transmission lines that pass within one mile of a designated urban area (ABB-Ventyx 2015).

Figure 35 shows that, depending on the assumed lifespan of overhead lines, the total Texas IOU line mileage converted to underground ranges from 40–55% by 2050. For comparison, undergrounding all rural and urban lines at the end of their useful lifespan resulted in 65–98% of the combined service territories being underground by 2050 (see Figure 26).

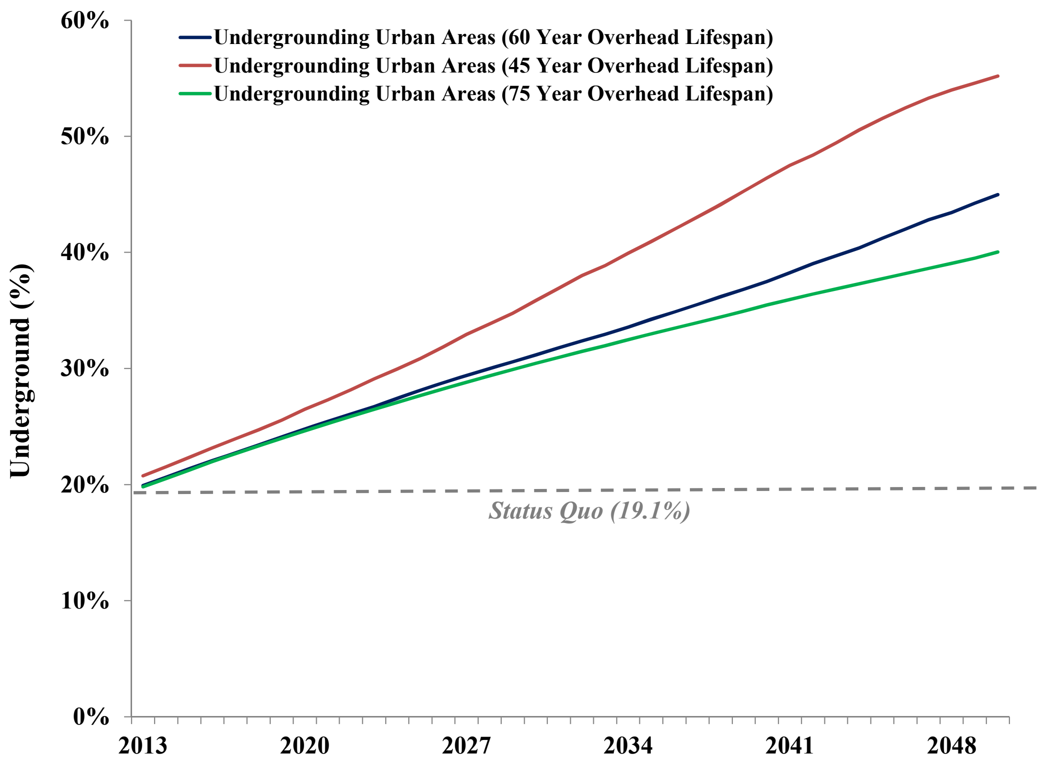

Figure 35. Share of underground line miles using alternative useful lifespans of overhead T&D lines

Power system reliability improvements

It was shown in previous sections that power systems with a larger share of underground lines miles typically have higher levels of reliability. Figure 36 shows that there have been a significant number of major storms impacting urban areas across the Texas IOU service territories, including hurricanes.

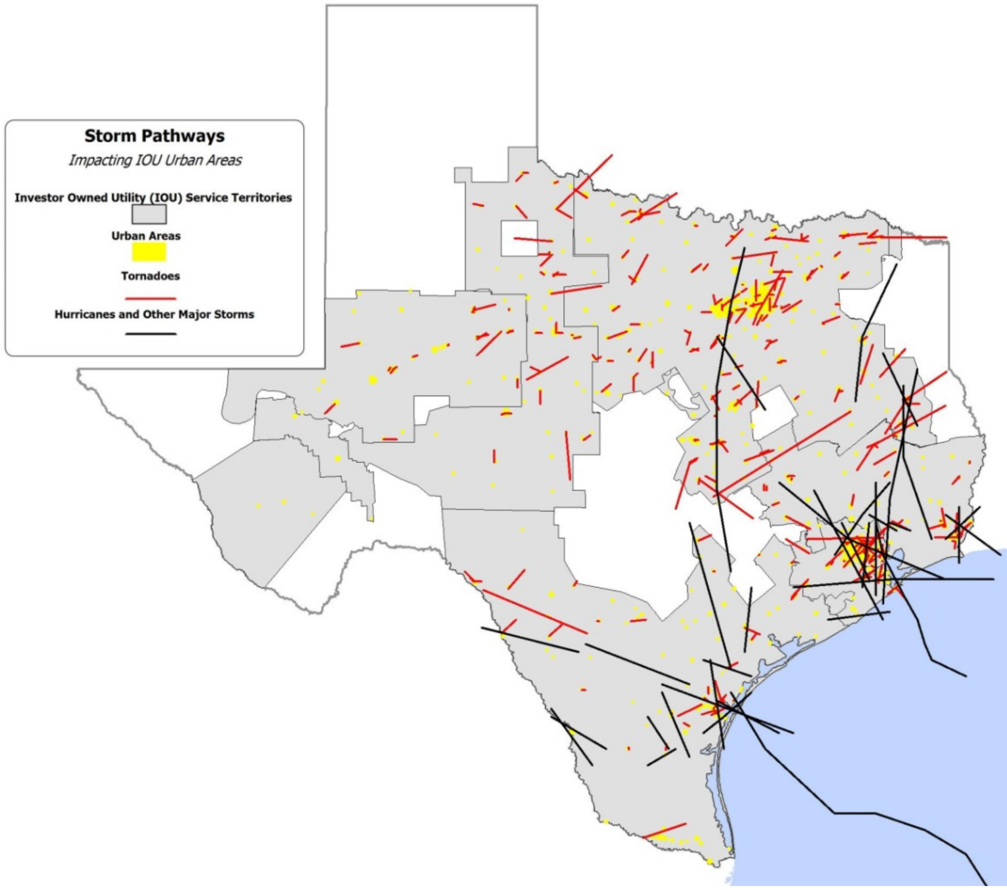

Figure 36. Major storm pathways impacting urban areas within investor-owned utility service territories

For this reason, the reliability impact from undergrounding is assumed to randomly vary within the range of the base case (-0.001) and maximum values (-0.0018) as reported in Table 16.

Higher ecosystem restoration costs for new overhead lines

Koplin (2015a; 2015b) stated that the right-of-way for underground lines is smaller relative to overhead distribution corridors. Accordingly, the model was reconfigured by assuming that the typical widths of an underground and overhead right-of-way are 60 feet and 180 feet, respectively. This change implies that newly sited overhead lines will have higher ecosystem restoration costs when compared to new underground lines. The overall effect is an avoided ecosystem restoration cost due to a larger share of underground lines.

Decreasing capital costs for underground lines

Finally, it is assumed that a strategic initiative to underground all urban, overhead T&D lines at the end of their existing useful lifespan can be achieved at a lower installation cost when compared to the unrestricted analysis assumptions introduced earlier. Urban areas, which have high customer population densities, will allow IOUs to achieve economies of scale. In many cities, there are existing and extensive underground rights-of-way, because of the placement of fiber optic lines and other telecommunications and public utility infrastructure (e.g., water/sewer corridors). This cost advantage—along with the ability of IOU workers to underground large expanses of lines within a small geographic area—are reasons why underground-overhead installation cost parity could be achieved in the not-so-distant future. For this analysis, it is assumed that the initial underground T&D line capital costs randomly vary within the range of the minimum and base case values (see Table 16) and are decreased linearly by 1.75% per year in each subsequent year.

3.7.2 Results

Compared to the unrestricted analysis (i.e., entire IOU service territories undergrounded), the restricted analysis (i.e., only urban areas within IOU service territories) assumes that there are (1) larger improvements in reliability due to undergrounding near storm pathways, (2) capital cost reductions for underground T&D lines initially and in subsequent years; (3) larger ecosystem restoration costs (i.e., wider right-of-way) for overhead T&D lines; and (4) a higher number of customers per square mile. This model configuration represents the minimum conditions necessary to achieve average net social benefits (see Table 19 and Figure 37).

Table 19. Comparison of unrestricted (urban and rural) and restricted Monte-carlo analyses

Results	Unrestricted Analysis (Rural + Urban)	Restricted Analysis (Urban)
Average net social benefit (loss) for 45/60/75 year overhead lifespans	-$21.6 billion	$0.05 billion
Average benefit-cost ratio for	0.3	1.0

45/60/75 year overhead lifespans		
Average % share of line miles underground by 2050 for 45/60/75 year overhead lifespans	79%	47%

If only urban areas are considered, then the percentage share of Texas IOU T&D line miles underground by 2050 drops from 79% to 47% (see Table 19). In other words, Texas IOUs could satisfy a social benefit-cost test if about half of their T&D line miles were underground by the middle of this century.

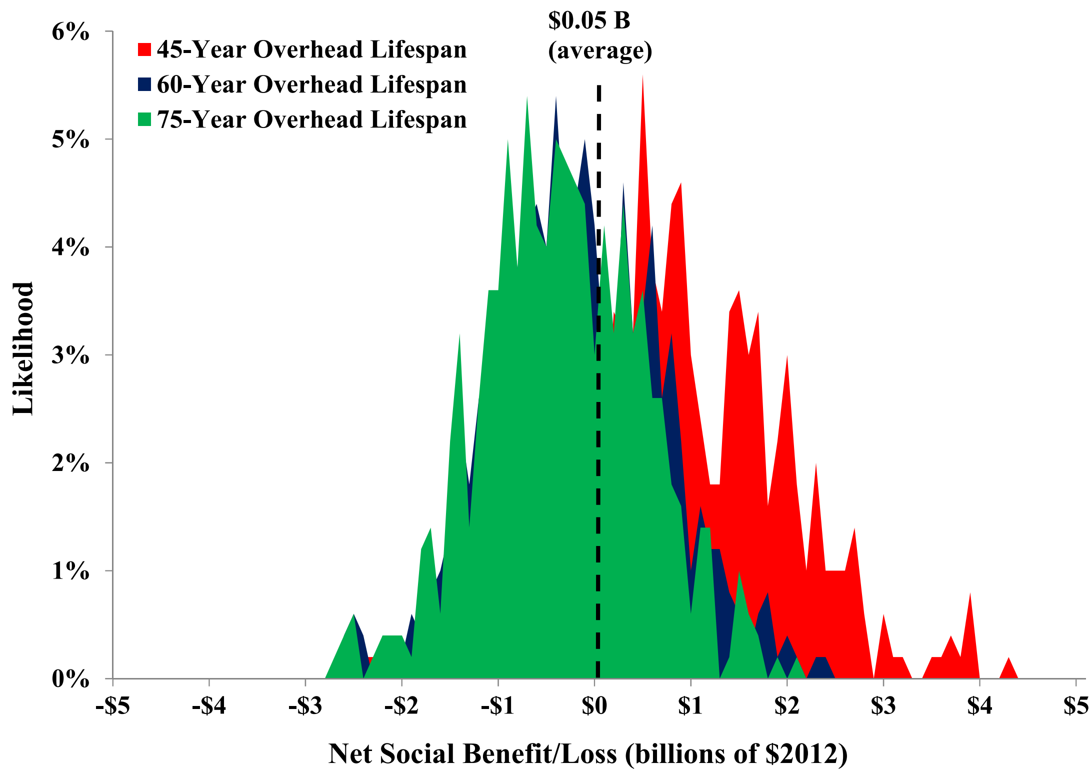

Figure 37. Monte Carlo simulation of net social benefit/loss for 45/60/75-year lifespan for overhead T&D lines (billions of $2012)

3.8 Summary and Opportunities for Future Research

3.8.1 Summary and Policy Recommendation

A general policy that mandates Texas electric utilities to underground line infrastructure had a base case net social loss of ~$21 billion through 2050 (or a 0.3 benefit-cost ratio). Varying all of the key parameters simultaneously leads to aggregate net social losses of ~$21.6 billion—on average. The model results are most sensitive to the choice of (1) discount rates; (2) replacement cost of undergrounding lines; (3) overhead T&D line lifespan; (4) value of lost load; and (5) customers per line mile. Based on the initial configuration of this model, the Texas public utility commission should *not* consider broadly mandating undergrounding when overhead T&D lines have reached the end of their useful life. However, a subsequent configuration of the model found that a policy specifically targeting urban areas could be cost-effective if a number of key criteria are met. Texas policymakers should consider requiring that T&D lines be undergrounded in places where most of the following conditions are present:

- there are a large number of customers per line mile (e.g., greater than forty customers per T&D line mile)
- there is an expected vulnerability to frequent and intense storms
- there is the potential for underground T&D line installation economies-of-scale (e.g., ~2% decrease in annual installation costs expected per year)
- overhead T&D line utility easements (i.e., rights-of-way) are larger than underground T&D utility easements

3.8.2 Model Limitations and Potential Research Opportunities

However, there are limitations to this analysis—and a number of possibilities for improvement in the future. First, it is assumed that the number of utility employees, real estate prices, and conservation easement prices are fixed at current levels. It is likely that these specific assumptions will increase over time, which could affect the benefit-cost ratio. It is also possible that a national model of electric utility reliability (Eto et al. 2012; Larsen et al. 2015) may not be appropriate for regional or local analyses. More research is needed to explore the factors that affect local utility reliability. This analysis assumed that the only stakeholders who have standing in this analysis include utilities, ratepayers, governments, and residents who live within the boundary of the Texas independent operating utilities. It is possible that there are other stakeholders who will be impacted if the share of underground line miles increases. It is assumed that future weather through 2050 (e.g., number of lightning strikes, annual temperature, precipitation, average wind speed) will be similar to weather observed during the 2000–2012 time period. However, it is highly likely that future weather (climate) will not be similar to what has been recently observed (IPCC 2014). Future research could entail mapping state-of-the-art projections of local storm activity and temperature to each utility and recalibrating the analysis. Increased annual temperatures and storm activity will increase the estimated benefits of undergrounding T&D lines. It is also possible that the estimates of increased injury costs due to undergrounding may be less than the economic value of quality life to injured electric utility workers—or that undergrounding may, in fact, reduce health and safety risks to the general population. There is also emerging research indicating that underground lines are less efficient than overhead lines, which would increase the costs of undergrounding relative to the overhead status quo. Another key assumption is that electric utilities in Texas are able to pass along all of their additional costs (due to undergrounding) to ratepayers. Despite these shortcomings, this section introduces a modeling framework that could be improved upon and extended to other regions which may be interested in the economics of electric utility reliability.

Part 4:
(Under)ground-truthing Empirical Results

ground truth, *n*.

1. A fundamental truth; Also: the real or underlying facts; information that has been checked or facts that have been collected at source.
2. Information obtained by direct observation of a real system, as opposed to a model or simulation; a set of data that is considered to be accurate and reliable, and is used to calibrate a model, algorithm, procedure, etc.

Source: Oxford English Dictionary (2015)

4.1 A Brief History of "Ground-truthing"

Hargrave (2006) and Sivakumar et al. (2004) note that modern ground-truthing traces its origins to the rapid deployment of aerial photography during the First and Second World Wars. In many historical applications, ground-truthing was a process used to verify and enhance the results of remote sensing studies (aerial photography, satellite imaging, radar, etc.) through the use of independent evidence (Hargrave 2006; Sivakumar et al. 2004). Ground-truthing techniques have also been applied in the performance evaluation of systems used to scan and compile information from digital documents (Antonacopoulos and Meng 2002; Yanikoglu and Vincent 1995). Character recognition software is often used to extract and interpret information from scanned documents and images. Not surprisingly, these types of software applications are not 100% accurate. Accordingly, ground-truthing—in this specific context—is used to improve the character recognition algorithms and, ultimately, increase the accuracy of the automated results.

Formal ground-truthing techniques have been applied less frequently to energy or electricity-related topics, but there are examples documented in the literature. Huntington et al. (1982) discuss the importance of conducting both individual energy model performance assessments and hosting *Energy Modeling Forums* where many models are compared against one another using a standard set of assumptions. It is noted that a “role for [energy model] evaluation emerges when models become viewed as tools more for developing insights than for forecasting numbers” (Huntington et al. 1982). Wittmann et al. (2008) used ground measurements to assess the impact of having ideal weather forecasts for solar power plant management…“treating ground-truthing data as forecast data allows for the determination of the theoretical optimum of the chosen plant operation strategy… the possible range of economic enhancement which can be gained by improving the forecast data with data assimilation techniques and earth observation measurements”. Shaw et al. (2010) built a spatial model to identify high-risk power lines that might be susceptible to collision by endangered Blue Cranes in South Africa. Ground-truthing was conducted by surveying over one hundred miles of power lines for bird fatalities. Shaw et al. (2010) indicate that Blue Cranes were the most commonly killed birds, but that the spatial model was “unable to predict lines with high collision risk for Blue Cranes”. The researchers conducted additional modeling to evaluate a wider range of explanatory factors, but only the presence of cultivated land—and not the presence of power lines—was statistically correlated with Blue Crane fatalities. In this example, the authors indicated that the model was hampered by a “lack of detailed spatial habitat data and recent information on Crane numbers and distributions” (Shaw et al. 2010). Zhao et al. (2013) designed an experiment to collect individual office appliance electricity consumption data and office occupant behavior concurrently over a pre-determined period of time. The occupant behavior was recorded to ground-truth a model used to predict appliance electricity consumption. The appliance electricity consumption model was found to be

~92% accurate when compared to cross-validated occupant behavior (Zhao et al. 2013). The section that follows evaluates the performance of the undergrounding model (see Sections 3.1–3.5) for a utility that has been actively converting its overhead lines to underground lines over the past forty years.

4.2 Case Study: Cordova Electric Cooperative (Alaska)

Background

Cordova, Alaska is a community of approximately 2,300 residents located on Prince William Sound. Cordova is not accessible by roads—boats and aircraft are the only way to access this coastal community. Cordova's economy relies heavily on the commercial fishing industry, and a number of major fish processing companies have large cold storage facilities located in and around Cordova. Cordova is often impacted by strong coastal storms. Not surprisingly, this community receives a significant amount of precipitation every year in the form of both rain (~90 inches on average) and snowfall (~100 inches on average) (Weatherbase 2015). In the past, severe storms had a major impact on the reliability of Cordova's electric distribution system (Koplin 2015a).

In 1978, the community transitioned from a municipality-run power system to a community-owned electricity cooperative, known as the Cordova Electric Cooperative (CEC). Around this same time, the decision was made to begin the process of undergrounding the community's entire electric distribution system (Koplin 2015a). The CEC serves approximately 1,600 customers and currently has a generating capacity of 18 MW including two hydroelectric facilities and a diesel-fired generation plant (CEC 2015).

Cordova Electric Cooperative as a case study

For a number of reasons, the CEC is the ideal candidate for a case study to ground-truth the method to estimate undergrounding costs and benefits. First, as discussed earlier, this community faced power system reliability challenges due, in part, to extreme weather conditions. Next, the CEC is a community-owned electric generation and distribution system—the cooperative business model is fundamentally different than the investor-owned utility business model described in the previous section. It follows that these different business models might influence the methods used to quantify costs and benefits of undergrounding. Some customers, including commercial fishing operations that are dependent on cold storage facilities, are at risk to significant economic losses if there are power outages for extended periods of time. The CEC is also just completing a multi-decadal effort to underground all of its distribution lines (Koplin 2015a). Accordingly, this case study can be conducted as an ex-post analysis to determine whether the benefits of undergrounding have exceeded the costs. Finally, and perhaps most importantly, CEC staff have generously agreed to provide specific assumptions for use in the analysis and preliminary opinions on the model's performance. Figure 38, below, is a recent picture of a CEC utility crew burying one of the last remaining sections of underground line along a road.

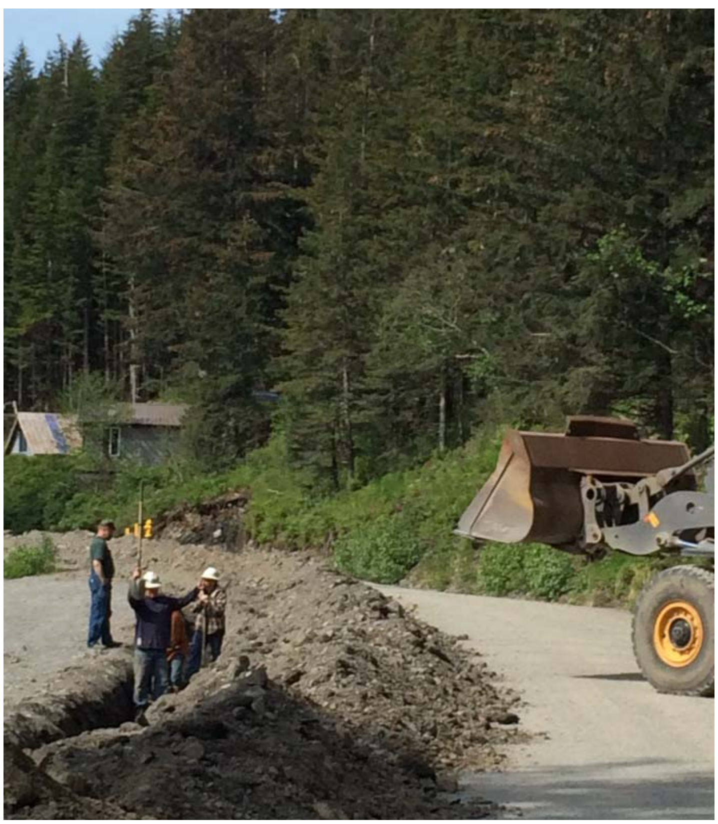

Figure 38. Burying distribution lines in Cordova, Alaska (Author 2015)

Information provided by CEC staff

The results that follow are based on information collected during an in-person interview that occurred in May 2015 (Koplin 2015a) and a series of phone and email conversations that took place after that initial discussion (Koplin 2015b; Koplin 2015c; Koplin 2015d).[29] CEC staff donated their time by providing critical assumptions, reviewing the model framework and initial results, and commenting on the accuracy of the model. It is important to note that the decision to underground CEC's distribution system, which was made in the late 1970s, pre-dates the hiring of staff that provided feedback on this analysis. Whenever possible, CEC staff provided information from the cooperative archives (e.g., power outage duration and cause by year). CEC staff also provided anecdotal evidence in cases where documentation was non-existent or not easily accessible. In a few cases, CEC staff was unable to provide information to confirm an assumption or result from the analysis. In these cases, which are discussed in more detail later, a wide range of assumptions were used and the results were presented using sensitivity analyses.

4.2.1 Study Perspective and Standing

This analysis is conducted from the perspective of the Chief Executive Officer of the CEC, Clay Koplin. Mr. Koplin cares about maximizing net social benefits for his community (Koplin 2015b). There are a number of stakeholders in this type of analysis including the community of Cordova, CEC ratepayers, the CEC, and developers/suppliers of distribution infrastructure. This ex-post analysis assumes that *any* additional costs to the CEC associated with replacing overhead or underground infrastructure will be passed along to Cordova ratepayers—including additional administrative, permitting, and siting expenses. Given this key assumption, the stakeholders with standing in this analysis are the CEC, CEC ratepayers, and all residents and businesses within its service territory.

[29] Phone and follow-up email discussions with CEC staff took place on or around the referenced dates.

4.2.2 Policy Alternatives

This analysis evaluates impacts of a past policy decision ("100% underground") against a baseline ("status quo"—do not increase 1978 percentage share of underground lines). The following sections evaluate the ex-post benefits and costs of a 1978 policy that directed the cooperative to underground (1) existing distribution lines at the end of their useful life; and (2) when new infrastructure is needed to meet projected growth.

4.2.3 Impact Categories

Table 20 describes a range of possible impacts (costs and benefits) for each alternative and group with standing (see above). It is expected that CEC ratepayers will bear the cost burden as the CEC passes-through all of the costs to install and maintain underground (overhead) power lines. It is anticipated that the largest beneficiaries of policies to encourage undergrounding of power lines would be the community's residents and businesses. Koplin (2015a; 2015b) stated that the right-of-way for underground lines is smaller relative to overhead distribution corridors. Koplin (2015a; 2015b) indicates that the capital costs of undergrounding and overhead lines are currently equivalent, but that there were relatively higher administrative, siting, and/or permitting costs for undergrounding. No information was given on the point in time when the costs of undergrounding lines became equivalent with overhead line costs. Koplin (2015b) believes that the undergrounded system requires less maintenance than a comparable overhead system—mostly due to reduction in costs associated with vegetation management. Koplin (2015c) indicates that there is a decreased risk to community member safety with more undergrounded line miles, but he did not speculate on how much that risk decreased as the underground line mile share increased. For this reason, benefits related to reductions in electrocution risk to the broader community were not considered. Finally, Koplin (2015d) could not recall any worker accidents related to overhead lines, but that there was a significant accident that took place at least a decade ago during the conversion of an overhead line to an underground line. For this reason, it is assumed that converting overhead lines to underground lines resulted in additional costs to the CEC related to worker health and safety.

Table 20. Potential impacts from a 1978 policy requiring the undergrounding of distribution lines

Key Stakeholders	1978 Decision to Underground 100% of Distribution System	
	Selected Costs	**Selected Benefits**[30]
Cordova Electric Cooperative	• Increased chance of worker accidents	
CEC ratepayers	• Additional administrative, siting, and permitting costs associated with undergrounding • Increased capital costs for undergrounding	• Lower operations and maintenance costs for undergrounding • Decreased ecosystem restoration/right-of-way costs
All residents/businesses within service area		• Avoided costs due to less frequent power outages • Avoided aesthetic costs • Decreased chance of community fatalities and accidents

4.2.4 Model Reconfiguration

It was necessary to make a number of modifications to the base underground modeling framework to account for the ex-post nature of this analysis and adjustments to the potential impact categorization. This section discusses changes that were necessary for several components of the undergrounding model first described in the previous section.[31] Key changes made to the base model are described in Table 21.

Simulating individual circuit age and length (1978)

Koplin (2015b) estimated the average age of existing underground and overhead lines in 1978 at twenty-five and thirty years old, respectively. Individual circuit age in 1978

[30] Potential impacts not evaluated in this study include societal benefits from improved local/regional/national security and changes to the likelihood of electrocution to the general public.
[31] Model notation and methods that are consistent between the base model and the model evaluated in this case study are not discussed in this section. Please review Section 3.4 for the base undergrounding model notation and Technical Appendix E for all key assumptions for this case study.

was estimated using the shape and scale parameters (see Section 3.4) adjusted for the averages as reported by CEC staff. Figure 39 is a histogram of existing overhead distribution line circuit ages that was simulated using this technique.

Table 21. Summary of changes made to base undergrounding model

Model Components	Comments on Model Reconfiguration
Individual circuit age and length	A new simulation was conducted to account for CEC input on average age of distribution lines and circuit length in 1978.
Discounting all costs and benefits	Given that this is an ex-post analysis, the effects of discounting were removed from all model components.
Reliability impact from undergrounding	Frequency and duration of outages under the status quo and undergrounding scenario were modeled differently—when compared to the base model described earlier—based on anecdotal information provided by CEC staff.
Value of lost load	The base undergrounding model assumed that the average outage lasted 30 minutes. This case study incorporates a wide range of outage costs based on different individual outage duration assumptions (Sullivan et al. 2015).
Avoided aesthetic costs from undergrounded distribution lines	The base model assumed that there were no avoided aesthetic costs for undergrounded distribution lines. This case study assumes that there are avoided aesthetic costs, because other utility lines (e.g., cable, internet) are often buried in the same trench with CEC distribution lines (Koplin 2015a).
Ecosystem restoration costs	CEC staff indicated that the right-of-way (i.e., size of conservation easement) for overhead lines is larger than underground lines (Koplin 2015b). Conversely, in the base model, it is assumed that the right-of-way was larger for underground lines than overhead lines.
Worker-related accident costs	This analysis accounts for actual injuries that occurred during the 37 year conversion to the undergrounded system (Koplin 2015c).

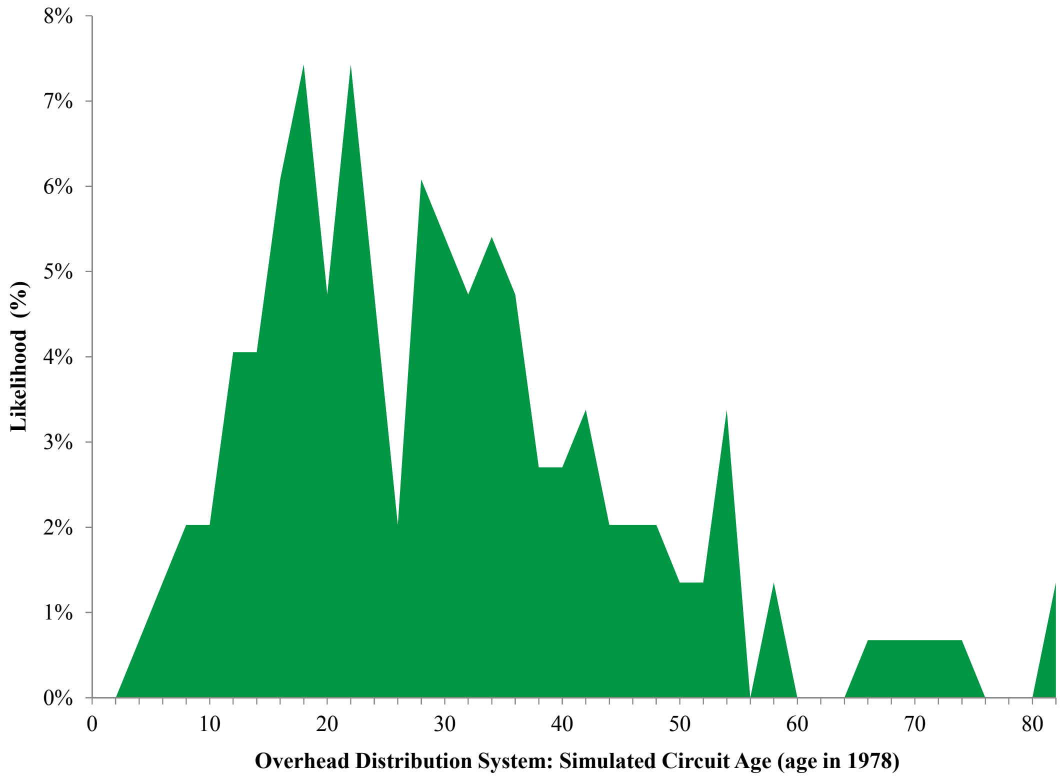

Figure 39. Simulated age profile of CEC overhead distribution circuits in 1978 (years)

It follows that the age of individual circuits during each year within the period of analysis (1978–2015) can be estimated using the simulated age in 1978 and assumptions about expected circuit lifespans (see Equation 46).

$$\mathrm{Age}_{it} = \begin{cases} \mathrm{Age1978}_{i} + (t - 1978), \ \text{if } \mathrm{Age}_{it} \leq \mathrm{Lifespan}_{x} \\ 1, \ \text{if } \mathrm{Age}_{it} - \mathrm{Lifespan}_{x} = 1 \\ \mathrm{Age}_{it\text{-}1} + 1, \ \text{if } \mathrm{Age}_{it} - \mathrm{Lifespan}_{x} > 1 \end{cases} \quad : \forall \ i,t,x \qquad (46)$$

Koplin (2015b) indicated that the average length of a CEC overhead or underground line circuit was approximately 1,000 feet. Given this average length, individual circuit length can be estimated using the same technique as described in Section 3.4. Figure 40 is a histogram of existing overhead distribution line circuit lengths (Length_i) that were simulated using this technique. The integral of this distribution is an estimate of the total mileage of overhead distribution lines in the CEC service territory in 1978 (i.e., 27.9 miles simulated versus 28 miles actual).

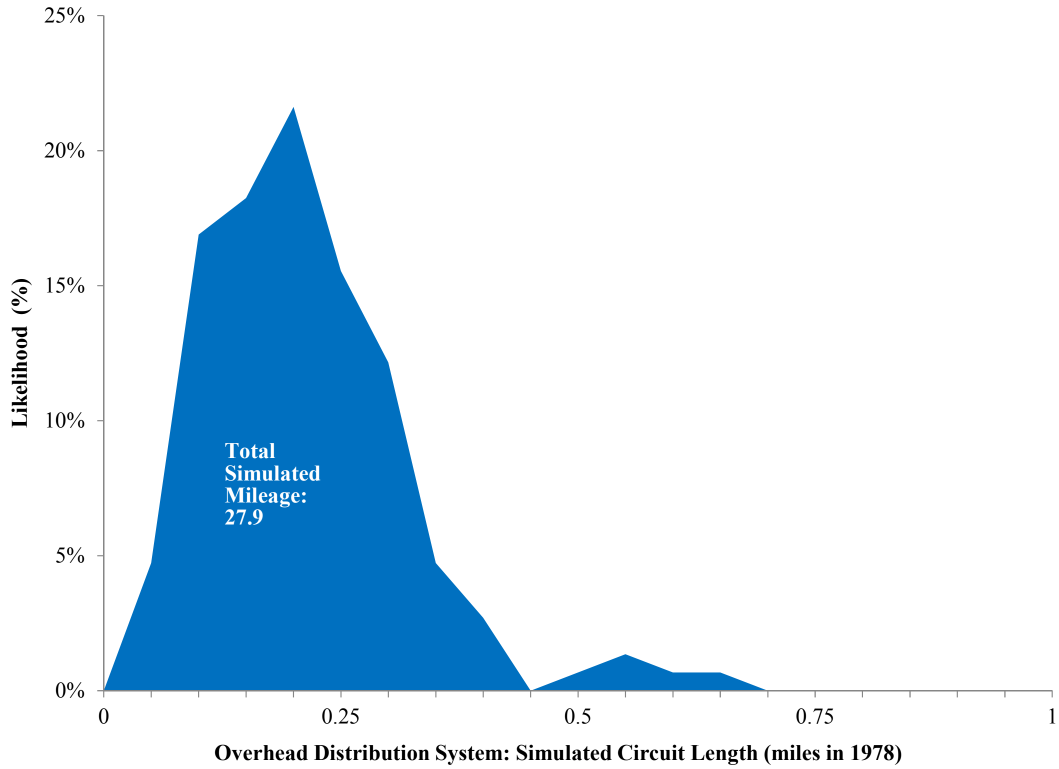

Figure 40. Simulated length of CEC overhead distribution circuits in 1978

Removing the effect of discounting on lifecycle infrastructure costs

The lifecycle infrastructure cost component of the model was reconfigured to account for the ex-post nature of the analysis. Equation 47 depicts how line replacement costs could increase (decrease) linearly in time at an annual growth (decay) rate expressed as Ψ_x. Koplin (2015b) indicated that there is replacement cost parity between underground and overhead lines, but he was unable to confirm if the replacement costs of underground and overhead lines were always equivalent. For the base case analysis, it is assumed that the costs of undergrounded lines were double the cost of overhead lines in 1978, and that the underground line replacement costs per mile decrease linearly until cost parity is achieved with overhead lines in 2015.

$$\mathrm{ReplCost}_{xt} = \begin{cases} \mathrm{ReplCost}_x, \text{ if } t = 1978 \\ \mathrm{ReplCost}_x + \Psi_x(t\text{-}1978)(\mathrm{ReplCost}_x), \text{ if } t > 1978 \end{cases} \quad : \forall\ i,t,x \qquad (47)$$

Equation 48 denotes status quo capital expenses (CAPEX) occurring over the entire analysis period (1978–2015) when the age (Age_i) of the circuit exceeds the expected useful lifespan. Note that all capital expenses incurred for each circuit (i) are not discounted back to 1978, because all financial assumptions were set to present-year dollars.

$$\mathrm{CAPEX}_i^{\mathrm{StatusQuo}} = \begin{cases} \sum_{t=1978}^{2015} \mathrm{ReplCost}_{xt}(\mathrm{Length}_i), \text{if } \mathrm{Age}_{it} = 1 \\ 0, \text{if } \mathrm{Age}_{it} \neq 1 \end{cases} \quad : \forall \text{ i,t,x} \tag{48}$$

Annual O&M expenses (OPEX) for each type of distribution line are estimated using the same approach as described in Equation 20 (see Section 3.4). Annual O&M expenses incurred for each circuit (i) are then summed over the entire analysis period, but not discounted (see Equation 50).

$$\mathrm{OPEX}_i^{\mathrm{StatusQuo}} = \sum_{t=1978}^{2015} (\mathrm{OPEX}_{xt})(\mathrm{Length}_i) \quad : \forall \text{ i,t} \tag{50}$$

Under the undergrounding alternative, the model replaces existing overhead distribution lines with underground lines in the first retirement year. Equation 51 describes how the first retirement year is determined using the expected useful lifespan and age of circuit in 1978.

$$\mathrm{FirstRetire}_i = \mathrm{Lifespan}_x \text{-} \mathrm{Age1978}_i + 1978 \quad : \forall \text{ i,x} \tag{51}$$

Equation 52 describe how at a specific point in time ($\mathrm{FirstRetire}_i$) and in all future retirement years, the overhead lines are replaced with underground lines that have a similar lifespan and higher capital costs (CAPEX) during most of the analysis period.

$$\mathrm{CAPEX}_i^{\mathrm{Under}} = \begin{cases} \sum_{t=1978}^{2015} \mathrm{ReplCost}_{(x+2)t}(\mathrm{Length}_i), \text{if } \mathrm{Age}_{it} = 1 \text{ and x=[2]} \\ \sum_{t=1978}^{2015} \mathrm{ReplCost}_{xt}(\mathrm{Length}_i), \text{if } \mathrm{Age}_{it} = 1 \text{ and x=[4]} \\ 0, \text{if } \mathrm{Age}_{it} \neq 1 \end{cases} \quad : \forall \text{ i,t} \tag{52}$$

For the undergrounding scenario and prior to the first retirement, annual overhead O&M expenses are estimated in the same fashion as described in Equation 20. However, after an overhead circuit is first converted to an underground circuit, then annual O&M expenses are re-estimated for the new underground line and these costs increase each year according to the amount specified in Equation 20. Equation 53, below, describes how circuit O&M costs reset as overhead lines are converted to underground lines. The key difference between this set of equations and what was reported for the base model is that no discounting occurs.

$$\mathrm{OPEX}_i^{\mathrm{Under}} = \begin{cases} \sum_{t=1978}^{2015} (\mathrm{OPEX}_{xt})(\mathrm{Length}_i), \text{ if } x=[4] \\ \sum_{t=1978}^{2015} (\mathrm{OPEX}_{xt})(\mathrm{Length}_i), \text{ if } t < \mathrm{FirstRetire}_i \text{ and } x=[2] \\ \sum_{t=1978}^{2015} (\mathrm{OPEX}_{(x+2)t})(\mathrm{Length}_i), \text{ if } t \geq \mathrm{FirstRetire}_i \text{ and } x=[2] \end{cases} \quad : \forall\ i,t \tag{53}$$

Equation 54 shows that future annual underground line mileage ($\mathrm{Underground}_t$) can be determined based on the existing amount of CEC underground line miles in 1978 ($\mathrm{Underground}_{1978}$) and the ongoing conversion from overhead to underground T&D lines described above.

$$\mathrm{Underground}_t = \begin{cases} \left(\mathrm{Underground}_{1978}\right) + \sum_i \mathrm{Length}_i, \text{ if } t \geq \mathrm{FirstRetire}_i \\ \left(\mathrm{Underground}_{1978}\right), \text{ if } t < \mathrm{FirstRetire}_i \end{cases} \quad : \forall\ i,t,x \tag{54}$$

Reliability impact from undergrounding

A number of modifications to the base undergrounding model were necessary in order to estimate changes in reliability (i.e., outage frequency and duration) due to undergrounding. It should be noted that collecting consistent and accurate information on the frequency and duration of outages from 1978–2015—and any associated reliability gains from undergrounding activities—proved to be extremely challenging. Koplin (2015b; 2015c) indicated that the CEC system "probably experienced about 25 distribution system-related outages per year in the late 1970s [Outages_{1978}] and that there are about three distribution-related outages per year now [Outages_{2015}]". Koplin (2015d) was unable to definitively state what share of that reduction in distribution system-related outages could be directly or indirectly attributed to undergrounding activities. However, Koplin believes that the vast majority of the reduction in distribution system-related outages could be attributed to CEC's decision to underground its distribution system. Koplin was able to provide information on the duration of distribution system outages during the analysis period—as well as the reported cause (Koplin 2015d). Figure 41 shows CEC-reported distribution system-related outage duration due to "storms" and "other" factors.[32] A simple linear trend line fit to the data shows that the total annual minutes customers were without power was ~240 minutes in the late 1970s (Duration_{1978}) and about ~83 minutes today (Duration_{2015}).

[32] The information reported in Figure 46 does not include customer outage minutes due to planned outages or from outages caused by offline generators.

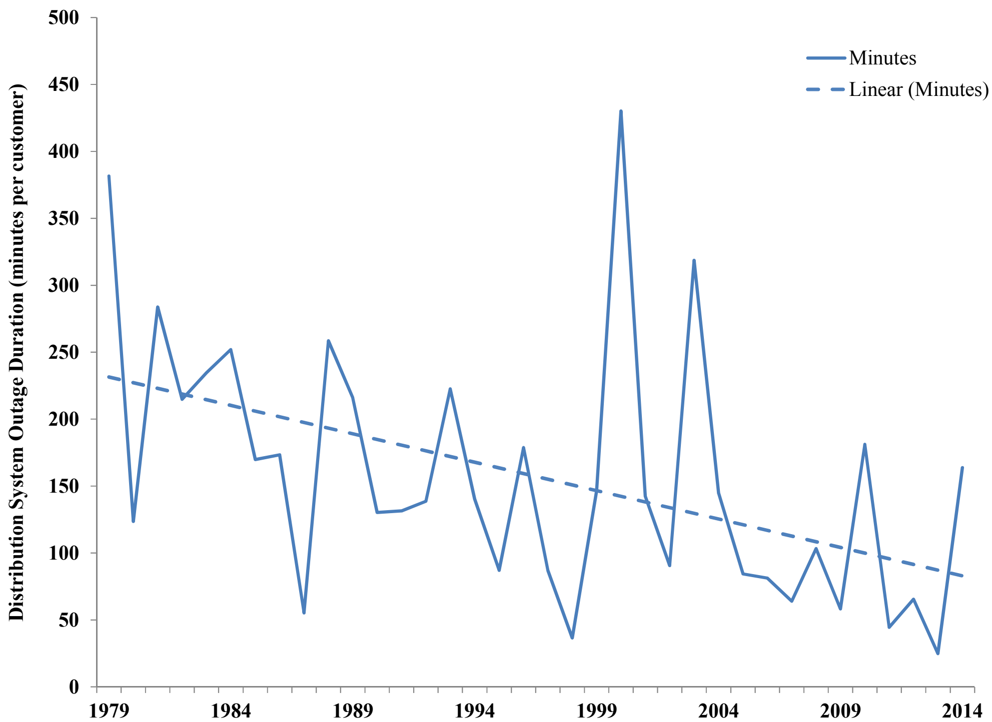

Figure 41. CEC-reported distribution system-related outage duration due to "storms" and "other" factors (Koplin 2015d)

As was the case with the significant decrease in outage frequency over time, it is unclear how much of this reduction in the total minutes customers were without power can be directly attributed to CEC's decision to underground. *For the base case analysis, it is assumed that half of all distribution-related reductions in the frequency and total minutes customers were without power are a result of the CEC's decision to underground lines (see Equations 56 and 57).* For the status quo, the number of outages in each year was held constant at twenty-five—the approximate number of distribution-related outages Koplin estimated for the late 1970s before the undergrounding process started (see Equation 54). The status quo total minutes customers were without power was also held constant over the period of analysis at 240 minutes (see Equation 55).

$$\text{Outages}_t^{\text{StatusQuo}} = 25 \quad : \forall\ t \tag{54}$$

$$\text{Duration}_t^{\text{StatusQuo}} = 240 \quad : \forall\ t \tag{55}$$

It is possible to calculate the reduction in frequency and total minutes customers are without power for corresponding increases in the amount of underground line miles. With this information, the number of outages (see Equation 56) and total minutes customers are without power (Equation 57) attributed to the undergrounding mandate can be estimated for each year of the analysis period.

$$\mathrm{Outages}_t^{\mathrm{Under}} = \left(\frac{\mathrm{Outages}_t^{\mathrm{StatusQuo}} - \left(\frac{\mathrm{Outages}_{2015}}{2} \right)}{\mathrm{Underground}_{2015} - \mathrm{Underground}_{1978}} \right) \left(\mathrm{Underground}_t - \mathrm{Underground}_{1978} \right) \tag{56}$$

$$\mathrm{Duration}_t^{\mathrm{Under}} = \left(\frac{\mathrm{Duration}_t^{\mathrm{StatusQuo}} - \left(\frac{\mathrm{Duration}_{2015}}{2} \right)}{\mathrm{Underground}_{2015} - \mathrm{Underground}_{1978}} \right) \left(\mathrm{Underground}_t - \mathrm{Underground}_{1978} \right) \tag{57}$$

Value of lost load

Koplin (2015b) indicated that the average amount of time a customer is without power is extremely important when determining the total economic impact of the outage. For example, there is a significant difference in the economic damages incurred by commercial fishing cold storage facilities between an outage that lasts thirty minutes when compared to an outage that lasts twelve hours or longer. For this reason, Koplin (2015b; 2015c) suggested using outage-cost assumptions that increase as the amount of time customers are without power during a given outage increases. Several steps are necessary to incorporate this suggestion. First, average outage duration can be estimated for the status quo (Equation 58) and undergrounding scenario (Equation 59) by dividing the annual number of outages from the total minutes customers are without power each year.

$$\mathrm{AvgDur}_t^{\mathrm{StatusQuo}} = \frac{\mathrm{Duration}_t^{\mathrm{StatusQuo}}}{\mathrm{Outages}_t^{\mathrm{StatusQuo}}} \tag{58}$$

$$\text{AvgDur}_t^{\text{Under}} = \frac{\text{Duration}_t^{\text{Under}}}{\text{Outages}_t^{\text{Under}}} \tag{59}$$

Next, information about the typical length of time customers are without power during an average interruption—under the status quo and undergrounding scenario—was merged with value of lost load assumptions that vary by the duration of the individual outage (Sullivan et al. 2015). Residential, commercial and industrial (C&I), and other outage cost curves, using the Sullivan et al. (2015) findings, were produced using a number of assumptions specific to the CEC service territory.[33] A "fuzzy merge" technique (Foley 1999) was used to match average annual outage durations per interruption calculated by the model (see Equations 58 and 59 above) with continuous outage duration and cost information from Sullivan et al. (2015) to produce VoLL_c. Figures 42–44 show the results from entering CEC-specific assumptions into the Sullivan et al. (2015) ICE Calculator. In addition, a marker on each figure indicates what Koplin (2015c) believes the outage costs might be for the different CEC customer classes during a thirty-minute outage.

[33] Residential, commercial and industrial (C&I), and other outage cost curves were generated by inputting a number of assumptions about the CEC service territory into the ICE Calculator (Sullivan et al. 2015). For CEC residential customers, average annual MWh per customer and median household income was inputted into the ICE Calculator. Annual electricity consumption per CEC residential customer (5.9 MWh) was estimated using a five-year average total annual MWh for all CEC residential customers (5,678 MWh; 1994-1998) and dividing by the number of residential customers (955 customers; 1994-1998). Information on customer electricity consumption was collected from the USDA Rural Utility Service and accessed through the Ventyx Velocity Suite system (U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx 2015). Median Cordova-area household income ($74,878) was collected from the U.S. Census Bureau (2015a). For CEC C&I customers, outage costs by duration were produced using information about annual consumption and the percentage share of various types of commercial and industrial categories present in Cordova. Average annual consumption for C&I customers was estimated by calculating a weighted average—by number of customers—of annual consumption for small and large C&I customers (U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx 2015). U.S. Census Bureau American Community Survey results were used to determine the percentage breakdown of business/industry share in Cordova for input into the ICE Calculator (U.S. Census Bureau 2015b). A simple average was taken of outage cost results for small C&I and residential customers to determine the cost curve for the other customer category. All cost curves were produced assuming that the outage took place in the afternoon on a typical summer weekday.

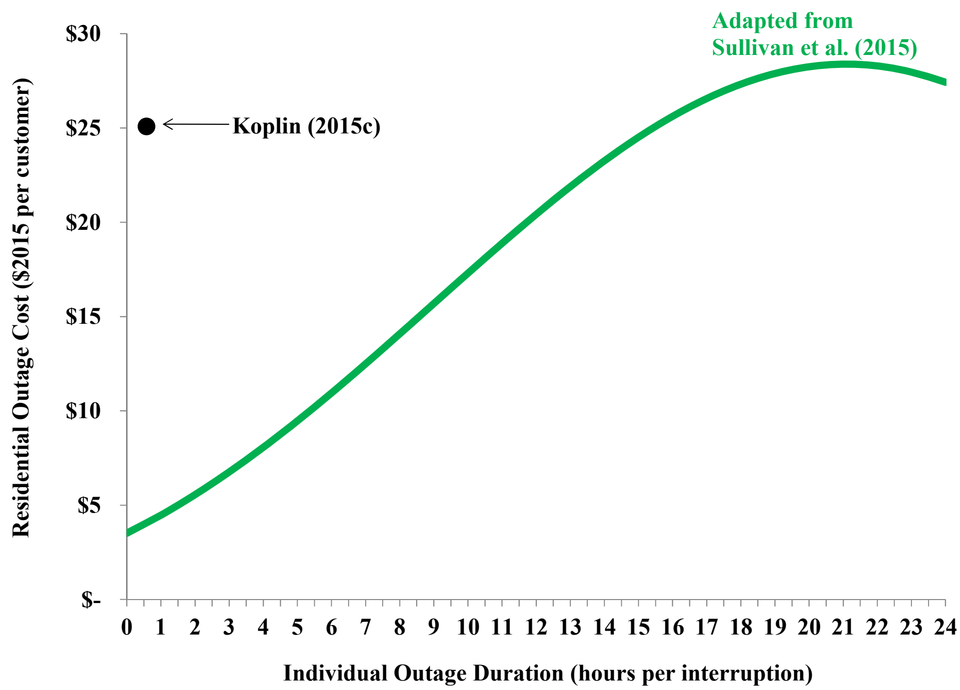

Figure 42. Residential customer outage cost by duration of interruption

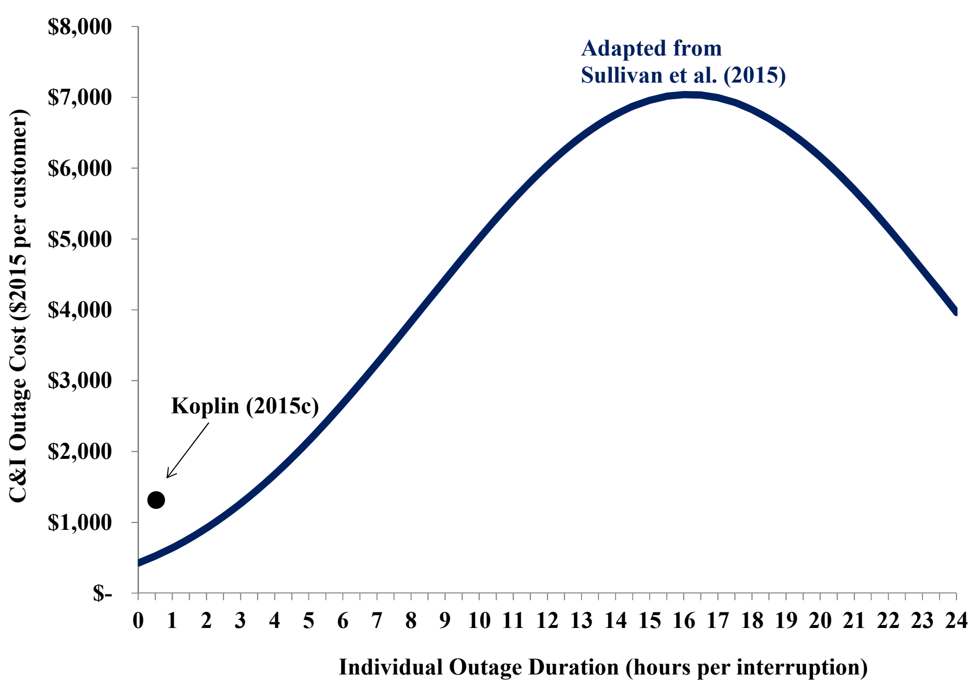

Figure 43. Commercial and industrial customer outage cost by duration of interruption

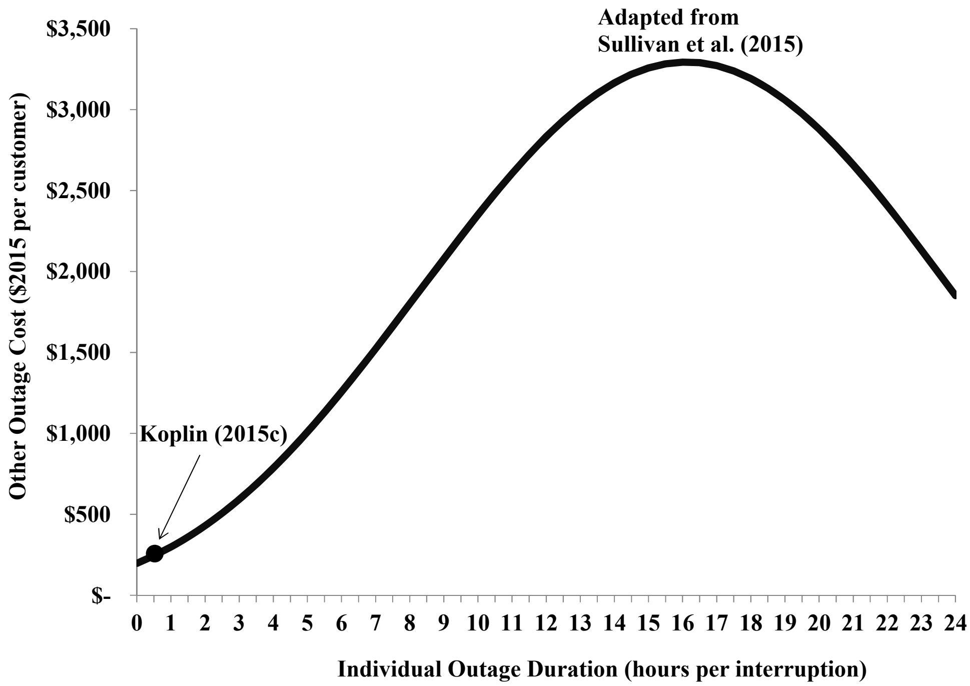

Figure 44. Other customer outage cost by duration of interruption

Finally, the total value of lost load can be estimated for both the status quo and undergrounding scenario and the net avoided cost of outages can be determining by subtracting the results calculated by Equation 61 from Equation 60.

$$\mathrm{VoLL}^{\mathrm{StatusQuo}} = \sum_{t=1978}^{2015}\left(\sum_{c=1}^{3}\mathrm{Outages}_t^{\mathrm{StatusQuo}}(\mathrm{Customers}_c)(\mathrm{VoLL}_c)\right)$$

(60)

$$\mathrm{VoLL}^{\mathrm{Under}} = \sum_{t=1978}^{2015}\left(\sum_{c=1}^{3}\mathrm{Outages}_t^{\mathrm{Under}}(\mathrm{Customers}_c)(\mathrm{VoLL}_c)\right)$$

(61)

Avoided aesthetic costs as a proxy for property value improvements

Unlike the analysis for Texas, it is assumed that CEC property owners will receive aesthetic benefits from undergrounding distribution lines. Koplin (2015a) indicated that undergrounding distribution lines was generally coordinated with television and internet cables undergrounding. It follows that CEC residents generally do not have views of power lines. Avoided aesthetic costs are estimated in a similar fashion as first described in Section 3. In this case, however, no discounting is necessary—as shown in Equation 62 (below).

$$\text{Aesthetic}^{\text{Under}} =$$

$$\sum_{t=1978}^{2015}\left(\frac{\left(\frac{\text{Corridor}}{5280}\right)\left(\text{Underground}_{t} - \text{Underground}_{t\text{-}1}\right)}{\text{ServiceArea}}\right)(\text{Customers}_{c})(\text{PropertyValue}_{c})(\text{PriceImpact}) \tag{62}$$

Ecosystem-related restoration costs

Equation 63 describes initial assumptions about the width, in feet, of the distribution line corridor for the overhead distribution (x=2) lines and underground distribution (x=4) lines. Koplin (2015a) indicated that the right-of-way for overhead lines was actually larger (180 feet) when compared to the right-of-way for underground lines (60 feet).

$$\text{Corridor}^{\text{Eco}} = \begin{cases} 180 : x = [2] \\ 60 : x = [4] \end{cases} \tag{63}$$

In addition to the right-of-way adjustment, the effects of discounting were also removed from the model specification (see Equations 64 and 65) for the status quo and undergrounding environmental restoration costs.

$$\text{Restoration}^{\text{StatusQuo}} =$$

$$\sum_{t=1978}^{2015}\left(\sum_{x=1}^{2}\sum_{i}\text{Length}_{it} - \sum_{x=1}^{2}\sum_{i}\text{Length}_{it\text{-}1}\right)\left(\frac{\text{Corridor}^{\text{Eco}}(640)}{5280}\right)(\text{EasementValue}) \tag{64}$$

$$\text{Restoration}^{\text{Under}} =$$

$$\sum_{t=1978}^{2015}\left(\text{Underground}_t - \text{Underground}_{t-1}\right)\left(\frac{\text{Corridor}^{\text{Eco}}(640)}{5280}\right)(\text{EasementValue}) \qquad (65)$$

The avoided environmental restoration costs due to undergrounding are treated as a benefit by reversing the order of subtraction for the status quo and undergrounding mandate restoration costs (see Equation 66).

$$\text{Restoration}^{\text{Net}} = \text{Restoration}^{\text{StatusQuo}} - \text{Restoration}^{\text{Under}} \qquad (66)$$

Overhead-to-underground conversion-related morbidity costs

As indicated earlier, Koplin (2015c; 2015d) believes that there were no significant worker accidents attributed to maintaining the overhead lines. Koplin did, however, indicate that he knew of at least one major accident that occurred during the undergrounding process. In this case, a worker sustained a major back injury and received significant compensation for injuries from the CEC. Koplin did not indicate the amount of the compensation. Accordingly, an assumption was made on the cost of this injury using national data from the U.S. Department of Labor Occupational Safety and Health Administration (OSHA). OSHA reports that the direct and indirect costs to employers from an accident causing "multiple physical injuries"—the closest category to a major back injury—is ~$160,000 per incident. This cost estimate represents the additional health/safety costs due to undergrounding. It is likely that other, relevant health/safety costs occurred during the forty-year conversion period, but these other costs—which may have been documented or undocumented—were unknown at the time of this analysis.

Sensitivity analysis assumptions

A sensitivity analysis was conducted by varying several of the key inputs for this case study—independently and together—including: (1) the replacement cost of undergrounding distribution lines; (2) alternative values of lost load; (3) alternative aesthetic-related property loss factors; (4) different purchase prices for conservation easements; (5) alternative lifespan assumptions for overhead infrastructure; (6) a wide range of reliability impacts from undergrounding; and (7) alternative assumptions related to the cost of worker injury compensation. Table 22 shows which sensitivity analyses apply to each of the selected impact categories.

Table 22. Sensitivity analyses and impact categories

		Range			Impact Category				
#	**Sensitivity/scenario analysis**	**Minimum value (10th %)**	**Base case value (50th %)**	**Maximum value (90th %)**	**Lifecycle assessment (cost)**	**Avoided outages (benefit)**	**Aesthetics (benefit)**	**Worker safety (cost)**	**Ecosystem restoration (benefit)**
1	1978 replacement cost of undergrounding dist. lines ($2015 per mile)	$60,814	$304,070	$547,326	*				
2	Alternative values of lost load for each customer class ($ per event)	-80% below base case values	See Figures 42–44	+80% above base case values		*			
3	Alternative aesthetic-related property loss factors (% of property value)	2.5%	12.5%	22.5%			*		
4	Alternative conservation easement prices ($/acre)	$1,091.2	$5,456	$9,820.8					*
5	Alternative lifespan assumptions for overhead dist. infrastructure (years)	20	40	60	*	*	*	*	*
6	Outage duration and frequency change due to undergrounding activities	25 outages/240 minutes (1978); 22.8 outages/224.3 minutes (2015)	25 outages/240 minutes (1978); 14 outages/161.5 minutes (2015)	25 outages/240 minutes (1978); 5.2 outages/98.7 minutes (2015)		*			
7	Workers compensation direct and indirect cost ($/accident)	$32,143.4	$160,717	$289,290.6				*	

4.2.5 Results

Costs

Figure 45 shows the impact of varying the assumed lifespan and average age in 1978 of overhead distribution lines. Not surprisingly, as the assumed average age is increased from twenty to forty years, the lifecycle algorithm replaces overhead lines with underground lines earlier in time—leading to a larger share of underground line miles by 2015. As was the case with the base undergrounding model, the share of underground line miles has important economic implications throughout this analysis. Accordingly, a sensitivity analysis is conducted on the assumed lifespan of existing overhead distribution lines. Interestingly, the simulated share of underground line miles, using the base case assumptions, becomes 100% underground in 2015—approximately the same year when the CEC's actual distribution system was fully underground.

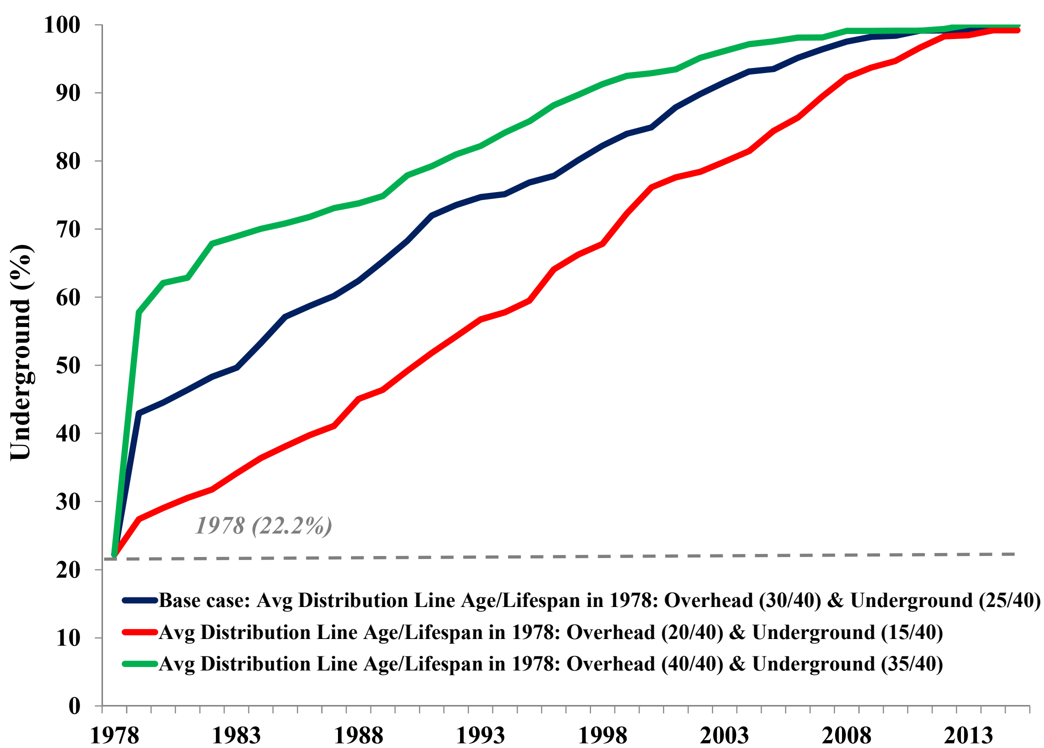

Figure 45. Simulated share of underground line miles over time

Figure 46 shows that the lifecycle replacement costs ranged from ~$31.1 million (status quo) to $35.3 million (undergrounding). Net increased replacement costs were ~$4.1 million. Base case health and safety costs were $0 and $0.2 million for the status quo and undergrounding alternative, respectively. Additional health and safety costs due to undergrounding are ~$0.2 million.

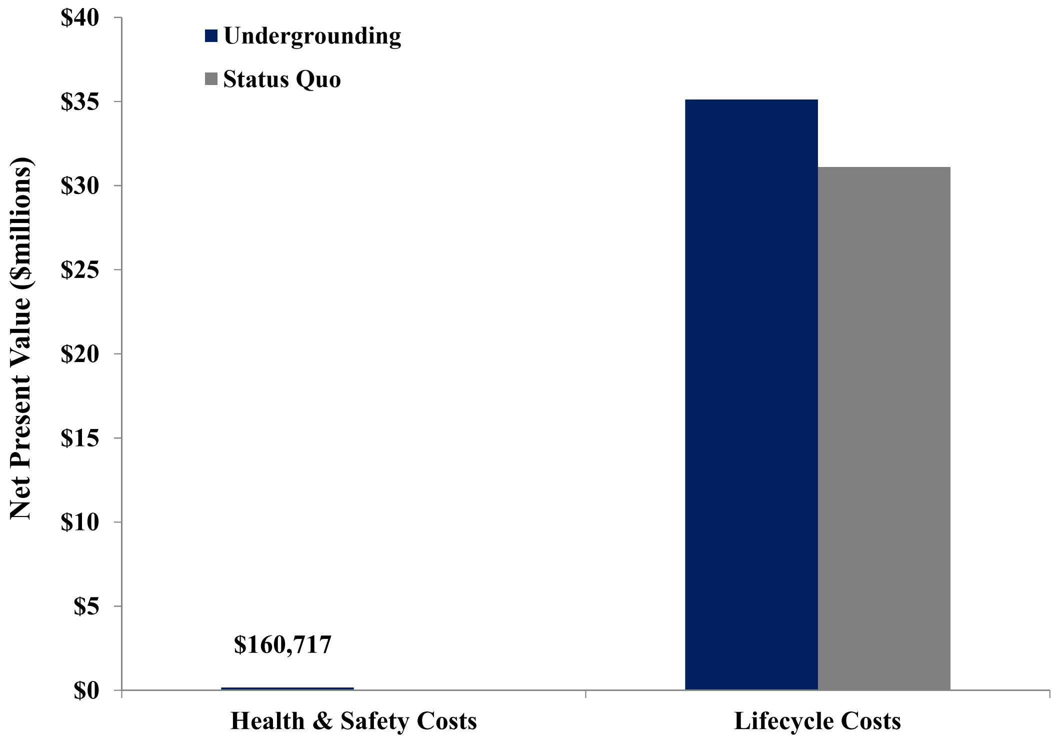

Figure 46. Costs for status quo and undergrounding alternative

Benefits

As the share of underground line miles increases, CEC customers experienced less frequent and fewer total minutes of power outages over time as the share of underground line miles increased (see Figure 47 and Figure 48). Figure 47 shows that the model simulated twenty-five outages in 1978 and only three outages in 2015 as the distribution system was completely underground. This model simulation result is consistent with anecdotal information shared by Koplin (2015b).

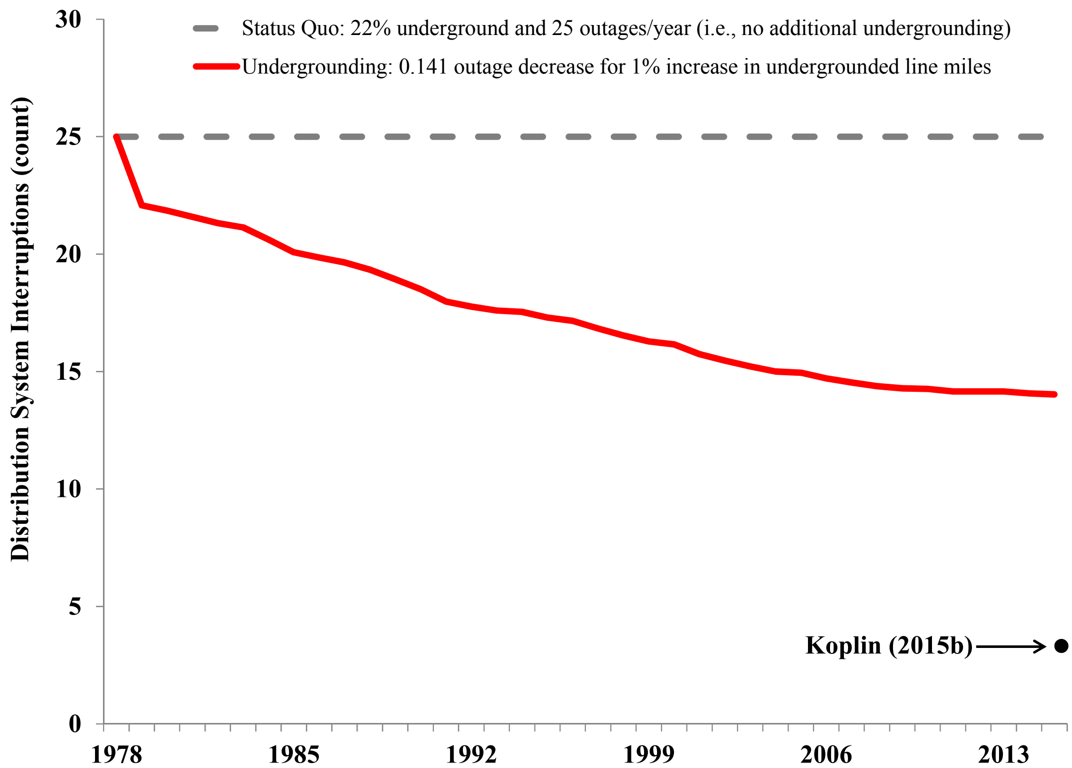

Figure 47. Distribution system-related outage frequency (interruptions per customer)

Figure 48 shows the simulated reduction in total number of minutes over time (red line) along with a comparison to actual outage duration information provided by Koplin (2015d).

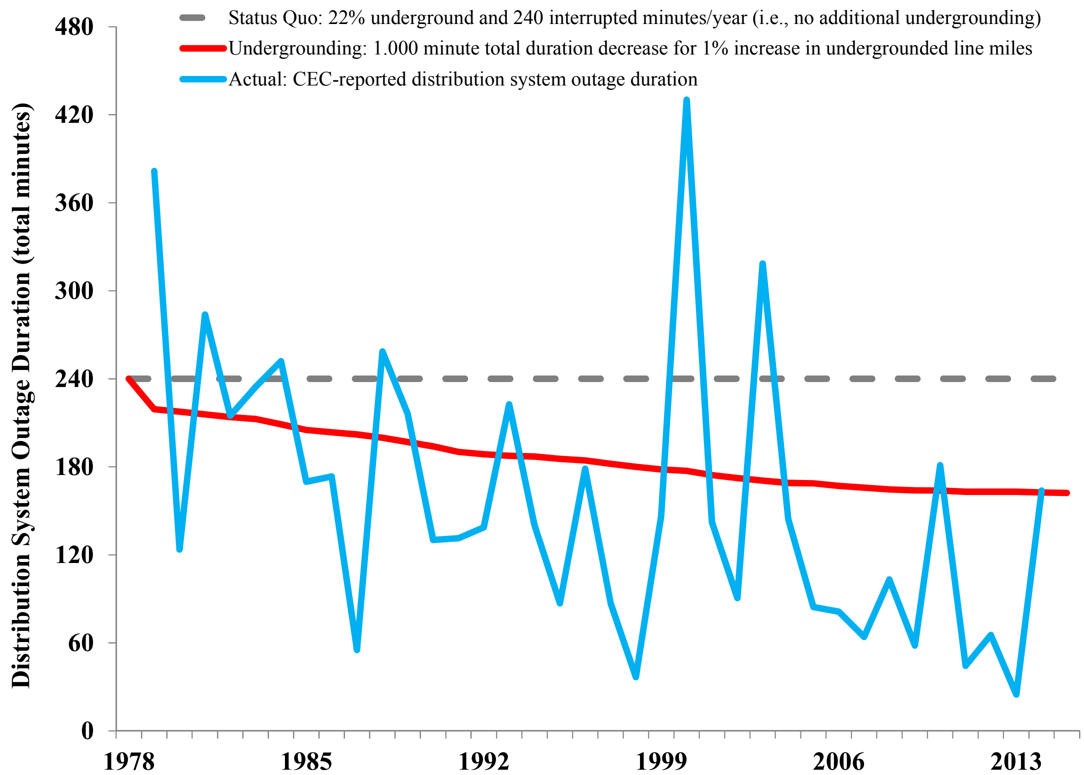

Figure 48. Distribution system-related outage duration over time (total minutes per customer)

Figure 49 shows the value of lost load for the status quo (~$194.7 million) and undergrounding alternative (~$130.1 million). Accordingly, the *avoided* interruption costs—due to undergrounding—are estimated at approximately $64.6 million. Figure 49 also shows that the total avoided aesthetic costs for the status quo is estimated at $24.4 million, with the avoided aesthetic costs increasing to $27.9 million for the undergrounding alternative. Net increased avoided aesthetic costs, which is a proxy for the property value benefits of undergrounding, is estimated at ~$3.5 million. Ecosystem restoration costs were ~$3.1 million for the status quo and ~$2.4 million for the undergrounding alternative. Accordingly, avoided ecosystem restoration costs due to undergrounding were ~$0.6 million.

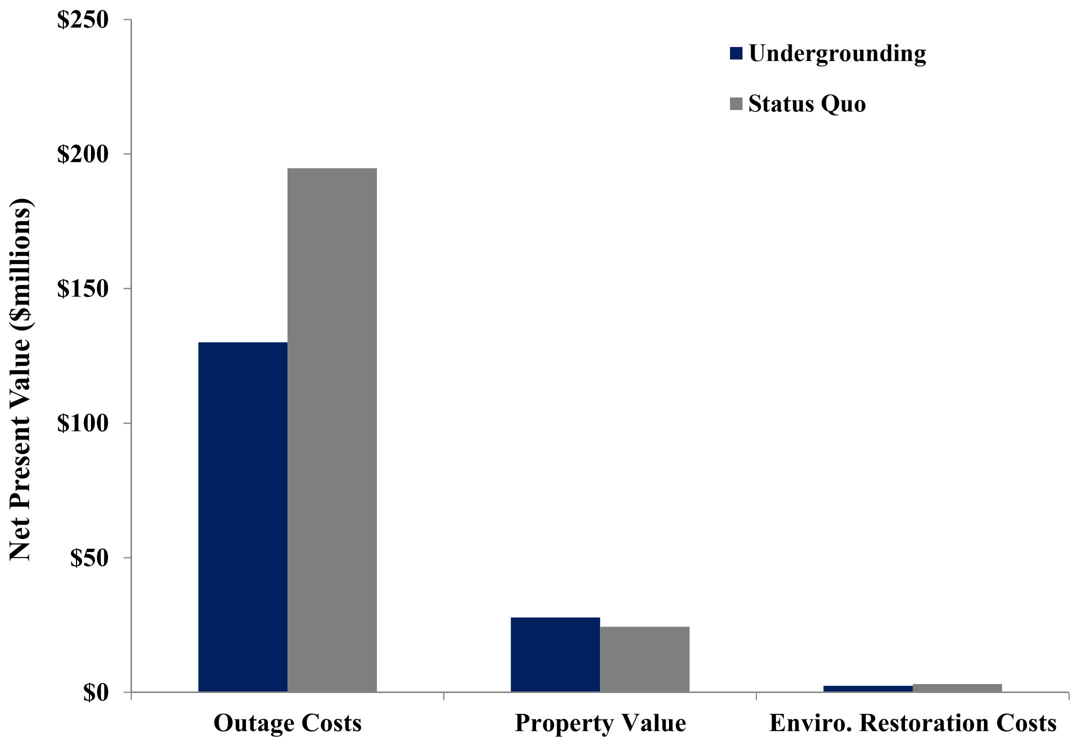

Figure 49. Benefits for status quo and undergrounding alternative

Figure 50 shows a breakdown of the net benefits of avoided outage costs by the three customer classes. Other and C&I customers are projected to receive the largest share of net benefits ($34.5 million and $29.0 million, respectively) primarily due to the relatively higher value of lost load assumption for this customer class when compared to the residential customer class.

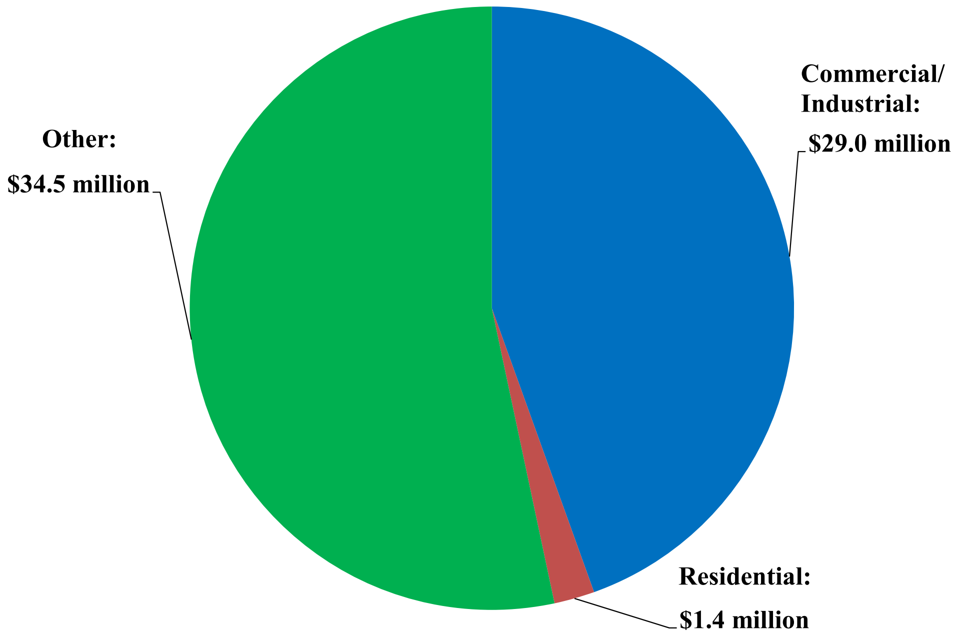

Figure 50. Avoided interruption costs by customer class

Figure 51 shows a breakdown of the net increase in avoided aesthetic costs by the three customer classes. Residential and other customers are projected to benefit from an approximately equal share ($1.3–1.4 million) of the avoided aesthetic cost gains.

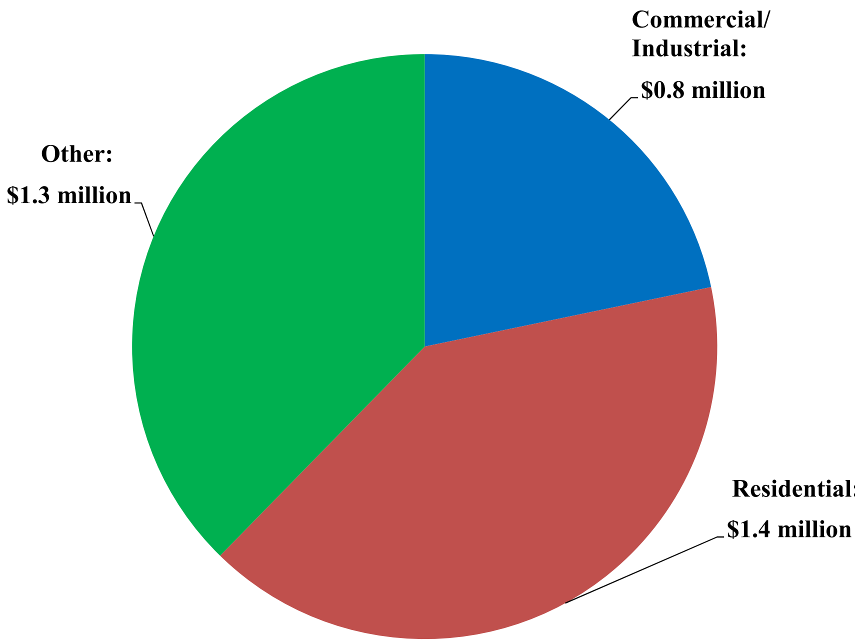

Figure 51. Avoided aesthetic costs by customer class

Net social benefit

Under the base case, the net costs from undergrounding are estimated at ~$4.3 million with net benefits of ~$68.7 million (see Table 23). It follows that the base case net social benefit from undergrounding all CEC distribution lines is ~$64.5 million, which is equivalent to a 16.1 benefit-cost ratio. As was the case with the Texas analysis, the external benefits (avoided aesthetic costs) are a relatively minor share of the total benefits when compared to the private benefits (e.g., avoided interruption costs).

Table 23. Summary of costs and benefits under status quo and 100% undergrounding mandate

Impact Category	100% Underground	Status Quo	Net Cost ($millions)
Health & safety costs	$0.2	$0	$0.2
Lifecycle costs	$35.3	$31.1	$4.1
Total net costs (Undergrounding)			$4.3
Impact Category	**100% Underground**	**Status Quo**	**Net Avoided Costs ($millions)**
Interruption costs	$130.1	$194.7	$64.6
Aesthetic costs	$27.9	$24.4	$3.5
Enviro. restoration costs	$2.4	$3.1	$0.6
Total net benefits (Undergrounding)			$68.7
Net Social Benefit (Undergrounding)			
Net social benefit (millions of $2015)			**$64.5**
Benefit-cost ratio			**16.1**

Sensitivity analysis

Figure 52 is a tornado diagram created by varying seven key input assumptions, separately, to evaluate the overall effect on the total net-benefit calculation.[34] This type of sensitivity analysis shows that the CEC's net benefit calculation is most sensitive to the choice of (1) value of lost load; (2) reliability impact from undergrounding; and (3) overhead distribution line lifespan. For example, substantially reducing the undergrounding impact on duration and frequency of outages produces a

[34] The results were generated by running the individual parameter minimum and maximum values as shown in Table 20.

small net social benefit (~$12 million). Alternatively, assuming that undergrounding led directly to nearly all of the reductions in outage duration (two hundred forty minutes in 1978 to ninety-nine minutes in 2015) and frequency (twenty-five outages in 1978 to five outages in 2015) yields net social benefits of ~$111 million, all else being equal.

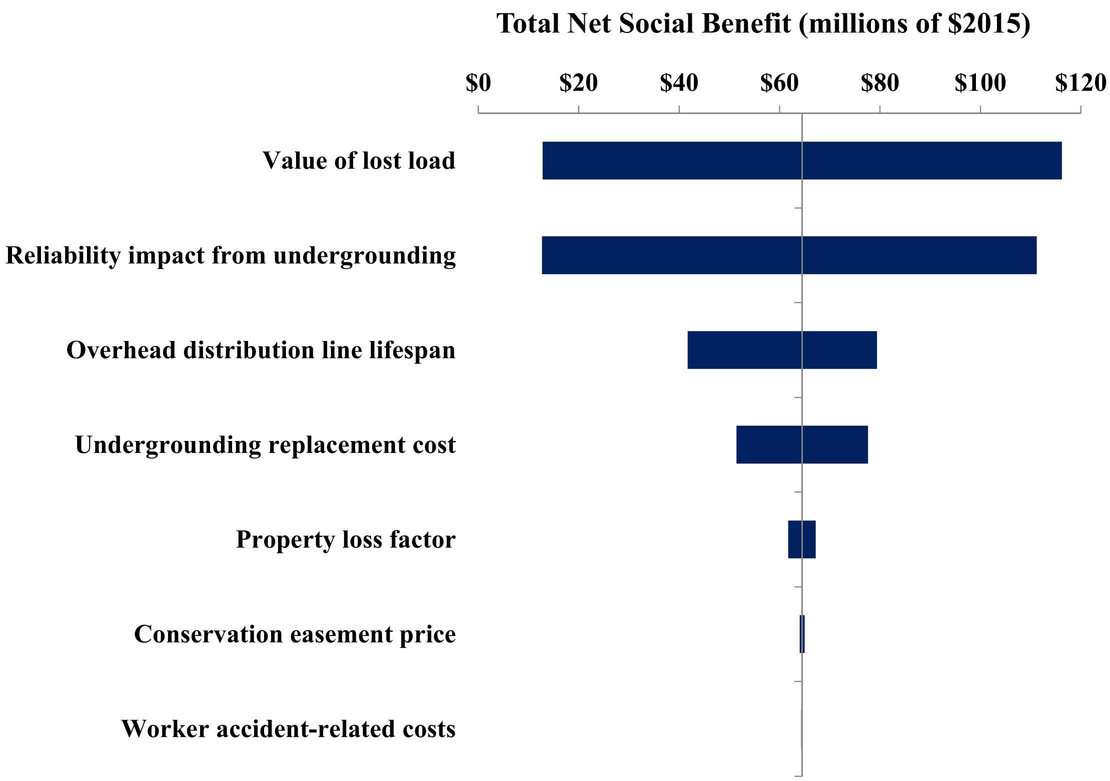

Figure 52. Sensitivity analysis of net social benefits using alternative model parameters

A Monte Carlo simulation was conducted by sampling all of the key input assumptions from uniform distributions—bounded by the minimum and maximum values reported in Table 22— *simultaneously*. The resulting distributions, which are based on repeated sampling (n=500), show the full range of net benefits possible if all key parameters vary simultaneously and independently of one another. Figure 53 shows the likelihood of total net social benefits for an assumed overhead distribution line lifespan of twenty years (red), forty years (dark blue), and sixty years (green). As discussed in Part Three, if overhead lifespans are assumed to be shorter, a larger share of lines are undergrounded—with corresponding relative increases in net social benefits. The results of the Monte Carlo simulations show that the average net social benefits are approximately $64.8 million. Varying all of the key parameters simultaneously leads to consistently positive average net social benefits.

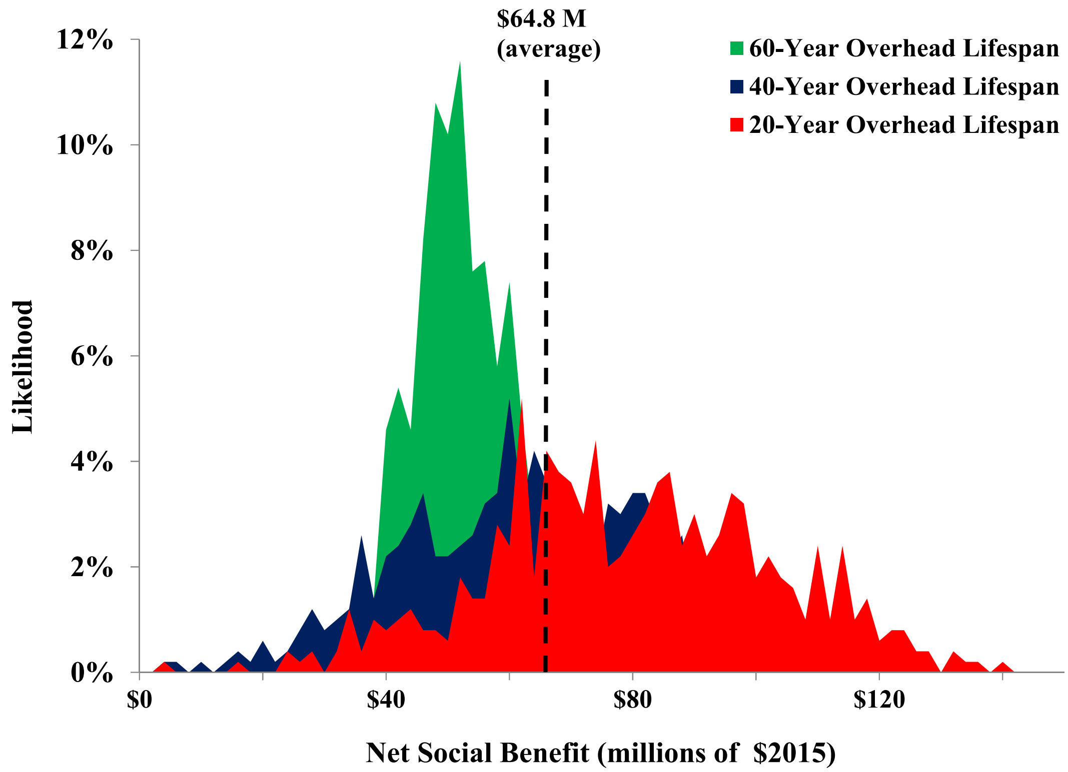

Figure 53. Monte Carlo simulation of net social benefit for 20/40/60 year lifespans for overhead distribution lines (millions of $2015)

These results also suggest that the true net social benefits are likely to fall within the vicinity of the base case result ($64.5 million). Recall that the base case assumed that half of the observed changes in the frequency and duration of outages could be attributed to the decision to underground lines. The Monte Carlo simulations, however, draw simultaneously from a number of independent uniform distributions including one with a lower bound at near-zero reliability impact from undergrounding and an upper bound approaching the full undergrounding-attributed reductions in outage duration (two hundred forty minutes in 1978 to ninety-nine minutes in 2015) and frequency (twenty-five outages in 1978 to five outages in 2015).

As shown in the tornado diagram (Figure 52), the model results are most sensitive to assumptions about what share of the long-term improvement in reliability in the Cordova Electric Cooperative service territory can be directly attributed to the late 1970s decision to underground. A one-way sensitivity is conducted to explore the range of net social benefits under the full range of reliability improvements that could be attributed to undergrounding. Figure 54 shows net social benefits under alternative values of distribution system outage duration and frequency improvements attributed to undergrounding activities. If no reliability improvement can be attributed to undergrounding, then there is a net social loss of ~$150,000. However, if 40–60% of the reliability improvements over time—both in duration and frequency—can be attributed to the decision to underground, then net social benefits range from $51.6–77.3 million.

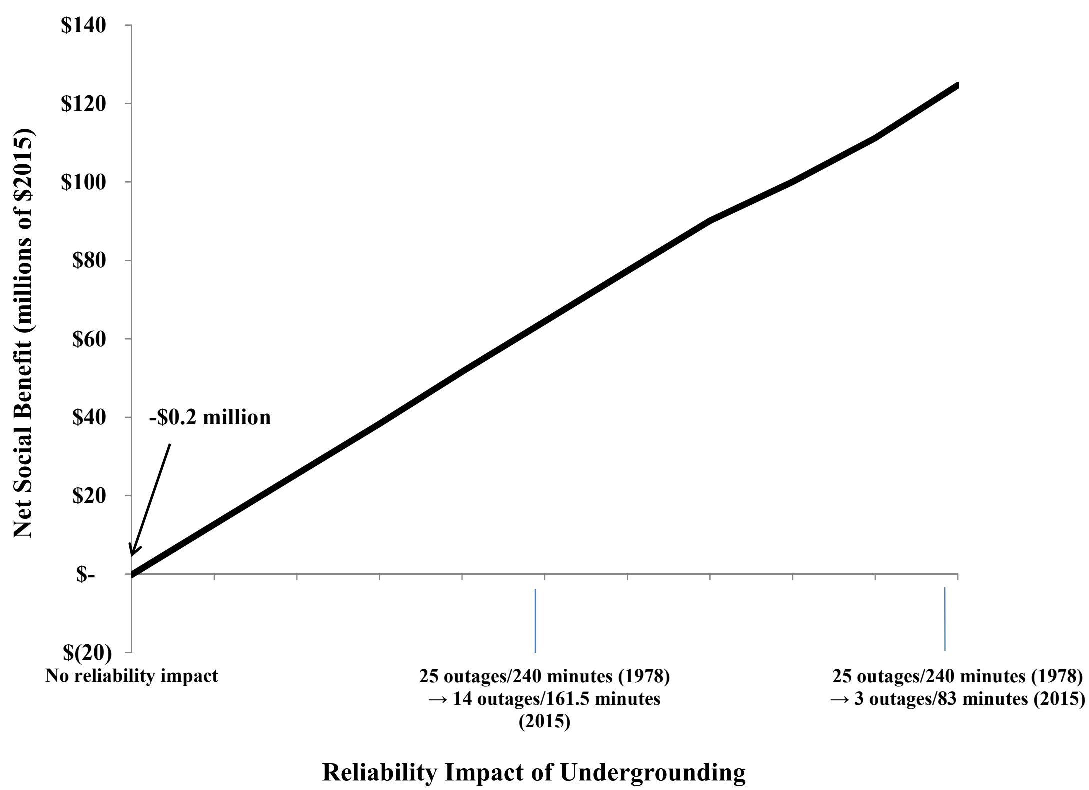

Figure 54. Net social benefit and alternative values of distribution system outage duration and frequency improvements attributed to undergrounding activities

4.2.6 Discussion

This case study was conducted in an effort to both (1) determine the net social benefit (or loss) of an actual mandate to underground an entire electric utility's service territory; and (2) ground-truth the model first described in Part Three.

Undergrounding CEC service territory resulted in significant net social benefits

It became clear through this analysis that residents and businesses within the Cordova Electric Cooperative have received significant net benefits—at least tens of millions of dollars—from a past decision to underground their system. This finding is contrary to the initial results presented in Part Three, which showed that a future decision to underground all Texas IOUs would lead to significant net social losses. There is considerable uncertainty, however, in the range of net social benefits—mainly due to unanswered questions about how much of CEC's reliability improvements can actually be attributed to the decision to underground.

Consistent set of conditions between Texas and Alaska analyses

The Texas IOU and Cordova Electric Cooperative analyses highlighted a consistent set of conditions when policymakers should consider requiring that T&D lines be undergrounded. For both the Texas IOU and the CEC analyses, it was shown that an undergrounding initiative could be cost-effective in places where a majority of the following conditions are present: (1) there are a large number of customers per line mile (e.g., greater than forty customers per T&D line mile); (2) there is an expected vulnerability to frequent and intense storms; (3) there is the potential for underground T&D line installation economies-of-scale (e.g., ~2% decrease in annual installation costs expected per year); and (4) overhead T&D line utility easements (i.e., rights-of-way) are larger than underground T&D utility easements. Furthermore, the external benefits (avoided aesthetic costs)—in both analyses—are a relatively minor share of the overall benefits when compared to the private benefits (e.g., avoided interruption costs).

Possibilities for base model improvements

There are a number of improvements that should be considered in future efforts to refine the undergrounding model first presented in Part Three. First, the CEC case study highlighted the need to conduct a more rigorous analysis into the role that undergrounding power systems have on improvements to both the duration and frequency of power interruptions. The base undergrounding model—tuned for Texas IOUs—focused only on future reductions to the frequency of outages by using an underground line-share correlation coefficient from the national reliability model presented in Part One. Clearly, a deeper exploration into more localized reliability gains from undergrounding, including improvements to outage frequency and duration, will lead to more accurate economic assessments.

Next, although not discussed in great detail, there are other benefit categories that should be considered in future economic analyses of decisions to underground power lines. For example, CEC staff indicated that underground lines probably reduce the electrocution risk to community members when compared to the risks from overhead lines. These relative reductions in risk have economic value, but there has been little or no public research into the risk of electrocution from overhead and underground lines. And there may be important externalities including national security benefits if critical electricity infrastructure (e.g., T&D lines, substations, transformers) is buried and generally inaccessible to intentional acts of terrorism or unintentional accidents.

The CEC case study also highlighted the importance of considering the typical duration of an individual power outage—as the length of time that customers are without power can have severe consequences for some industries (e.g., cold storage facilities for commercial fishing companies). The case study employed assumptions about the value of lost load that were collected through utility-administered surveys that were conducted all over the country (Sullivan et al. 2015)—despite concerns that outage cost surveys may under-estimate the value customers place on reliability (London Economics 2013; Growitsch et al. 2014; Rose et al. 2005). Utilities, including the CEC, who are considering significant capital investments would benefit from sponsoring research into how much their customers—and the broader local/regional economy—value reliable electric service.

Finally, the base undergrounding model and CEC case study did not consider the possibility that customers installed technologies to mitigate the impact of distribution system-related outages. For example, many critical public and private facility owners install backup generators that turn on automatically when a power interruption is detected. Future improvements to the model could include accounting for the presence of these types of technologies by adjusting both the reliability impact from undergrounding and the value of lost load for customers employing these types of technologies.

Conclusion and Future Research Opportunities

This dissertation systematically (1) evaluates the factors that impact U.S. electric utility reliability; (2) reviews research conducted on the value of reliability within a planning context; (3) develops a cost-benefit analysis framework to weigh a future decision to improve reliability; and (4) ground-truths the cost-benefit analysis framework with information provided directly by a utility.

Overarching findings

There are a number of overarching findings from this research effort. First, when major events (i.e., severe weather) are included in reliability performance metrics, both the frequency and total minutes customers are without power are increasing at a more pronounced rate than when major events are not included. This finding implies that a typical U.S. utility may be having a more difficult time preventing and responding to power outages as weather becomes more frequent and/or severe. Next, there have been significant advances in the estimation of customer power outage costs, but there are still unsettled questions about the accuracy of survey methods used by utilities to quantify the value of lost load to their customers. It has also been generally assumed that the costs of undergrounding transmission and distribution lines far exceed the benefits from avoided outages. This dissertation shows that undergrounding power system infrastructure can improve reliability and that the comprehensive benefits of this strategy can exceed the all-in costs. However, this finding on cost-effectiveness depends, in part, on the age/lifespan of existing overhead infrastructure, capital cost of underground lines, assumed value of lost load to customers, degree to which reliability is actually improved by undergrounding, the number of customers per line mile, and a number of other factors. The Texas IOU and Cordova Electric Cooperative analyses highlighted the conditions when policymakers should consider requiring that T&D lines be undergrounded. For example, undergrounding will be cost-effective in places where most of the following conditions are present: (1) there are a large number of customers per line mile (e.g., greater than forty customers per T&D line mile); (2) there is an expected vulnerability to frequent and intense storms; (3) there is the potential for underground T&D line installation economies-of-scale (e.g., ~2% decrease in annual installation costs expected per year); and (4) overhead T&D line utility easements (i.e., rights-of-way) are larger than underground T&D utility easements. A number of empirical techniques are employed to explore questions throughout the analysis including: sequential regression analysis; expert elicitation; lifecycle simulation; cost-benefit analysis; and uncertainty quantification using one-way sensitivity analysis and simultaneous Monte Carlo simulations.

Recent reliability of the U.S. power system

Several studies have quantified the annual cost of U.S. power outages with estimates ranging from $28 billion to $209 billion (LaCommare and Eto 2005, 2006; Swaminathan and Sen 1998; Primen 2001). Despite the critical importance of reliable electricity to the economy, there has been little or no research conducted—at the national level—to determine if reliability is getting better or worse over time. One notable exception was conducted by Eto et al. (2012) who developed an early econometric model of U.S. power system reliability by including basic measures of weather (heating and cooling degree-days), utility sales per customer, and the presence of outage management systems. The first part of this dissertation builds on Eto et al. (2012) by expanding the list of utilities evaluated, increasing the number of possible regressors, and conducting a more rigorous approach to model specification.

An econometric analysis is conducted to explore the factors that are correlated with both the duration and frequency of power outages at nearly two hundred utilities over a thirteen-year period. A number of factors were considered including "abnormal" weather (above/below average temperature, precipitation, wind speed, and lightning), transmission and distribution operations and maintenance (O&M) spending, electricity sales, customers per line mile, the installation of outage management systems, and the share of underground line miles.

If major events are included in SAIDI and SAIFI, there are a number of statistically significant factors that are correlated with changes in both the frequency and total number of minutes customers are without power. First, reliability events are both lasting longer and increasing in frequency. The total annual number of minutes customers are without power and the frequency of reliability events have increased approximately 10% and 1% per year since 2000, respectively. The time trend within the duration regression is statistically significant, but the trend for the frequency regression is not statistically significant. This time trend associated with major events suggests that severe weather-related impacts (or how they are being defined and/or reported) are becoming slightly more frequent, but this increase in weather-related events is strongly correlated with more total minutes customers are without power. Second, abnormally high precipitation and wind speed are consistently correlated with more total minutes customers are without power. Third, abnormally warm weather (i.e., cooling degree-day deviation variable) and the share of underground line miles are correlated with lower SAIDI. Finally, lightning strikes and abnormally windy and dry conditions are correlated with increased frequency of interruptions.

If major events are *not* included in SAIDI and SAIFI, there are also a number of statistically significant factors that are correlated with changes in both the frequency and total number of minutes customers are without power. First, the total number of minutes customers are without power is increasing, and the number of interruptions are becoming slightly more frequent. However, there is no statistically significant trend in the frequency of events, while there is a statistically significant increase in

SAIDI when major events are not included (~1% increase per year). Second, above-average wind is correlated with more frequent interruptions, and higher population density is correlated with less frequent interruptions.

There are a number of limitations with the reliability model that should be considered when evaluating the results. First, utilities are using inconsistent criteria to define a “major event” (Eto and LaCommare 2008; Eto et al. 2012). For this reason, it follows that this inconsistency may bias the results in a pooled regression. However, the effects models (random or fixed) which were used in this study were implemented to fully (or partially) mitigate the effect of these types of utility-by-utility differences (Larsen et al. 2015). Furthermore, the causes of reliability interruptions are inconsistently reported across utilities—which makes identifying consistent regressors that can explain reliability across the United States challenging. Surprisingly, T&D O&M expenditures did not have a statistically significant correlation with improvements in reliability. This finding (or lack thereof) is counterintuitive, because it was expected that increased utility T&D O&M expenditures would be significantly correlated with improved reliability. Future research should explore detailed breakdowns on annual utility capital and O&M expenditures related to T&D. It is suspected that reliability is affected differently depending on whether utilities spend relatively more on preventative maintenance when compared to reactive maintenance. There are a number of other unobservable or intangible factors that could significantly affect utility reliability. One example of an unobservable factor is the share of utility customers who have installed Smart Grid technologies. It is suspected that these technologies could improve reliability, but penetration rates of Smart Grid technologies are not currently reported for a significant number of utilities. Utility-by-utility Smart Grid penetration rates should be considered by future researchers as this information becomes more widely available. Despite these limitations, the model presented in this dissertation is the most comprehensive assessment of national reliability trends ever conducted (Larsen et al. 2015).

Review of value-based reliability planning

For nearly sixty years, researchers have acknowledged that reliable electric service (or lack thereof) has economic benefits (or costs) to society. As the electric industry evolved over this time period, so have the methods used by researchers to value reliability. Examples are provided of early and recent research into the value of reliability and value-based reliability planning.

The earliest studies into the value of reliability focused on the need to design methods to quantify the costs of power interruptions or, conversely, the cost of improved reliability. The term *value of service reliability* (VOS) may have been formally introduced around the time that papers by Hall et al. (1988) and Burns and Gross (1990) were published, but informally referred to in earlier presentations, lectures, and tutorials by Billinton (Billinton 2015). VOS is defined as a "reliability evaluation that explicitly incorporates into the planning process customer choices regarding reliability 'worth' and service costs" (Burns and Gross 1990). In the optimum, additional costs of any resource employed to improve reliability should equal the benefits associated with reducing outages by "explicitly incorporating customer outage cost information" (Burns and Gross 1990). There have been four general methods used to quantify customer outage costs including (1) proxy methods; (2) market-based methods; (3) after-the-fact-measurement; and (4) survey-based methods. It was noted that electric utilities have concentrated their efforts on conducting four different customer surveying techniques, which include: direct costs; willingness to pay; willingness to accept; and revealed preference (Burns and Gross 1990).

In more recent years, research efforts focused on delineating customer outage costs for different durations of planned and unplanned interruptions; whether the outage was related to transmission, distribution, or generation; and under other circumstances (Sullivan et al. 1996; Sullivan et al. 1997). The most recent studies involve quantifying regional and macroeconomic effects of outages; refining value of lost load (VoLL) estimation techniques—especially for households; and compiling utility outage cost surveys into accessible meta-datasets and applied software tools. For example, Sullivan et al. (2015) updates earlier work and compiles a U.S. outage cost meta-database containing utility VoLL survey data. This update increased the number of utility studies to thirty-four, and expands the analysis time period by seven years (from 1989–2005 to 1989–2012).

Part Two concludes with results from an expert-elicitation exercise designed to evaluate the hypothesis that utility outage cost surveys may be inaccurate in their assessment of the aggregate value of lost load (see, e.g., London Economics 2013; Growitsch et al. 2014; Rose et al. 2005). This simple exercise, which took place during power industry workshops in 2014 and 2015, suggests that utility cost surveys may under-estimate the value of lost load to different customer classes.

Method to estimate the costs and benefits of undergrounding power lines

Despite the high costs attributed to power outages, there has been little or no research to quantify both the benefits and costs of improving electric utility reliability—especially within the context of decisions to underground T&D lines (e.g., EEI 2013; Nooij 2011; Brown 2009; Navrud et al. 2008). Part Three introduces a general method to quantify the costs and benefits of undergrounding electricity infrastructure—a strategy that has been linked to improved reliability (Larsen et al. 2015; Brown 2009). Some researchers have found that the costs—in general—of undergrounding electric utility transmission and distribution (T&D) infrastructure far exceed the benefits of reduced outages (Brown 2009).

To test this finding, this dissertation introduces the first-known modeling framework to assess the costs and benefits of undergrounding power system infrastructure. Specifically, an infrastructure lifecycle simulation model is developed in order to evaluate the costs and benefits of undergrounding as existing overhead lines reach the end of their useful life. A number of impact categories are considered, including costs due to infrastructure replacement/conversion, changes in worker health and safety risk, and environmental restoration. Benefits from reduced power outages and increased property values are also considered as part of the cost-benefit framework. The model was initially configured to explore the costs and benefits within the footprint of Texas investor-owned utilities (IOUs). Texas was selected as a case study because Brown (2009) concluded that widespread undergrounding in Texas was probably not cost-effective.

Results from the initial model configuration indicate that a general policy that mandates Texas IOUs to underground line infrastructure had a base case net social loss of ~$22 billion through 2050 (or a 0.3 benefit-cost ratio). Varying all of the key parameters simultaneously leads to aggregate net social losses of $21.6 billion—on average. The base undergrounding model results were most sensitive to the choice of (1) discount rates; (2) replacement cost of undergrounding lines; (3) overhead T&D line lifespan; (4) value of lost load; and (5) customers per line mile. Based on the initial configuration of this model, Texas policymakers should not consider broadly mandating the undergrounding of T&D lines. However, a subsequent configuration of the model found that a policy specifically targeting areas where certain conditions are met could be cost-effective. If only urban areas are considered, then the percentage share of Texas IOU T&D line miles underground by 2050 drops from 79% to 47%. In other words, Texas IOUs could satisfy a social benefit-cost test if about half of their T&D line miles were underground by the middle of this century.

There are limitations to this analysis, however, and a number of possibilities for improvement in the future. First, it was assumed that the number of utility employees, real estate prices, and conservation easement prices are fixed at current levels. It is likely that these specific assumptions will increase over time, which could affect the benefit-cost ratio. It is also possible that the national model of electric utility reliability (Larsen et al. 2015), which was used to estimate future power outages across Texas, may not be appropriate for regional or local analyses. More research is needed to explore the factors that affect local utility reliability. It was also assumed that future weather through 2050 (e.g., number of lightning strikes, annual temperature, precipitation, average wind speed) will be similar to weather observed during the 2000–2012 time period. However, it is highly likely that future weather (climate) will not be similar to what has been recently observed (IPCC 2014). Future research could entail mapping state-of-the-art projections of local storm activity and temperature to each utility and recalibrating the analysis. Increased annual temperatures and storm activity will increase the estimated benefits of undergrounding T&D lines. It is also possible that the estimates of increased injury costs due to undergrounding may be less than the economic value of quality life to injured electric utility workers—or that undergrounding may, in fact, reduce health and safety risks to the general population. There is also emerging research indicating that underground lines are less efficient that overhead lines, which would increase the costs of undergrounding relative to the overhead status quo. Another key assumption is that electric utilities in Texas are able to pass along all of their additional costs (due to undergrounding) to ratepayers. Despite these shortcomings, this model could be extended to other regions in order to evaluate the economics of power grid resiliency.

(Under)ground-truthing empirical results

Part Four begins with a brief discussion of the importance of ground-truthing models. The base undergrounding model is then refined for a specific utility, Cordova Electric Cooperative (CEC), which has spent the last forty years converting overhead lines to underground lines. An ex-post analysis of CEC is conducted to determine if the benefits of undergrounding exceeded the costs. It became clear through this analysis that residents and businesses within the CEC have received significant net benefits—at least tens of millions of dollars—from a 1978 decision to underground their system. This finding is contrary to the initial results presented in Part Three, which showed that a future decision to underground all Texas IOUs would lead to significant net social losses. There is considerable uncertainty, however, in the range of net social benefits—mainly due to unanswered questions about how much of CEC's reliability improvements can actually be attributed to the decision to underground.

There are a number of improvements that should be considered in future efforts to refine the undergrounding model first presented in Part Three. First, the CEC case study highlighted the need to conduct a more rigorous analysis into the role that undergrounding power systems have on improvements to both the duration and frequency of power interruptions. The base undergrounding model—tuned for Texas IOUs—focused only on future reductions to the frequency of outages by using an underground line share correlation coefficient from the national reliability model presented in Part One. Clearly, a deeper exploration into more localized reliability gains from undergrounding, including improvements to outage frequency and duration, will lead to more accurate economic assessments. Next, although not discussed in great detail, there are other benefit categories that should be considered in future economic analyses of decisions to underground power lines. For example, CEC staff indicated that underground lines probably reduce the electrocution risk to community members when compared to the risks from overhead lines. These relative reductions in risk have economic value, but there has been little or no public research into the risk of electrocution from overhead and underground lines. And there may be important national security benefits if critical electricity infrastructure (e.g., T&D lines, substations, transformers) is buried and generally inaccessible to intentional acts of terrorism or unintentional accidents.

The CEC case study also highlighted the importance of considering the typical duration of an individual power outage—as the length of time that customers are without power can have severe consequences for some industries (e.g., cold storage facilities for commercial fishing companies). The case study employed assumptions about the value of lost load that were collected through utility-administered surveys that were conducted all over the country (Sullivan et al. 2015)—despite concerns that outage cost surveys may under-estimate the value customers place on reliability (London Economics 2013; Growitsch et al. 2014; Rose et al. 2005). Utilities, including the CEC, who are considering significant capital investments would benefit from sponsoring research into how much their customers—and the broader local/regional economy—value reliable electric service. Finally, the base undergrounding model and CEC case study did not consider the possibility that customers installed technologies to mitigate the impact of distribution system-related outages. For example, many critical public and private facility owners install backup generators that turn on automatically when a power interruption is detected. Future improvements to the model could include accounting for the presence of these types of technologies by adjusting both the reliability impact from undergrounding and the value of lost load for customers employing these types of technologies.

Despite the importance of considering indirect (external) costs and benefits, policymakers have not always recognized their use within the economic evaluation of proposed policies (Arrow et al. 1996). It is possible that proposed undergrounding initiatives could pass a societal benefit-cost test, yet fail a private benefit-cost test and, ultimately, not be mandated by a public utility commission. Travis Kavulla, a Montana Public Service Commissioner, makes an insightful observation about what utility regulators expect within the context of important investment decisions:

> The "general attitude that we have as a regulator is that we expect privately owned companies to exercise managerial discretion to make prudent investment decisions, ensuring a cost-effective (least-cost/least-risk) approach. Challenges to those management decisions are largely made after-the-fact, in utility rate proceedings. I have no real preconceptions about under-grounding except to say decisions to magnify the costs up front by doing so are largely dependent on the ability to quantify the benefits of improved reliability (or to avoid the damages of outages). The benefits seem, to me, highly locational. There are some circuits that would suffer dramatically if out of power twice a month; others, not so much" (Kavulla 2015).

This dissertation builds on insights from a number of different academic disciplines—including power system engineering, meteorology, and economics—to answer a number of important societal questions that transcend any one field of research. In the end, policymakers at all levels of government need better information on whether reliability is getting better or worse over time and the cost-effectiveness of different strategies that have been proposed to improve reliability. This dissertation introduces a pair of modeling frameworks intended to respond to the needs of these policymakers and, ultimately, members of the broader society who value reliable electric service.

Appendix A. Base Model Robustness Tests

Table A - 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)

Model specification:	**Model 1-A**	**Model 1-B**	**Model 1-C**	**Model 1-D**	**Model 1-E**	**Model 1-F**	**Model 1-G**
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)
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 O&M 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

Model specification:	Model 1-A	Model 1-B	Model 1-C	Model 1-D	Model 1-E	Model 1-F	Model 1-G
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 A - 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)

Model specification:	**Model 2-A**	**Model 2-B**	**Model 2-C**	**Model 2-D**	**Model 2-E**	**Model 2-F**	**Model 2-G**
Year	0.028***	0.038***	0.039***	0.046***	0.055***	0.095***	0.093***
	(0.011)	(0.012)	(0.012)	(0.015)	(0.015)	(0.025)	(0.025)
Abnormally cold weather (% above average HDDs)		-0.006**	-0.009	-0.004	-0.004	0.004	-0.036
		(0.003)	(0.007)	(0.008)	(0.003)	(0.013)	(0.028)
Abnormally warm weather (% above average CDDs)		-0.002	0.002	0.004	-0.003	-0.008*	-0.006
		(0.002)	(0.005)	(0.005)	(0.002)	(0.004)	(0.01)
Abnormally high # of lightning strikes (% above average strikes)		0.001*	0.001	0.002**	0.003***	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Abnormally windy (% above average wind speed)		0.03***	0.103***	0.079***	0.081***	0.121***	0.118***
		(0.01)	(0.022)	(0.021)	(0.021)	(0.031)	(0.031)
Abnormally wet (% above average total precipitation)		0.006***	0.018***	0.019***	0.007***	0.01*	0.016*
		(0.002)	(0.004)	(0.005)	(0.003)	(0.005)	(0.009)
Abnormally dry (% below average total precipitation)		0.001	-0.006	-0.001	0.002	0.001	-0.007
		(0.002)	(0.006)	(0.006)	(0.003)	(0.005)	(0.012)
Abnormally cold weather squared			0	0			0.004
			(0)	(0)			(0.003)
Abnormally warm weather squared			0	0*			0
			(0)	(0)			(0)
Abnormally windy squared			-0.007***	-0.005***	-0.006***	-0.007***	-0.006***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Abnormally wet squared			0***	0***			0
			(0)	(0)			(0)
Abnormally dry squared			0	0			0
			(0)	(0)			(0)
Lagged T&D O&M expenditures ($2012 per customer)				-0.004	0.002	0	-0.005
				(0.047)	(0.046)	(0.07)	(0.073)

Model specification:	Model 2-A	Model 2-B	Model 2-C	Model 2-D	Model 2-E	Model 2-F	Model 2-G
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 A - 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)						

Model specification:	**Model 3-A**	**Model 3-B**	**Model 3-C**	**Model 3-D**	**Model 3-E**	**Model 3-F**	**Model 3-G**
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)
Abnormally wet squared			0 (0)	0 (0)			0 (0)

Model specification:	Model 3-A	Model 3-B	Model 3-C	Model 3-D	Model 3-E	Model 3-F	Model 3-G
Abnormally dry squared			0 (0)	0 (0)			0 (0)
Lagged T&D O&M 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 A - 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)

Model specification:	Model 4-A	Model 4-B	Model 4-C	Model 4-D	Model 4-E	Model 4-F	Model 4-G
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)
Abnormally wet squared			0 (0)	0 (0)			0 (0)
Abnormally dry squared			0 (0)	0 (0)			0 (0)
Lagged T&D O&M 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 B. Full Regression Results for Primary Base Models

Table B - 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	0.002	-0.007	-0.034*	-0.011	-0.02

Explanatory variables:	**Log of SAIDI (without major events)**			**Log of SAIDI (with major events)**		
	Pooled	***Fixed Effects***	***Random Effects***	***Pooled***	***Fixed Effects***	***Random Effects***
	(0.009)	(0.01)	(0.009)	(0.02)	(0.036)	(0.025)
Year	0	0.009	0.013*	0.087***	0.085***	0.095***
	(0.008)	(0.007)	(0.007)	(0.02)	(0.032)	(0.025)
Lagged T&D O&M expenditures ($2012 per customer)	-0.084**	-0.017	-0.005	-0.05	-0.347	0
	(0.035)	(0.035)	(0.026)	(0.038)	(0.538)	(0.07)
Number of customers per line mile	-0.009***	0.002	-0.003	-0.003	0.033*	0.006
	(0.001)	(0.004)	(0.003)	(0.004)	(0.017)	(0.007)
Share of underground T&D miles to total T&D miles	-0.005***	0.002	-0.002	-0.015***	-0.006	-0.014**
	(0.002)	(0.005)	(0.004)	(0.003)	(0.012)	(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

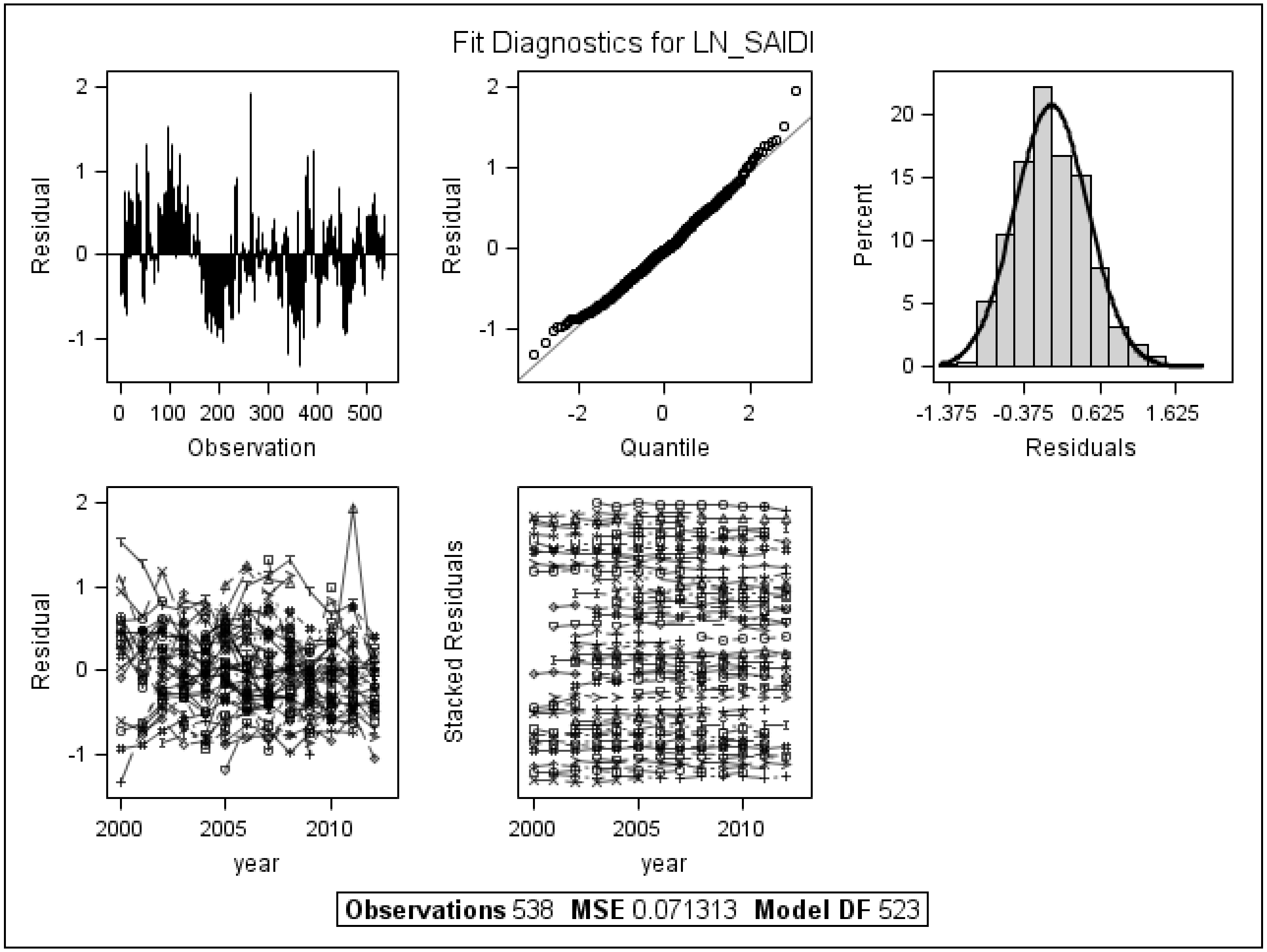

Figure B - 1. SAIDI base model fit diagnostics (without major events included)

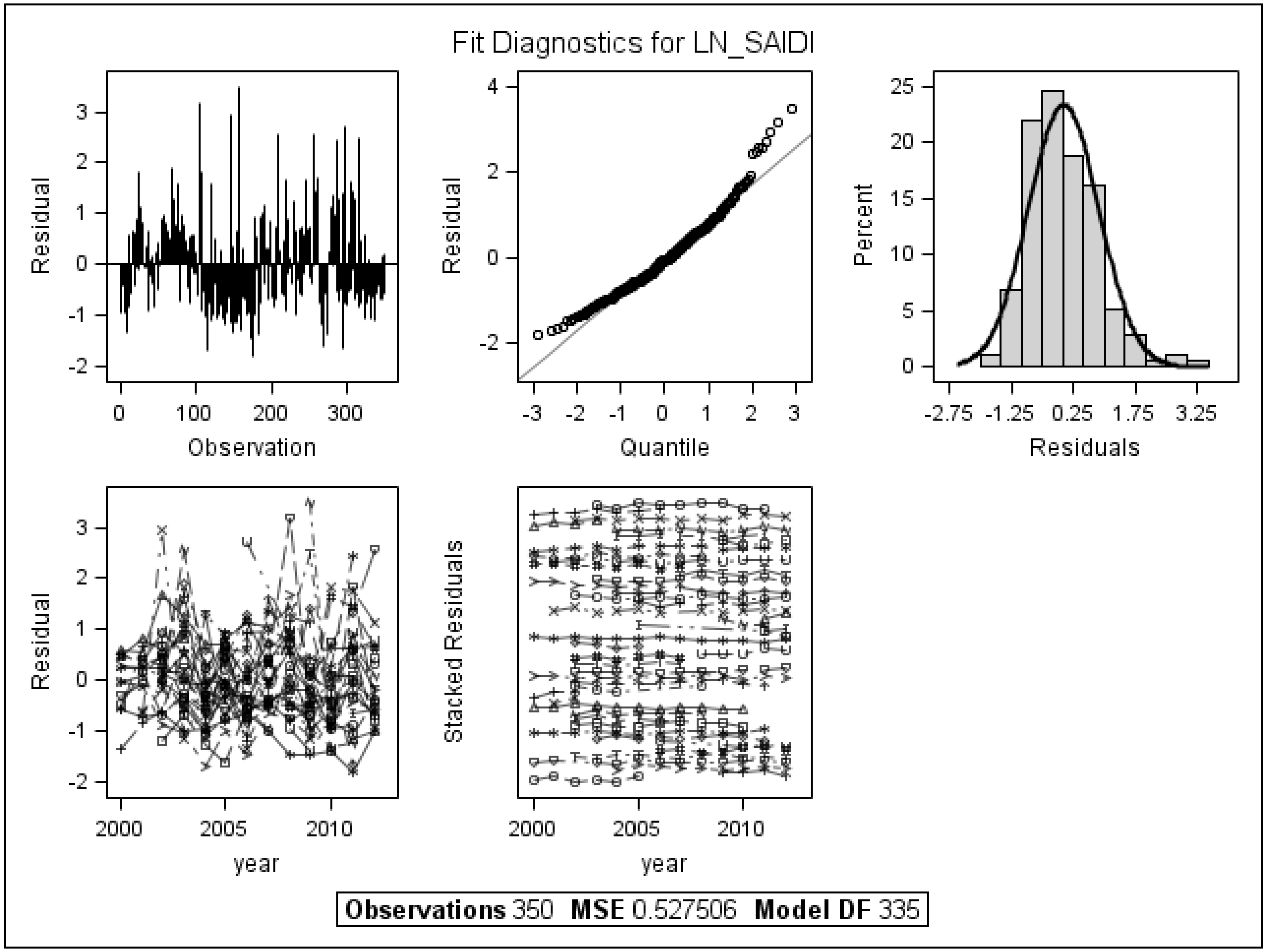

Figure B - 2. SAIDI base model fit diagnostics (with major events included)

Table B - 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	0.509	-8.622	-57.398***	-23.488	-39.159**
	(18.676)	(18.277)	(15.225)	(16.256)	(20.295)	(16.705)
Electricity delivered (MWh per customer)	0.001*	0.003	0.002	0	-0.005	0.002
	(0.001)	(0.007)	(0.002)	(0.002)	(0.011)	(0.004)
Abnormally cold weather (% above average HDDs)	0.001	-0.001	-0.001	-0.001	0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.007)	(0.005)	(0.005)
Abnormally warm weather (% above average CDDs)	-0.003	0	0	-0.002	0	0
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Abnormally high # of lightning strikes (% above average strikes)	0	0	0	0.002**	0.002**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Abnormally windy (% above average wind speed)	0.012	0.023**	0.023**	0.025	0.04***	0.04***
	(0.016)	(0.011)	(0.011)	(0.016)	(0.012)	(0.012)
Abnormally windy squared	-0.001	-0.002***	-0.002**	0	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Abnormally wet (% above average total precipitation)	-0.002	-0.001	-0.001	0.001	0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Abnormally dry (% below average total precipitation)	0.001	0.001	0.001	0.003	0.003*	0.003*
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Outage management system?	-0.072	0.011	0.003	0.017	-0.02	-0.028
	(0.053)	(0.039)	(0.038)	(0.066)	(0.051)	(0.05)
Years since outage management system installation	-0.009	0.003	-0.003	-0.022**	0	-0.006
	(0.007)	(0.008)	(0.006)	(0.009)	(0.012)	(0.009)
Year	0.003	0	0.004	0.029***	0.012	0.02**
	(0.009)	(0.009)	(0.008)	(0.008)	(0.01)	(0.008)
Lagged T&D O&M expenditures ($2012 per customer)	-0.08***	0.027	-0.02	-0.06***	-0.069	-0.026
	(0.021)	(0.035)	(0.021)	(0.022)	(0.184)	(0.049)
Number of customers per line mile	-0.007***	0.001	-0.004**	-0.004**	0.008	0

Explanatory variables:	**Log of SAIFI (without major events)**			**Log of SAIFI (with major events)**		
	Pooled	***Fixed Effects***	***Random Effects***	***Pooled***	***Fixed Effects***	***Random Effects***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.005)	(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

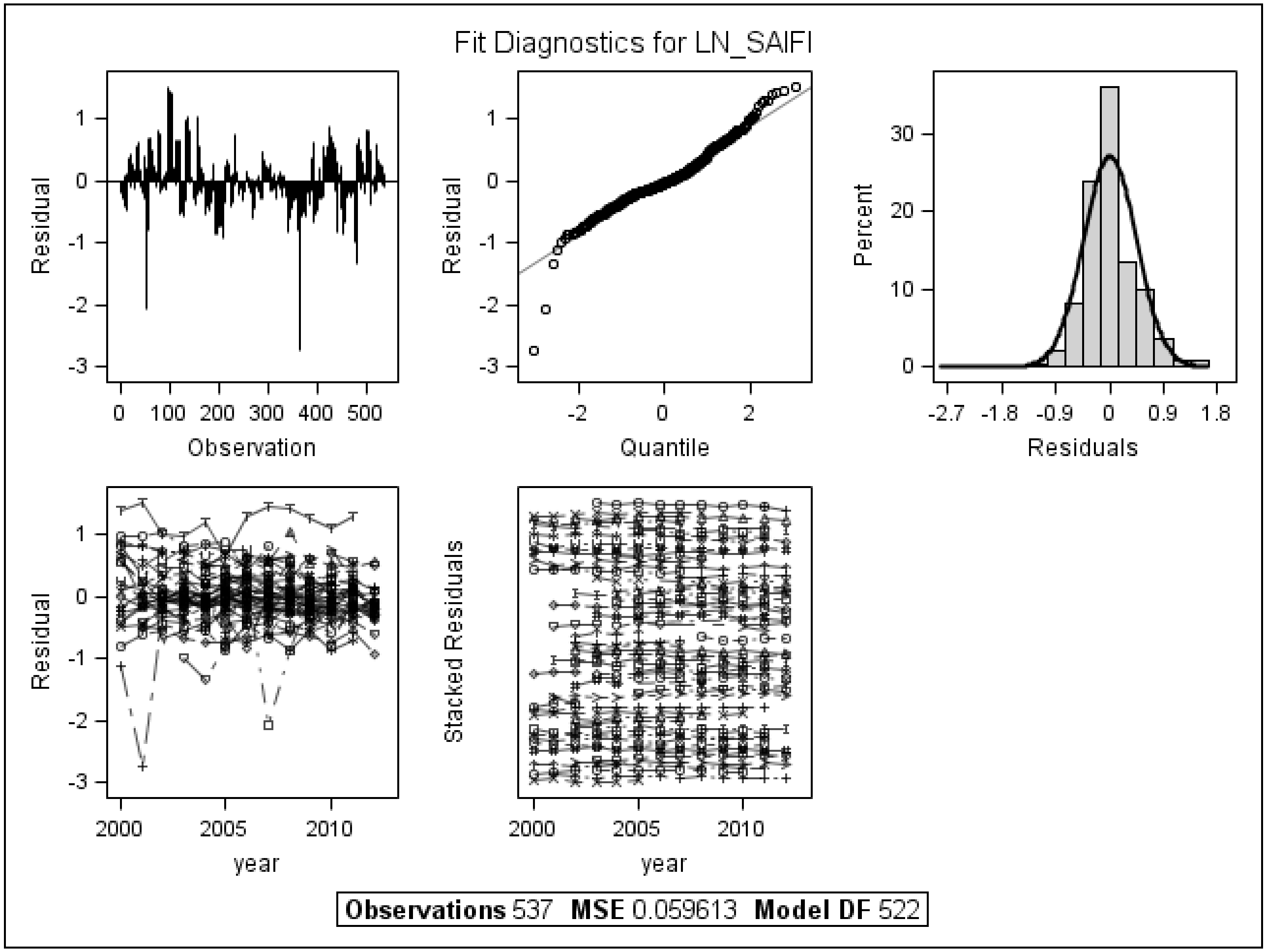

Figure B - 3. SAIFI base model fit diagnostics (without major events included)

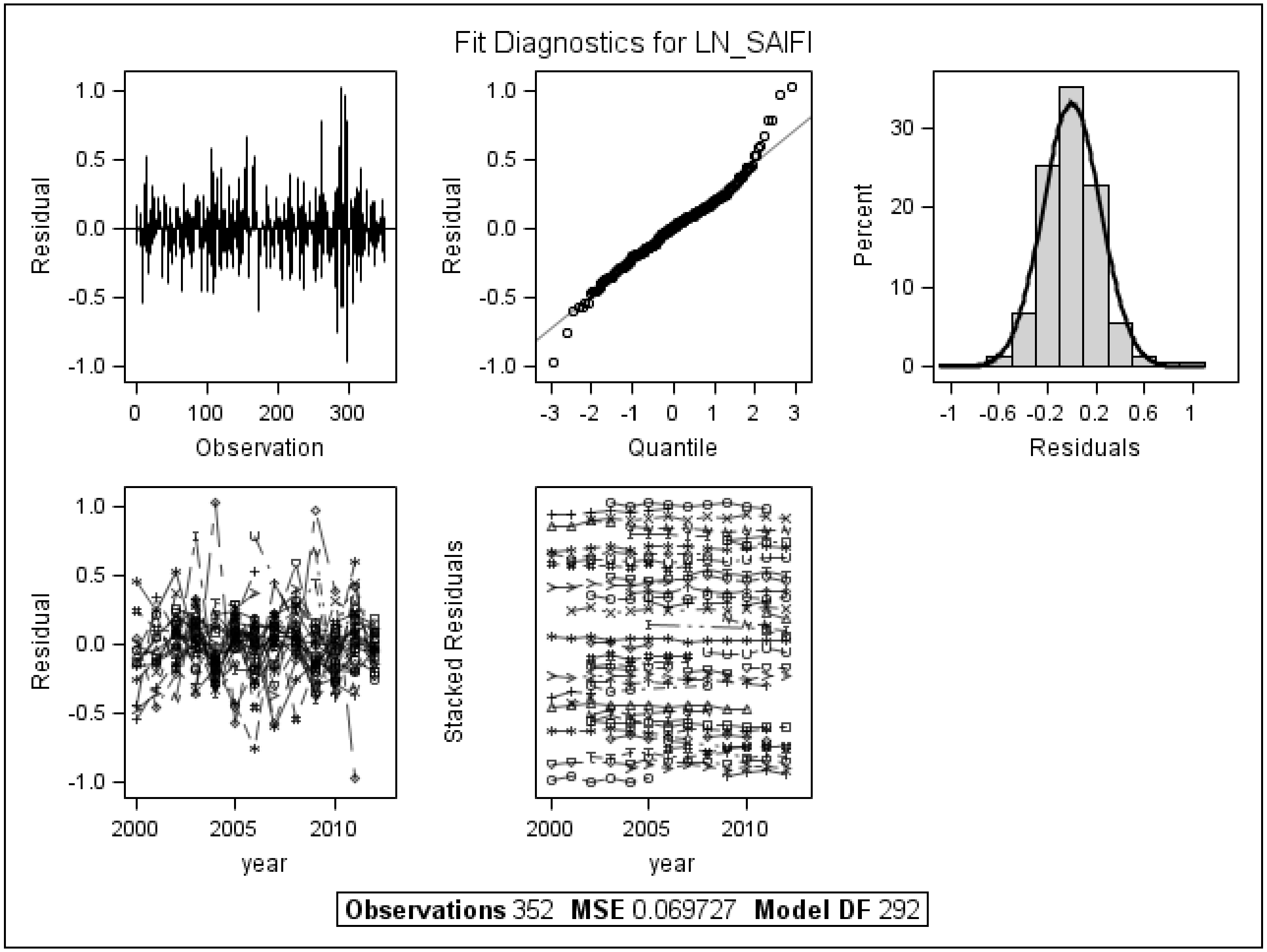

Figure B - 4. SAIFI base model fit diagnostics (with major events included)

Appendix C. 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* thirteen 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* thirteen 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 thirteen 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). Table C - 1 through Table C - 4 compare the panel regression results under these three cases for SAIDI and SAIFI, respectively.

Table C - 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 O&M 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	-0.003	0	-0.003	0	-0.003

Regression:	Unrestricted panel		Partially restricted panel		Fully restricted panel	
	Model E	*Model F*	*Model E*	*Model F*	*Model E*	*Model F*
	(0)	(0.003)	(0)	(0.005)	(0)	(0.005)
Share of underground T&D miles to total T&D miles		-0.002		-0.002		-0.002
		(0.004)		(0.007)		(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 C - 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***	-185.236***	-91.928**	-191.25***	-74.808*	-181.833***
	(29.124)	(49.627)	(44.745)	(64.892)	(42.778)	(64.928)
Electricity delivered (MWh per customer)	0.007	0.004	0.013	0.017	0.017	0.022
	(0.012)	(0.015)	(0.012)	(0.024)	(0.012)	(0.023)
Abnormally cold weather (% above average HDDs)	-0.004	0.004	-0.004	-0.006	-0.003	0
	(0.003)	(0.013)	(0.01)	(0.02)	(0.01)	(0.019)
Abnormally warm weather (% above average CDDs)	-0.003	-0.008*	-0.004	-0.009	-0.003	-0.005
	(0.002)	(0.004)	(0.003)	(0.006)	(0.003)	(0.005)
Abnormally high # of lightning strikes (% above average strikes)	0.003***	0.001	0.003**	0.002	0.004**	0.005**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Abnormally windy (% above average wind speed)	0.081***	0.121***	0.087***	0.101**	0.094***	0.114***

Regression:	**Unrestricted panel**		**Partially restricted panel**		**Fully restricted panel**	
	Model E	***Model F***	***Model E***	***Model F***	***Model E***	***Model F***
	(0.021)	(0.031)	(0.027)	(0.041)	(0.027)	(0.039)
Abnormally windy squared	-0.006***	-0.007***	-0.006***	-0.004*	-0.006***	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Abnormally wet (% above average total precipitation)	0.007***	0.01*	0.013***	0.032***	0.013***	0.028***
	(0.003)	(0.005)	(0.005)	(0.009)	(0.005)	(0.008)
Abnormally dry (% below average total precipitation)	0.002	0.001	-0.002	-0.014**	-0.003	-0.016***
	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)
Outage management system?	0.196**	0.128	0.172	0.217	0.188	0.212
	(0.09)	(0.136)	(0.125)	(0.214)	(0.119)	(0.191)
Years since outage management system installation	0.013	-0.02	0.06**	-0.049	0.07**	-0.04
	(0.017)	(0.025)	(0.028)	(0.051)	(0.027)	(0.049)
Year	0.055***	0.095***	0.048**	0.098***	0.039*	0.093***
	(0.015)	(0.025)	(0.022)	(0.033)	(0.021)	(0.033)
Lagged T&D O&M expenditures ($2012 per customer)	0.002	0	0.056	-0.071	0.062	-0.076
	(0.046)	(0.07)	(0.06)	(0.118)	(0.061)	(0.114)
Number of customers per line mile	0	0.006	0	-0.005	0	-0.009
	(0)	(0.007)	(0)	(0.014)	(0)	(0.014)
Share of underground T&D miles to total T&D miles		-0.014**		-0.025**		-0.022*
		(0.007)		(0.012)		(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 C - 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 O&M 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	-0.004**	0	-0.003	0	-0.003

Regression:	Unrestricted panel		Partially restricted panel		Fully restricted panel	
	Model E	*Model F*	*Model E*	*Model F*	*Model E*	*Model F*
	(0)	(0.002)	(0)	(0.003)	(0)	(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 C - 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***	0.04***	0.035***	0.035***	0.037***	0.033**

Regression:	Unrestricted panel		Partially restricted panel		Fully restricted panel	
	Model E	***Model F***	***Model E***	***Model F***	***Model E***	***Model F***
	(0.01)	(0.012)	(0.011)	(0.013)	(0.012)	(0.015)
Abnormally windy squared	-0.003***	-0.003***	-0.002***	-0.002**	-0.003***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Abnormally wet (% above average total precipitation)	0.003***	0.002	0.003**	0.004**	0.003**	0.006*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Abnormally dry (% below average total precipitation)	0.002	0.003*	0	0	0	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Outage management system?	0.121***	-0.02	0.083	-0.004	0.108**	0.059
	(0.046)	(0.051)	(0.052)	(0.071)	(0.054)	(0.074)
Years since outage management system installation	0.012	0	0.031***	-0.028	0.035***	-0.034
	(0.009)	(0.012)	(0.012)	(0.018)	(0.013)	(0.021)
Year	0.005	0.012	0.011	0.028**	0.009	0.024*
	(0.007)	(0.01)	(0.01)	(0.012)	(0.01)	(0.014)
Lagged T&D O&M expenditures ($2012 per customer)	-0.01	-0.069	0.066	-0.044	0.08	-0.173
	(0.119)	(0.184)	(0.092)	(0.06)	(0.091)	(0.185)
Number of customers per line mile	0	0.008	0*	-0.004	0*	0.013
	(0)	(0.005)	(0)	(0.007)	(0)	(0.016)
Share of underground T&D miles to total T&D miles		-0.001		-0.013***		-0.02***
		(0.004)		(0.004)		(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

Appendix D. Key Data Sources for Basic Undergrounding Analysis: Texas Investor Owned Utilities

Table D - 1. Key data sources for lifecycle cost analysis

Data	Value	Original units	Source
Existing distribution lines (underground)	46,669	Total miles	Brown (2009)
Existing distribution lines (overhead)	165,158	Total miles	Brown (2009)
Existing transmission lines (overhead)	33,060	Total miles	Brown (2009)
Existing transmission lines (underground)	81	Total miles	Brown (2009)
Age of existing underground distribution line circuits (2012)	Derived	Age in years	Derived by author using average age of other T&D systems—20 years (Northwestern Energy 2011; Southern California Edison 2013)
Age of existing overhead distribution line circuits (2012)	Derived	Age in years	Derived by author using average age of other T&D systems—20 years (Northwestern Energy 2011; Southern California Edison 2013)
Age of existing overhead transmission line circuits (2012)	Derived	Age in years	Derived by author using average age of other T&D systems—20 years (Northwestern Energy 2011; Southern California Edison 2013)
Age of existing underground transmission line circuits (2012)	Derived	Age in years	Derived by author using average age of other T&D systems—20 years (Northwestern Energy 2011; Southern California Edison 2013)
Discount rate	10%	Weighted average cost of capital (%)	Public Utilities Fortnightly (2013); Brown (2009)
Annual line mile growth rate	2%	% per year	Author
Useful lifespan (underground infrastructure)	40	Years	Brown (2009)
Useful lifespan (overhead infrastructure)	60	Years	Brown (2009)
Annual O&M cost; first year (overhead transmission lines)	5%	% of replacement cost	Author estimated based on information submitted to FERC/RUS/EIA/Ventyx (2014)

Data	Value	Original units	Source
Annual O&M cost; first year (overhead distribution lines)	0.5%	% of replacement cost	Author estimated based on information submitted to FERC/RUS/EIA/Ventyx (2014)
Annual O&M cost; first year (underground transmission lines)	5%	% of replacement cost	Author estimated based on information submitted to FERC/RUS/EIA/Ventyx (2014)
Annual O&M cost; first year (underground distribution lines)	0.5%	% of replacement cost	Author estimated based on information submitted to FERC/RUS/EIA/Ventyx (2014)
Annual O&M cost growth rate; subsequent years (overhead transmission lines)	5%	% per year	Author estimated based on past annual T&D cost growth rate (Whitman, Requardt and Associates, LLP 2013)
Annual O&M cost growth rate; subsequent years (overhead distribution lines)	5%	% per year	Author estimated based on past annual T&D cost growth rate (Whitman, Requardt and Associates, LLP 2013)
Annual O&M cost growth rate; subsequent years (underground transmission lines)	5%	% per year	Author estimated based on past annual T&D cost growth rate (Whitman, Requardt and Associates, LLP 2013)
Annual O&M cost growth rate; subsequent years (underground distribution lines)	5%	% per year	Author estimated based on past annual T&D cost growth rate (Whitman, Requardt and Associates, LLP 2013)
Replacement cost (overhead transmission lines)	$180,000	$ per mile	Brown (2009)
Replacement cost (overhead distribution lines)	$104,000	$ per mile	EEI (2013) minimum values plus 20%
Replacement cost (underground transmission)	$1,680,000	$ per mile	EEI (2013) minimum values plus 20%
Replacement cost (underground distribution)	$357,000	$ per mile	EEI (2013) minimum values plus 20%
Replacement cost annual growth/decay rate (overhead transmission lines)	0%	% per year	Author
Replacement cost annual growth/decay rate (overhead distribution lines)	0%	% per year	Author
Replacement cost annual growth/decay rate (underground transmission lines)	0%	% per year	Author
Replacement cost annual growth/decay rate (underground distribution lines)	0%	% per year	Author
Length of each T&D system circuit	Derived	Length in miles	Derived by author using average circuit length of 25 miles

Table D - 2. Key data sources for administrative, permitting, and siting costs

Data	Value	Original units	Source
Administrative, permitting, and siting cost adder in first year	1% of installation cost in first year	%	Author
Administrative, permitting, and siting cost adder for converting overhead to underground in first year	2% of installation cost in first year	%	Author

Table D - 3. Key data sources for benefits of avoided power outages

Data	Value	Original units	Source
Model of U.S. electric utility reliability	See Technical Appendix	Regression coefficients	Author
Delivered electricity per customer	33.96	MWh/customer	Author
Lagged T&D expenditures	0.39	$ per customer	Author
Years since outage management system installed	2.28	Years	Author
Presence of outage management system	1	Dummy variable	Author
Heating degree-days (positive deviation)	3.64	% deviation above mean	Author
Cooling degree-days (positive deviation)	3.74	% deviation above mean	Author
Lightning strikes (positive deviation)	14.54	% deviation above mean	Author
Wind speed (positive deviation)	1.85/10.69	% deviation above mean and % deviation squared	Author
Precipitation (positive deviation)	11.4	Positive precipitation deviation and deviation squared	Author
Precipitation (negative deviation)	-11.4	Negative precipitation deviation and deviation squared	Author
Year	Derived	Years (2013-2050)	Author
Customers per line mile	75	Customers per line mile	Author—variable is used to calibrate status quo SAIFI estimates; Brown (2009) reports 28.5 customer per line mile and author database reports 239.1 for Texas/ERCOT utilities
Existing share of T&D line miles underground	19.1%	%	Brown (2009)
Future share of underground T&D line	Derived	%	Author derived during

Data	Value	Original units	Source
miles			lifecycle analysis
Outage cost—commercial and industrial customers	$9,217	$ per customer outage	Sullivan et al. (2010) for large commercial and industrial (30 min. duration)
Outage cost—residential customers	$2.7	$ per customer outage	Sullivan et al. (2010) assumption for residential (30 min. duration)
Outage cost—other customers	$435	$ per customer outage	Sullivan et al. (2010) assumption for small commercial and industrial (30 min. duration)
Number of customers	6,983,069	Customers	Brown (2009)
Share of commercial and industrial customers	11.9%	%	Author derived based on U.S. Energy Information Administration via Form 861 (EIA 2013); Ventyx Velocity Suite via FERC (2014); and U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx (2015)
Share of residential customers	86.5%	%	Author derived based on U.S. Energy Information Administration via Form 861 (EIA 2013); Ventyx Velocity Suite via FERC (2014); and U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx (2015)
Share of other customers	1.6%	%	Author derived based on U.S. Energy Information Administration via Form 861 (EIA 2013); Ventyx Velocity Suite via FERC (2014); and U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx (2015)

Table D - 4. Key data sources for aesthetic benefits

Data	Value	Original units	Source
Median value of Texas residential real estate	$139,400	$	Zillow (2014)
Approximate median value of Texas commercial and	$1,000,000	$	Lincoln Institute (2011)

Data	Value	Original units	Source
industrial real estate			
Median value of Texas other real estate	$500,000	$	Author
Total service area for Texas IOUs	190,597	Square miles	Author derived from public sources
Width of transmission viewing corridor	600	Feet	Approximate average of Sims and Dent (2005) and Colwell (1990)
Property loss factor attributed to view of transmission line	12.5%	%	Influenced by Des Rosiers (2002)

Table D - 5. Key data sources for impacts to ecosystems

Data	Value	Original units	Source
Width of ecosystem footprint (overhead transmission line)	60	Feet	Author
Width of ecosystem footprint (underground transmission line)	120	Feet	Author
Conservation easement price (Texas)	$3,000	$ per acre	The Nature Conservancy (2014)

Table D - 6. Key data sources for health and safety costs

Data	Value	Original units	Source
Value of statistical life	$6,900,000	Dollars	Executive Office of the President (2013b)
Aggregate number of employees	8,514	Number of employees	Author estimated from public sources
Maximum cost of utility-related accident (electric shock)	$130,658	$ per accident	OSHA (2014)
Incidence rate for electric utility (non-fatal injury)	2,100	Accidents per 100,000 workers	OSHA (2014)
Incidence rate for electric utility (fatality)	15	Fatalities per 100,000 workers	BLS (2014a)

Table D - 7. Results for base SAIFI and SAIDI regressions

	Dependent variable:	
Explanatory variables:	**Log of SAIDI (with major events)**	**Log of SAIFI (with major events)**
Intercept	-185.236*** (49.627)	-23.488 (20.295)
Electricity delivered (MWh per customer)	0.004 (0.015)	-0.005 (0.011)
Abnormally cold weather (% above average HDDs)	0.004 (0.013)	0.002 (0.005)
Abnormally warm weather (% above average CDDs)	-0.008* (0.004)	0 (0.001)

Explanatory variables:	Dependent variable: Log of SAIDI (with major events)	Log of SAIFI (with major events)
Abnormally high # of lightning strikes (% above strikes)	0.001 (0.002)	0.002** (0.001)
Abnormally windy (% above average wind speed)	0.121*** (0.031)	0.04*** (0.012)
Abnormally windy squared	-0.007*** (0.002)	-0.003*** (0.001)
Abnormally wet (% above average total ation)	0.01* (0.005)	0.002 (0.001)
Abnormally dry (% below average total ation)	0.001 (0.005)	0.003* (0.002)
Outage management system?	0.128 (0.136)	-0.02 (0.051)
Years since outage management system installation	-0.02 (0.025)	0 (0.012)
Year	0.095*** (0.025)	0.012 (0.01)
Lagged T&D O&M expenditures ($2012 per r)	0 (0.07)	-0.069 (0.184)
Number of customers per line mile	0.006 (0.007)	0.008 (0.005)
Share of underground T&D miles to total T&D miles	-0.014** (0.007)	-0.001 (0.004)
Degrees of freedom:	335	292
Number of utilities:	46	46
Adjusted R^2	0.14	0.71
Root mean square error	0.73	0.26
Utility effects:	Random	Fixed

Notes:
(1) Standard errors are presented in parentheses underneath coefficient
(2) *** represents coefficients that are significant at the 1% level
(3) ** represents coefficients that are significant at the 5% level
(4) * represents coefficients that are significant at the 10% level
(5) † represents preferred model specification

Appendix E. Key Data Sources for Case Study: Cordova Electric Cooperative

Table E - 1. Key data sources for lifecycle cost analysis

Data	Value	Original units	Source
Existing distribution lines (1978) (underground)	8	Total miles	Koplin (2015b; 2015c; 2015d)
Existing distribution lines (1978) (overhead)	28	Total miles	Koplin (2015b; 2015c; 2015d)
Age of existing underground distribution line circuits (1978)	Derived	Age in years	Derived by author using average age reported by Koplin (2015b; 2015c; 2015d)—25 years in 1978
Age of existing overhead distribution line circuits (1978)	Derived	Age in years	Derived by author using average age reported by Koplin (2015b; 2015c; 2015d)—30 years in 1978
Discount rate	3.5%	Weighted average cost of capital (%)	Koplin (2015b; 2015c; 2015d)
Annual line mile growth rate (1978-2015)	1.76%	% per year	Estimated by author based on information from Koplin (2015b; 2015c; 2015d): 36 line miles in 1978; 69 line miles in 2015
Useful lifespan in 1978 (underground infrastructure)	40	Years	Author
Useful lifespan in 1978 (overhead infrastructure)	40	Years	Author
Annual O&M cost; first year (overhead distribution lines)	3.9%	% of replacement cost	Author estimated based on information provided by Koplin (2015b; 2015c; 2015d)
Annual O&M cost; first year (underground distribution lines)	1.9%	% of replacement cost	Author estimated based on information provided by Koplin (2015b; 2015c; 2015d)
Annual O&M cost growth rate; subsequent years (overhead distribution lines)	0.2%	% of replacement cost	Author estimated based on information provided by Koplin (2015b; 2015c; 2015d)
Annual O&M cost growth rate; subsequent years (underground distribution lines)	0.1%	% of replacement cost	Author estimated based on information provided by Koplin (2015b; 2015c; 2015d)
1978 replacement cost in 2015 dollars (overhead distribution lines)	$152,035	$ per mile	Koplin (2015b; 2015c; 2015d) reports $25,000/mile ($1978); Inflated this value using 5% HWI annual value based on Pacific region

Data	Value	Original units	Source
1978 replacement cost in 2015 dollars (underground distribution); 2015 replacement cost in 2015 dollars; -1.85% annual cost decrease	$304,070 (1978); $152,035 (2015)	$ per mile	Koplin (2015b; 2015c; 2015d) reports $25,000/mile ($1978); Inflated this value using 5% HWI annual value based on Pacific region
Length of each distribution system circuit	Derived	Length in feet	Derived by author using average circuit length of 1,000 feet

Table E - 2. Key data sources for administrative, permitting, and siting costs

Data	Value	Original units	Source
Administrative, permitting, and siting cost adder in first year (existing overhead or underground lines)	1% of installation cost in first year	%	Author
Administrative, permitting, and siting cost adder for converting overhead to underground in first year (conversion of overhead to underground)	2% of installation cost in first year	%	Author

Table E - 3. Key data sources for benefits of avoided power outages

Data	Value	Original units	Source
Decrease in annual outage frequency for each additional 1% of line miles undergrounded	-0.141	Frequency of outages (annual)	Estimated by author based on information from Koplin (2015b; 2015c; 2015d): ~25 outages per year in 1978 (22% underground); ~3 outages per year in 2015 (100% underground)
Decrease in annual outage duration for each additional 1% of distribution line miles undergrounded	-1.0	Minutes (total annual outage duration)	Estimated by author based on information from Koplin (2015b; 2015c; 2015d): ~240 distribution system-related outage minutes per year in 1978 (22% underground); ~83 minutes total outage duration in 2015 (100% underground)
Existing share of distribution line miles underground (1978)	22.2%	%	Koplin (2015b; 2015c; 2015d)
Future share of underground T&D line miles	Derived	%	Author derived during lifecycle analysis
Outage cost—commercial and	Primary estimates adapted from Sullivan et al.	$ per customer outage of	Adapted from Sullivan et al. (2015); Average

Data	Value	Original units	Source
industrial customers	(2015)/$1,250 estimated from information by Koplin	varying duration (Sullivan et al. 2015)/$ per customer outage for 30 minute duration (Koplin)	of large industrial and commercial customer outage costs for 30 minutes as reported by Koplin (2015b; 2015c; 2015d)
Outage cost—residential customers	Primary estimates adapted from Sullivan et al. (2015)/$25 estimated from information by Koplin	$ per customer outage of varying duration (Sullivan et al. 2015)/$ per customer outage for 30 minute duration (Koplin)	Adapted from Sullivan et al. (2015); Residential customer outage cost for 30 minutes as reported by Koplin (2015b; 2015c; 2015d)
Outage cost—other customers	Primary estimates adapted from Sullivan et al. (2015)/$250 estimated from information by Koplin	$ per customer outage of varying duration (Sullivan et al. 2015)/$ per customer outage for 30 minute duration (Koplin)	Adapted from Sullivan et al. (2015); Average of small and large C&I customer outage costs for 30 minutes as reported by Koplin (2015b; 2015c; 2015d)
Number of customer meters	1,455	Customer meters	Koplin (2015b; 2015c; 2015d)
Share of commercial and industrial customers	10.7%	%	Koplin (2015b; 2015c; 2015d)
Share of residential customers	61.9%	%	Koplin (2015b; 2015c; 2015d)
Share of other customers	27.5%	%	Koplin (2015b; 2015c; 2015d)

Table E - 4. Key data sources for aesthetic benefits

Data	Value	Original units	Source
Median value of Alaska residential real estate	$260,300	$	Zillow (2015) reports $260,300 for median value of residential in 2015
Approximate median value of Cordova (Alaska) commercial and industrial real estate	$780,900	$	Author; triple 2015 residential real estate value
Median value of Cordova (Alaska) other real estate	$520,600	$	Author; double 2015 residential real estate value
Total service area for Cordova (Alaska)	65	Square miles	Author derived from public sources
Width of distribution line viewing corridor	200	Feet	Half of approximate average of Sims and Dent (2005) and Colwell (1990) estimates for

Data	Value	Original units	Source
			transmission lines
Property loss factor attributed to view of distribution line	12.5%	%	Influenced by Des Rosiers (2002)

Table E - 5. Key data sources for impacts to ecosystems

Data	Value	Original units	Source
Width of right-of-way (overhead distribution line)	180	Feet	Author based on comments from Koplin (2015b; 2015c; 2015d)
Width of right-of-way (underground distribution line)	60	Feet	Author based on comments from Koplin (2015b; 2015c; 2015d)
Conservation easement price (Alaska)	$5,456	$ per acre	Average of all U.S. easement prices reported by The Nature Conservancy (2014)

Table E - 6. Key data sources for health and safety costs

Data	Value	Original units	Source
Number of employees seriously injured due to underground conversion	1	Number of employees	Author based on comments from Koplin (2015b; 2015c; 2015d)
Number of employees seriously injured under status quo	0	Number of employees	Author based on comments from Koplin (2015b; 2015c; 2015d)
Direct and indirect worker compensation costs for multiple physical injuries	$160,717	$ per accident	OSHA (2014)
Number of employee fatalities under status quo or underground conversion	0	Number of employees	Koplin (2015d)

Bibliography

ABB-Ventyx. *Ventyx Velocity Suite Energy Mapping Software.* Boulder, December 12, 2015.

Abdullah, S., and P. Mariel. "Choice Experiment Study on the Willingness to Pay to Improve Electricity Services." *Energy Policy* 38 (2010): 4570-4581.

AEP Southwestern. *2011 Service Quality Report To The Public Utility Commission of Texas,.* Report (February), SWEPCO, 2012.

Alinsato, A. "Economic Valuation of Electrical Service Reliability for Households' in Developing Country: A Censored Random Coefficient Model Approach." *International Journal of Energy Economics of Policy* 5, no. 1 (2015): 352-359.

Arrow, K., et al. "Is There a Role for Benefit-Cost Analysis in Environmental, Health, and Safety Regulation?" *Science* 272 (1996): 221-222.

Baltagi, B. H, and Y. Chang. "Incomplete Panels: A Comparative Study of Alternative." *Journal of Econometrics* 62, no. 2 (1994): 67-89.

Baltagi, B., G. Bresson, and A. Pirotte. "Fixed Effects, Random Effects or Hausman–Taylor? A Pretest Estimator." *Economics Letter* 79 (2003): 361-369.

Beenstock, M. "Generators and the Cost of Electricity Outages." *Energy Economics* 13, no. 4 (1991): 283-289.

Bental, B., and S. Ravid. "A Simple Method for Evaluating the Marginal Cost of Unsupplied Electricity." *The Bell Journal of Economics* 13, no. 1 (1982): 249-253.

Billinton, R., interview by Michael Sullivan. *Email Discussing Origins of Term "Value-based Reliability Planning"* (September 17, 2015).

Billinton, R., G Wacker, and E. Wojczynski. "Comprehensive Bibliography on Electrical Service Interruption Costs." *IEEE Transactions on Power Apparatus and Systems* PAS-102, no. 6 (June 1983).

Boardman, A., D. Greenberg, A. Vining, and D. Weimer. *Cost-benefit Analysis: Concepts and Practice.* Fourth. Pearson Education, 2010.

Brown, R. *Cost-Benefit Analysis of the Deployment of Utility Infrastructure Upgrades.* Final report prepared for the Public Utility Commission of Texas, Quanta Technology, 2009.

Burns, S, and G. Gross. "Value of Service Reliability." *IEEE Transactions on Power Systems* 5, no. 3 (August 1990).

Buse, A. "Goodness of Fit in Generalized Least Squares Estimation." *American Statistician* 27 (1973): 106-108.

California Energy Commission. *Value-based Planning for Electric Utilities.* P300-87-001, California Energy Commission, 1986.

Cameron, A.C., and P. Trivedi. *Microeconometrics Using Stata.* Texas: Stata Press, 2009.

Caves, D., J. Herriges, and R. Windle. "The Cost of Electric Power Interruptions in the Industrial Sector: Estimates Derived from Interruptible Service Programs." *Land Economics* 68, no. 1 (1992): 49-61.

Chen, R., K. Allen, and R. Billinton. "Value-based Distribution Reliability Assessment and Planning." *IEEE Transactions on Power Delivery* 10, no. 1 (1995): 421-429.

Choi, J., S. Moon, H.S. Kim, J. Kang, H.Y. Kim, and R. Billinton. "Development of an Analytical Method for Outage Cost Assessment in a Composite Power System." *Proceedings from the IEEE 2000 International Conference on Power System.* Perth: IEEE, 2000.

Chowdhury, A., and D. Koval. "Value-based Distribution System Reliability Planning." *IEEE Transactions on Industry Applications* 34, no. 1 (1998).

Chowdhury, A., and D. Koval. "Value-based Power System Reliability Planning." *IEEE Transactions on Industry Applications* 35, no. 2 (1999).

City Council of San Diego. *City Council Policy 600-08: Underground Conversion of Utility Lines by Utility Company.* San Diego, May 28, 2002.

Colwell, P. "Power Lines and Land Value." *The Journal of Real Estate Research*, March 1990.

Consulting, PA, interview by Peter Larsen and K.H. LaCommare. *Discussion of Intangible Factors that Affect Utility Reliability* (January 2014).

Cordova Electric Cooperative. "CEC History." 2015. http://cordovaelectric.com/ .

Corwin, J., and W. Miles. *Impact Assessment of the 1977 New York City Blackout.* Washington D.C.: U.S. Department of Energy, 1978.

Dalton, J., D. Garrison, and C. Fallon. "Value-based Reliability Transmission Planning." *IEEE Transactions on Power Systems* 11, no. 2 (August 1996).

Delea, F., and J. Cassazza. *Understanding Electric Power Systems: An Overview of the Technology, the Marketplace, and Government Regulation.* Second. Wiley-IEEE Press, 2010.

Des Rosiers, F. "Power Lines, Visual Encumbrance, and House Values." *Journal of Real Estate Research* 23, no. 3 (2002).

Dickinson, W.H. "Economic Evaluation of Industrial Power-system Reliability." *AIEE Transactions, part II: Applications and industry* 1957, no. 76 (1957): 264-272.

Edison Electric Institute. *Out of Sight, Out of Mind.* Prepared by Kenneth Hall for EEI, Edison Electric Institute, 2013.

Electric Power Research Institute. *Cost-benefit Analysis of Power System Reliability: Determination of Interruption Costs.* Prepared for EPRI by RCG/Hagler, Bailly, Inc., Palo Alto: Electric Power Research Institute (EPRI), 1990.

Erdogdu, E. "The Impact of Power Market Reforms on Electricity Price-Cost Margins and Cross-Subsidy Levels: A Cross Country Panel Data Analysis." *Energy Policy* 39 (2011).

Eto, J. E., K. H. LaCommare, P. Larsen, A. Todd, and E. Fisher. *An Examination of Temporal Trends in Electricity Reliability Based on Reports from U.S. Electric Utilities.* LBNL Report-5268E, Berkeley: Lawrence Berkeley National Laboratory, 2012.

Eto, J., and K. LaCommare. *Tracking the Reliability of the U.S. Electric Power System: An Assessment of Publicly Available Information Reported to State Public Utility Commissions.* LBNL-1092E, Berkeley: Lawrence Berkeley National Laboratory, 2008.

Eto, J., et al. *Scoping Study on Trends in the Economic Value of Electricity Reliability to the U.S. Economy.* LBNL-47911, Berkeley: Lawrence Berkeley National Laboratory, 2001.

Eto, J., K. LaCommare, P. Larsen, A. Todd, and E. Fisher. *An Examination of Temporal Trends in Electricity Reliability Based on Reports from U.S. Electric Utilities.* LBNL-5268E, Berkeley: Lawrence Berkeley National Laboratory, 2012.

Executive Office of the President. *2014 Discount rates for OMB circular A-94.* White House Memorandum, Washington D.C.: The White House, 2014.

Executive Office of the President. *Draft Report to Congress on the Benefits and Costs of Federal Regulations.* Draft report, Washington D.C.: Executive Office of the President, 2013b.

Executive Office of the President. *Economic Benefits of Increasing Electric and Grid Resilience to Weather Outages.* Washington D.C.: The White House, 2013a.

Federal Energy Regulatory Commission/Rural Utilities Service/EIA/ABB Ventyx. *Transmission and Distribution System Line Miles.* Processed by ABB Ventyx. Compiled by ABB Ventyx from FERC Form 1, EIA-412, RUS Form 7, and RUS Form 12, January 2014.

Fisher, E., J. Eto, and K. Hamachi-LaCommare. "Understanding Bulk Power Reliability: The Importance of Good Data and a Critical Review of Existing Sources." *Proceedings of the 45th Annual Hawaii International Conference on System Sciences.* Wailea, 2012.

Florida Public Utilities Company. "Reliability, Wood Pole Inspections, Storm Hardening Plan, and Storm Preparedness Initiatives." Tallahassee: FPUC, 2012.

Foley, M. "Fuzzy Merges: Examples and Techniques." *Proceedings of the 24th SAS User Group International Conference.* Miami Beach: SAS Institute, 1999.

Gaver, D., F. Montmeat, and A. Patton. "Power system reliability I: measures of reliability and methods of calculation." *Proceedings of IEEE Power Engineering Society Winter Meeting.* IEEE, 1964. 727-737.

Goel, L. "Power System Reliability Cost/Benefit Assessment and Application in Perspective." *Computers and Electrical Engineering* 24 (1998): 315-324.

Gonen, T. *Electric Power Distribution Engineering.* Vol. Third Edition. CRC Press/Taylor and Francis Group, 2014.

Goulder, L., and D. Kennedy. *Interpreting and Estimating the Value of Ecosystem Services.* Working Paper, Stanford: Stanford University Department of Economics, 2009.

Gralla, J. "East Hampton Residents Protest PSEG LI Plan to Install Taller Power Lines." *Newsday*, April 5, 2014.

Greenberg, M., N. Mantell, M. Lahr, N. Felder, and R. Zimmerman. "Short and Intermediate Economic Impacts of a Terrorist Initiated Loss of Electric Power: Case Study of New Jersey." *Energy Policy* 35, no. 1 (2007): 722-733.

Greene, W. *Econometric Analysis.* Vol. Fourth Edition. Upper Saddle River: Prentice-Hall, 2000.

Growitsch, C., R. Malischek, S. Nick, and H. Wetzel. "The Costs of Power Interruptions in Germany: A Regional and Sectoral Analysis." *German Economic Review*, 2014: 1-17.

Hall, G.C., M.T. Healy, and W.B. Poland. "PG&E's New Methodology for Value-Based Generation Reliability Planning." Minneapolis: System Planning Committee, Edison Electric Institute, 1986.

Hargrave, M. "Ground Truthing the Results of Geophysical Surveys." In *Remote Sensing in Archaeology: An Explicitly North American Perspective*, edited by Jay Johnson, 269-303. Tuscaloosa: University of Alabama Press, 2006.

Hausman, J. "Specification Tests in Econometrics." *Econometrica* 46 (1978): 1251-1271.

Hausman, J., and W. Taylor. "Panel Data and Unobservable Individual Effects." *Econometrica* 49 (1981): 1377-1398.

Headwaters Economics. *Transmission Lines and Property Value Impacts.* Prepared for the MSTI Review Project, Bozeman: Headwaters Economics, 2012.

Heal, G. "Reflections-Defining and Measuring Sustainability." *Review of Environmental Economics and Policy* 28 (2012): 1-21.

Hines, P., J. Apt, and S. Talukdar. "Large Blackouts in North America: Historical Trends and Policy Implications." *Energy Policy* 37 (2009): 5249-5259.

Hitz, S., and J. Smith. "Estimating Global Impacts from Climate Change." *Global Environmental Change* Part A 14, no. 3 (2004): 201-218.

Hoen, B., R. Wiser, P. Cappers, M. Thayer, and G. Sethi. *The Impact of Wind Power Projects on Residential Property Values in the United States: A Multi-Site Hedonic Analysis.* LBNL-2829E, Berkeley: Lawrence Berkeley National Laboratory, 2009.

Horowitz, J., and K. McConnell. "A Review of WTA/WTP Studies." *Journal of Environmental Economics and Management* 44, no. 3 (2002): 426-447.

Howard, R. "Decision Analysis: Practice and Promise." *Management Science* 34, no. 6 (1988): 679-695.

Huntington, H., J. Weyant, and J. Sweeney. "Modeling for Insights Not Numbers: The Experiences of the Energy Modeling Forum." *Omega* 10, no. 5 (1982): 449-462.

IEEE. *IEEE 1366-2012: IEEE Guide for Electric Power Distribution Reliability Indices.* Guides and Standards, IEEE Power and Energy Society, 2012.

IEEE. *IEEE Benchmark Year 2013: Results for 2012 Data.* 2013.

IEEE. *IEEE Std 1366-2003: Guide for Electric Power Distribution Reliability Indices.* Guides and Standards, IEEE Power Engineering Society, 2004.

Intergovernmental Panel on Climate Change. *Fifth Assessment Report Summary for Policymakers: Impacts, Adaptation, and Vulnerability.* Intergovernmental Panel on Climate Change, 2014.

Interstate Power and Light. *2012 Annual Reliability Report.* Reliability Report (April), Interstate Power and Light, 2013.

Jersey Central Power and Light. *2012 Annual System Report.* System Report (May), Jersey Central Power and Light, 2013.

Jones, N., and L. Pejchar. "Comparing the Ecological Impacts of Wind and Oil & Gas Development: A Landscape Scale Assessment." *PLOS One* 8, no. 11 (2013).

Kavulla, T. *Email correspondence with author.* June 24, 2015.

Kennedy, P. *A Guide to Econometrics.* Vol. Fifth Edition. Cambridge: MIT Press, 2003.

Kolstad, C., and R. Guzman. "Information and the Divergence between Willingness to Accept and Willingness to Pay." *Journal of Environmental Economics and Management* 38, no. 1 (1999): 66-80.

Koplin, Clay, interview by Peter Larsen. *CEO Cordova Electric Cooperative* (August 12, 2015b).

Koplin, Clay, interview by Peter Larsen. *CEO Cordova Electric Cooperative* (August 24, 2015c).

Koplin, Clay, interview by Peter Larsen. *CEO Cordova Electric Cooperative* (October 14, 2015d).

Koplin, Clay, interview by Peter Larsen. *CEO Cordova Electric Cooperative* Cordova, AK, (May 28, 2015a).

Krohm, G. *A Survey of Disruption and Consumer Costs Resulting from a Major Residential Power Outage.* Technical Memo for U.S. Department of Energy, Washington D.C.: Argonne National Laboratory, 1978.

LaCommare, K., and J. Eto. "Cost of Power Interruptions to Electricity Consumers in the United States." *Energy* 31 (2005).

LaCommare, K.H. *Collection and Documentation of Utility-specific Reliability Metrics and Other Sources of Information.* Berkeley, 2013.

LaCommare, K.H., and J.H. Eto. "Cost of Power Interruptions to Electricity Consumers in the United States." *Energy* 31 (2006): 1845-1855.

Larsen, P. "Workshop Exercise to Estimate the Cost of Residential, Commercial, and Industry Power Outages." Power Grid Resilience Conference: San Diego, September 1, 2015.

—. "Workshop Exercise to Estimate the Cost of Residential, Commercial, and Industry Power Outages." Power Grid Resilience Conference: San Francisco, September 8, 2014.

Larsen, P., et al. "Estimating Future Costs for Alaska Public Infrastructure at Risk from Climate Change." *Global Environmental Change* 18 (2008): 442-457.

Larsen, P., K. Hamachi-LaCommare, J. Eto, and J. Sweeney. *Assessing Changes in the Reliability of the U.S. Electric Power System.* LBNL-188741, Berkeley: Lawrence Berkeley National Laboratory, 2015.

Lawrence Berkeley National Laboratory/Nexant. *About the Calculator.* 2015. http://ICECalculator.com (accessed September 22, 2015).

Lawton, L., M. Sullivan, K. Van Liere, A. Katz, and J. Eto. *A Framework and Review of Customer Outage Costs: Integration and Analysis of Electric Utility Outage Cost Surveys.* LBNL-54365, Berkeley: Lawrence Berkeley National Laboratory, 2003.

Leahy, E., and R. Tol. "An Estimate of the Value of Lost Load for Ireland." *Energy Policy* 39 (2011): 1514-1520.

Lehtonen, M., and B. Lemstrom. "Comparison of the Methods for Assessing Customers' Outage Costs." *Proceedings of the International Conference on Energy Management and Power Delivery.* IEEE, 1995.

Lincoln Institute. *50-State Property Tax Comparison Study.* Prepared for the Minnesota Taxpayers Association, St. Paul: Lincoln Institute, 2011.

Linstone, H., and M. Turoff. *The Delphi method: Techniques and Applications.* Edited by H. Linstone and M. Turoff. London: Addison-Wesley, 1975.

London Economics. "The Value of Lost Load for Electricity in Great Britain." Final Report for OFGEM and DECC, London, 2013.

Loomis, J., P. Kent, L. Strange, K. Fausch, and A. Kovich. "Measuring the Total Economic Value of Restoring Ecosystem Services in an Impaired River Basin: Results from a Contingent Valuation Survey." *Ecological Economics* 33 (2000).

Madison Gas and Electric. *2012 Annual Reliability Report.* Annual Reliability Report (April), Madison: Madison Gas and Electric, 2013.

Manville, A. *Bird Strikes and Electrocutions at Power Lines, Communication Towers, and Wind Turbines: State of the Art and State of the Science – Next Steps Toward Mitigation.* Technical Report PSW-GTR-191, U.S. Department of Agriculture-Forest Service, 2005.

McIntosh, C., and W. Schlenker. *Identifying Non-linearities in Fixed Effects Models.* Working Paper, San Diego: University of California-San Diego, 2006.

Melillo, J., T. Richmond, G. Yohe (Eds.). *Highlights of Climate Change Impacts in the United States: The Third National Climate Assessment* . Washington D.C.: U.S. Global Change Research Program, 2014.

Most, W., and S. Weissman. *Trees and Power Lines: Minimizing Conflicts between Electric Power Infrastructure and the Urban Forest.* Report, Berkeley: University of California Center for Law, Energy, and the Environment, 2012.

Munasinghe, M., and A. Sanghvi. "Reliability of Electricity Supply, Outage Costs, and Value." *The Energy Journal* 9 (1988).

Munasinghe, M., and M. Gellerson. "Economic Criteria for Optimizing Power System Reliability Levels." *The Bell Journal of Economics* 10, no. 1 (1979): 353-365.

National Climatic Data Center/ABB Ventyx. *U.S. Department of Commerce/NOAA: U.S. Climate Normals; Area-Weighted State, Regional, and National Temperature.* Processed by ABB Ventyx. December 2013.

National Climatic Data Center/ABB Ventyx. *U.S. Department of Commerce/NOAA: U.S. Precipitation and Windspeed.* Processed by ABB Ventyx. January 2014.

National Grid-UK. *UK Electricity Network: Underground Cables.* January 15, 2016. http://www2.nationalgrid.com/uk/services/land-and-development/planning-authority/electricity-network-underground-cables/.

National Lightning Detection Network/LBNL. *Historic Data Set of Lightning Strike Location for Each Strike.* Processed by Lawrence Berkeley National Laboratory. 2013.

National Oceanic and Atmospheric Administration. *National Weather Service Assessment: Hurricane/Post-Tropical Cyclone Sandy.* Technical Assessment, National Weather Service, 2013.

National Research Council. *Models in Environmental Regulatory Decision Making.* Washington, D.C.: The National Academies Press, 2007.

Navrud, S., R. Ready, K. Magnussen, and O. Bergland. "Valuing the Social Benefits of Avoiding Landscape Degradation from Overhead Power Transmission Lines: Do Underground Cables Pass the Benefit-Cost Test?" *Landscape Research* 33, no. 3 (2008): 281-296.

New York Department of Public Service. *2012 Electric Reliability Performance Report.* Performance Report (June), Albany: NYDPS Office of Electric, Gas, and Water, 2013.

Newman, J. *The World of Mathematics.* Vol. Two. New York City: Simon and Shuster, 1956.

Nguyen, T., K. Chang, and S. Hui. "Word Cloud Model for Text Categorization." *Proceedings from the 2011 IEEE 11th International Conference on Data Mining.* Vaoncouver: IEEE, 2011. 487-496.

Nooij, M. "Social Cost-benefit Analysis of Electricity Interconnector Investment: A Critical Appraisal." *Energy Policy* 39 (2011).

Northwestern Energy. "Response to Montana Public Service Commission Data Requests: 001-007." Vol. Docket D2011.1.7. Helena: Montana Public Service Commission, February 11, 2011.

NYC Office of Long-Term Planning and Sustainability. *Utilization of Underground and Overhead Power Lines in the City of New York.* New York City: Office of the Mayor, 2013.

Oxford English Dictionary. "ground truth, n." In *Oxford English Dictionary (Online).* Oxford: Oxford University Press, 2015.

Ozbafli, A., and G. Jenkins. "The Willingness to Pay by Households for Improved Reliability of Electricity Service." No 2015-02, Development Discussion Papers, JDI Executive Programs, 2015.

Pacific Gas and Electric. *Reliability Performance Incentive Mechanism Results for Performance Year 2007.* Advice Letter 3337-E, San Francisco: Pacific Gas and Electric, 2009.

Pasha, H., A. Ghaus, and S. Malik. "The Economic Cost of Power Outages in the Industrial Sector of Pakistan." *Energy Economics*, 1989: 301-318.

Portland General Electric. *2012 Annual Reliability Report.* Reliability Report (April), Portland: Portland General Electric, 2012.

Praktiknjo, A. "Stated Preferences Based Estimation of Power Interruption Costs in Private Households: An Example from Germany." *Energy* 76 (2014): 82-90.

Praktiknjo, A., A. Hahnel, and G. Erdmann. "Assessing Energy Supply Security: Outage Costs in Private Households." *Energy Policy* 39 (2011): 7825-7833.

Primen/EPRI. *The Cost of Power Disturbances to Industrial and Digital Economy Companies.* Technical Report-1006274, Palo Alto: EPRI, 2001.

PSE&G. *2012 Annual System Performance Report.* Report, PSEG Services Corporation, 2013.

Public Service Commission of Wisconsin. *Environmental Impacts of Transmission Lines.* Electric 10 (07/13), Madison: State of Wisconsin, 2013.

Public Utilities Fortnightly. "2013 Rate Case Study." *Public Utilities Fortnightly*, November 2013.

Reilly, T. "Sensitivity Analysis for Dependent Variables." *Decision Sciences* 31, no. 3 (2000): 551-572.

Rocky Mountain Power. *First Half 2011 Service Quality Review Report.* Report (November), Rocky Mountain Power, 2011.

Rohlfs, C., R. Sullivan, and T. Kniesner. "New Estimates of the Value of a Statistical Life Using Air Bag Regulations as a Quasi-Experiment." *Proceedings of the American Economic Association.* 2012.

Rose, A., G. Oladosu, and D. Salvino. *Economic Impacts of Electricity Outages in Los Angeles.* Vol. 47, in *Obtaining the Best from Regulation and Competition*, edited by M. Crew and M. Spiegel, 179-210. Springer-Verlag US, 2005.

Rose, A., J. Benavides, S. Chang, P. Szczesniak, and D. Lim. "The Regional Economic Impact of an Earthquake: Direct and Indirect Effects of Electricity Lifeline Disruptions." *Journal of Regional Science* 37, no. 3 (1997): 437-458.

Samuelson, P. "Tax Deductibility of Economic Depreciation to Insure Invariant Valuations." *Journal of Political Economy* 72, no. 4 (1964): 604-606.

Sanghvi, A. "Economic Costs of Electricity Supply Interruptions: U.S. and Foreign Experience." *Energy Economics*, 1982: 180-198.

Sanghvi, A., N. Balu, and M. Lauby. "Power System Reliability Planning Practices in North America." *IEEE Transactions on Power Systems* 6, no. 4 (1991).

Sanstad, A. *Regional Economic Modeling of Electricity Supply Disruptions: A Review.* LBNL Draft (Under Review), Lawrence Berkeley National Laboratory, July, 2015.

SAS Institute. *Documentation for One-way Fixed Effects Model within SAS PROC Panel Procedure.* 2015a. http://support.sas.com/documentation/cdl/en/etsug/63939/HTML/default/viewer.htm#etsug_panel_sect025.htm.

—. *Documentation for One-way Random Effects Model within SAS PROC PANEL Procedure.* 2014. http://support.sas.com/documentation/cdl/en/etsug/63348/HTML/default/viewer.htm#etsug_panel_sect031.htm .

—. *Documentation for SAS 9.3 Functions and CALL Routines: RAND Function.* 2015b. http://support.sas.com/documentation/cdl/en/lefunctionsref/63354/HTML/default/viewer.htm#p0fpeei0opypg8n1b06qe4r040lv.htm.

Satchwell, A., C. Goldman, P. Larsen, D. Gilligan, and T. Singer. *A Survey of the U.S. ESCO Industry: Market Growth and Development from 2008 to 2011.* LBNL-3479E, Berkeley: Lawrence Berkeley National Laboratory, 2010.

Sathaye, J., L. Dale, P. Larsen, G. Fitts, S. Lewis, K. Koy, and A. Lucena. "Estimating Impacts of Warming Temperatures on California's Electricity System." *Global Environmental Change* 23, no. 2 (2013): 499-511.

Schwarz, G. "Estimating the Dimension of a Model." *Annals of Statistics* 6, no. 2 (1978): 461-464.

Shaw, J., A. Jenkins, J. Smallie, and P. Ryan. "Modelling Power-line Collision Risk for the Blue Crane Anthropoides Paradiseus in South Africa." *IBIS: The International Journal of Avian Science* 152 (2010): 590-599.

Shipley, R., A. Patton, and J. Dension. "Power Reliability Cost Versus Worth." *Prepared for the IEEE Power System Engineering Society Winter Meeting: Paper T 72 143-1.* IEEE, 1972.

Sims, S., and P. Dent. "High-voltage Overhead Power Lines and Property Values: A Residential Study in the UK." *Urban Studies* 42, no. 4 (2005).

Sivakumar, M., P. Roy, K. Harmsen, and S. Saha. "Satellite Remote Sensing and GIS Applications in Agricultural Meteorology." *Proceedings of the World Meterological Organisation Training Workshop.* Dehra Dun: World Meterological Organization, 2004.

Southern California Edison. "2015 General Rate Case: Transmission and Distribution Volume 4-Infrastructure Replacement Programs." *U 338-E.* California Public Utilities Commission, 2013.

StackExchange. *How to Get Only Positive Values when Imputing Data.* July 2015. http://stats.stackexchange.com/questions/107679/how-to-get-only-positive-values-when-imputing-data .

Sullivan, M., B. Suddeth, T. Vardell, and A. Vojdani. "Interruption Costs, Customer Satisfaction and Expectations for Service Reliability." *IEEE Transactions on Power Systems* 11, no. 2 (1996).

Sullivan, M., J. Schellenberg, and M. Blundell. *Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States.* LBNL-6941E/Spreadsheet, Berkeley: Lawrence Berkeley National Laboratory, 2015.

Sullivan, M., M. Mecurio, J. Schellenberg, and J. Eto. "How to Estimate the Value of Service Reliability Improvements." *Proceedings from the 2010 IEEE Power and Energy Society General Meeting.* IEEE, 2010.

Sullivan, M., M. Mercurio, and J. Schellenberg. *Estimated Value of Service Reliability for Electric Utility Customers in the United States.* LBNL-2132E, Berkeley: Lawrence Berkeley National Laboratory, 2009.

Sullivan, M., T. Vardell, and M. Johnson. "Power Interruption Costs to Industrial and Commercial Consumers of Electricity." *IEEE Transactions on Industry Applications* 33, no. 6 (1997).

Sun, T., X. Wang, and X. Ma. "Relationship between the Economic Cost and the Reliability of the Electric Power Supply System in City: A Case in Shanghai of China." *Applied Energy* 86 (2009): 2262-2267.

Swaminathan, S., and R. Sen. *Review of Power Quality Applications of Energy Storage Systems.* Contractor Report SAND98-1513, Bethesda: Sandia National Laboratories, 1998.

Telson, M. "The Economics of Alternative Levels of Reliability for Electric Power Generation Systems." *The Bell Journal of Economics* 6, no. 2 (1975): 679-694.

The Nature Conservancy. *Conservation Buyer Program.* 2014. http://www.nature.org/about-us/private-lands-conservation/conservation-buyer/properties/index.htm .

Tishler, A. "Optimal Production with Uncertain Interruptions in the Supply of Electricity." *European Economic Review* 37 (1993): 1259-1274.

U.S. Bureau of Labor Statistics. "Census of Fatal Occupational Injuries and Survey of Occupational Injuries and Illnesses." April 2014a. http://www.bls.gov.

—. "Consumer Price Index by Expenditure Category." January 2014b. http://www.bls.gov/news.release/cpi.toc.htm (accessed 2014).

—. "Consumer Price Index Inflation Calculator." 2015. http://www.bls.gov/data/inflation_calculator.htm (accessed September 2015).

U.S. Census Bureau. *American Community Survey.* Washington D.C., November 4, 2015b.

U.S. Census Bureau. *Quickfacts about the Valdez/Cordova Census Area.* Washington D.C., November 4, 2015a.

U.S. Department of Agriculture Rural Utilities Service/ABB Ventyx. *Electricity consumption and customer information (Form 7).* Washington D.C.: ABB Ventyx, November 4, 2015.

U.S. Department of Energy. *DOE/EIA Today in Energy: Power Outages Often Spur Questions around Burying Power Lines.* July 25, 2012. http://www.eia.gov/todayinenergy/detail.cfm?id=7250.

U.S. Department of Energy. *Electric Emergency Incident and Disturbance Report: Annual Summaries (OE-417).* Washington, D.C., October 2015.

U.S. Department of Energy. *Form EIA-861 Data Files.* Washington D.C.: Energy Information Administration, 2013.

U.S. Department of Labor. *Safety Pays Program: Statistics on Direct and Indirect Costs of Accidents.* Washington D.C.: Occupational Safety and Health Administration, 2014.

U.S. Environmental Protection Agency. *Emissions & Generation Resource Integrated.* Washington D.C., 2011.

Wansbeek, T., and A. Kapteyn. "Estimation of the Error-Components Model with Incomplete Panels." *Journal of Econometrics* 41 (1989): 341-361.

Washington D.C. Power Line Undergrounding Task Force. *Findings and Recommendations Report.* Washington D.C.: Office of City Administrator, 2014.

Weatherbase. *Monthly—All Weather Averages for Cordova, Alaska.* 2015. http://www.weatherbase.com/ .

Whitman, Requardt, and Associates. *Handy-Whitman Index: Regional Cost Indices for Transmission and Distribution Systems.* Baltimore, December 2013.

Wittmann, M., H. Breitkreuz, M. Schroedter-Homscheidt, and M. Eck. "Case Studies on the Use of Solar Irradiance Forecast for Optimized Operation Strategies of

Solar Thermal Power Plants." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 1, no. 1 (2008).

Wooldridge, J. *Econometric Analysis of Cross Section and Panel Data.* Cambridge: MIT Press, 2002.

Yanikoglu, B., and L. Vincent. "Ground-truthing and Benchmarking Document Page Segmentation." *Proceedings from the Third International Conference on Document Analysis and Recognition.* Montreal, 1995.

Zhao, J., et al. "Occupant Behavior and Schedule Prediction Based on Office Appliance Energy Consumption Data Mining." *Proceedings of the 2013 International Conference on Cleantech for Smart Cities and Buildings.* Lausanne, 2013.

Zillow. *Median Value of Alaska Residential Housing.* 2015. http://www.zillow.com/ak/home-values/.

—. *Median Value of Texas Residential Housing.* 2014. http://www.zillow.com/tx/home-values/.