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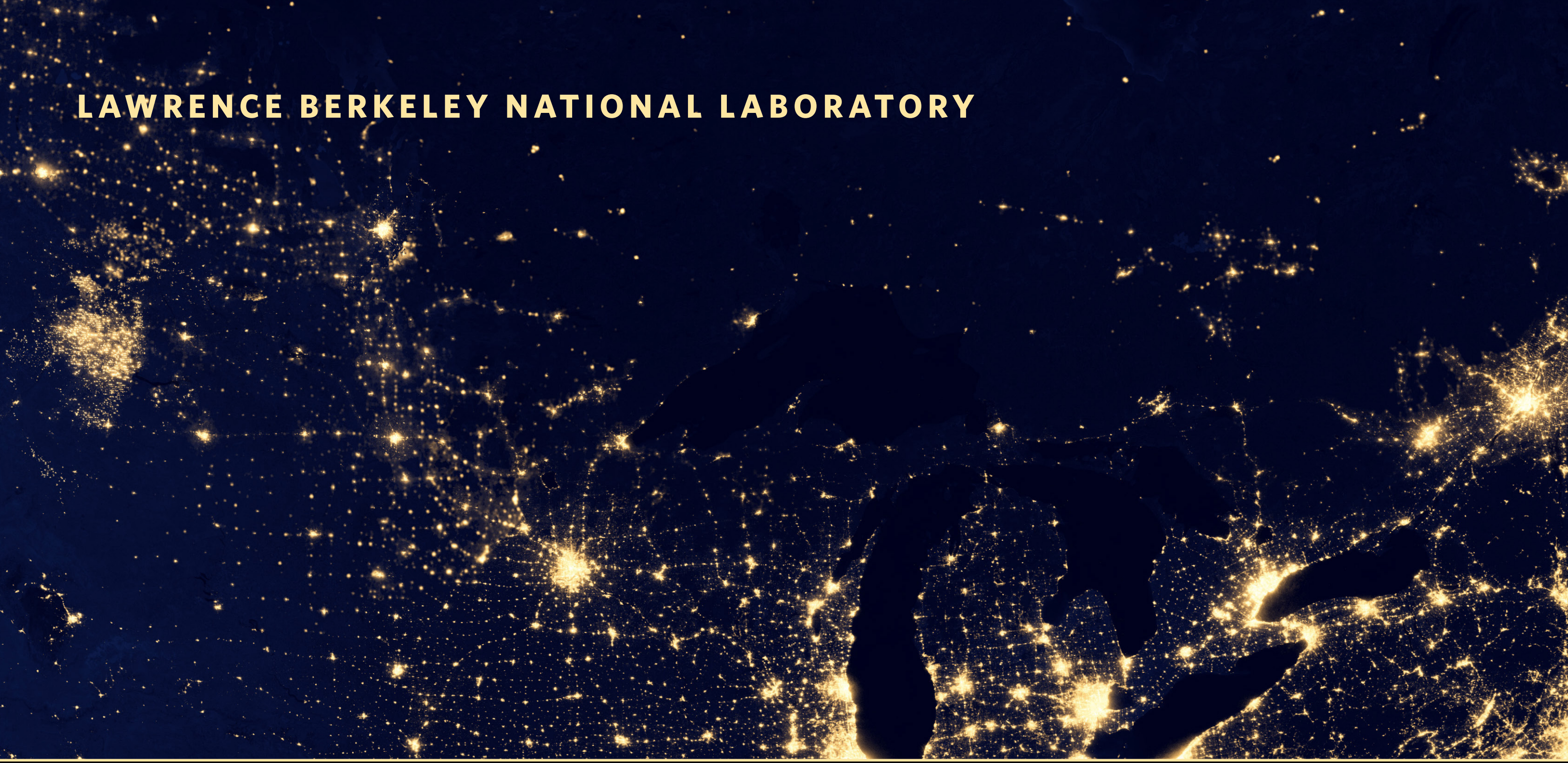

Frontiers in the Economics of Widespread, Long-Duration Power Interruptions

Proceedings from an Expert Workshop

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Energy Analysis and Environmental Impacts Division
Lawrence Berkeley National Laboratory

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Acronyms and Abbreviations

BCA	Benefit-Cost Analysis
BCAR	Benefit-Cost Analysis Reengineering
BCRs	Benefit-Cost Ratios
BI	Business Interruption
BLS	Bureau of Labor Statistics
C&I	Commercial and Industrial
CA DOF	State of California Department of Finance
CAIDI	Customer Average Interruption Duration Index
CAISO	California Independent System Operator
CBA	Cost-Benefit Analysis
CGE	Computable General Equilibrium
Con Edison	Consolidated Edison
DCE	Discrete-choice Experiment
DG	Distributed Generation
DHS	Department of Homeland Security
DOE	Department of Energy
EMS	Emergency Medical Service
EPRI	Electric Power Research Institute
ERCOT	Electric Reliability Council of Texas
FEMA	Federal Emergency Management Agency
FERC	Federal Energy Regulatory Commission
FPL	Florida Power and Light
GDP	Gross Domestic Product
GE	General Equilibrium
ICE	Interruption Cost Estimator tool
I/C programs	Interruption and Curtailment programs
MSA	Metropolitan Statistical Area
MTurk	(Amazon) Mechanical Turk
NAICS	North American Industry Classification System
NERC	North American Electric Reliability Corporation
NIPP	National Infrastructure Protection Plan
NOAA	National Oceanic and Atmospheric Administration
NRC	National Research Council
NYISO	New York Independent System Operator
NYSERDA	New York State Energy Research and Development
OE	Office of Electricity
PE	Partial Equilibrium
PSE&G	Public Service Electricity and Gas
PUC	Public Utility Commissions
RUT	Random-utility Theory
SAIDI	System Average Interruption Duration Index
vSAIFI	System Average Interruption Frequency Index
USEOP	United States Executive Office of the President
VoLL	Value of Lost Load
WTP	Willingness-to-Pay
WLD-outage	Widespread and Long-Duration Outage

List of Attendees

Name	Affiliation
Tim Allison	Argonne National Lab
Jay Apt	Carnegie Mellon University
Sunhee Baik	Carnegie Mellon University
Rakesh Batra	U.S. DOE
Riccardo Boero	Los Alamos National Lab
Rebecca Carroll	FEMA
Paul Centolella	Paul Centolella & Associates, LLC
Corrie Clark	Congressional Research Service
Myles Collins	Nexant, Inc.
Alexander Davis	Carnegie Mellon University
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Richard Jones	Hartford Steam Boiler/Verrisk
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Granger Morgan	Carnegie Mellon University
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Daniel Shawhan	Resources for the Future
Jody Springer	FEMA
Ian Sue Wing	Boston University
Vanessa Vargas	Sandia National Lab
Mark Weimar	Pacific Northwest National Lab
Cynthia Wilson	U.S. DOE

Foreword

The costs to electric utility customers from short-term, limited geographic-scale power disruptions have been studied for many years. However, there is increasing interest among regulators, policy-makers, and utilities in developing and implementing methods for analyzing interruptions that are of longer duration (days, weeks, or longer) and of a larger geographic scope (entire metropolitan areas or regions which may extend across multiple service territories). A 2017 report from the U.S. National Academies of Sciences, Engineering, and Medicine indicated the importance of "develop[ing] comprehensive studies to assess the value to customers of improved reliability and resilience…during large-area, long-duration blackouts."

As a contribution toward fulfilling this recommendation, the U.S. Department of Energy's (DOE) Office of Electricity's Transmission Permitting and Technical Assistance Division, in partnership with Lawrence Berkeley National Laboratory (LBNL), convened a workshop to identify research needs and discuss potential avenues for methodological advances in the economics of widespread, long-duration power interruptions.

The workshop was organized around six key themes in the economics of widespread, long-duration interruptions. LBNL conducted a competitive solicitation for white papers on these themes, and the authors selected were leading experts in academia, industry, and the non-profit sector. They were tasked with assessing the state of knowledge on particular topics, and identifying research needs and promising directions to expand it. These topics included definitions of resilience and reliability; regional economic modeling approaches; uncertainty quantification; data challenges and opportunities; contingent valuation survey techniques; and reduced-form analytical tools for assessing the impacts of power interruptions of this scale.

The authors of the six white papers presented their findings at the workshop, titled "Frontiers in the Economics of Widespread, Long-Duration Power Interruptions," and held in Washington, D.C., on March 6, 2018. Each paper was the subject of its own session, with the presentations followed by comments by assigned discussants, and in turn a general discussion of the papers, their findings, and the issues they raised. In addition to the authors, discussants, and LBNL and DOE staff, the workshop participants comprised government, industry, and academic thought leaders from across the country.

This proceedings document presents the full papers and discussants' comments. They are preceded below in this Executive Summary by summaries of the presentations, comments, and general discussions. This document is intended for a multi-stakeholder audience, including not only researchers, but also regulators, utility experts, and policy-makers. Our goal is that information created through this workshop will help form the basis of research activities to improve estimates of the economic costs of long-duration, widespread power interruptions.

Executive Summary

Topic 1: "Mitigation and Resilience Trade-offs In Electricity Outages"

Authors: *Jonathan Eyer and Adam Rose (University of Southern California)*
Discussant: *Benjamin Hobbs (Johns Hopkins University)*

Jonathan Eyer and Adam Rose of the University of Southern California developed a micro-economic framework for defining and analyzing resilience in response to widespread, long-duration power outages.[1] They distinguish between two types of resilience: (1) what they call "static" resilience, which has to do with efficient use of readily available resources in the short term (i.e., hours, days) after the outage occurs, such as rescheduling production once a disruption occurs; (2) what they call "dynamic" resilience, which refers to the efficient use of resources that enable an economy to recover from an outage over time, such as making investments to replace damaged equipment or structures during the ensuing weeks, months, and years. In this framework, the term "resilience" pertains to actions taken after an outage has begun, and the term "mitigation" refers to proactive or preventive actions to reduce vulnerability to outages. The overall structure of the Eyer and Rose approach is to analyze how a hypothetical decision-maker can make optimal trade-offs between investments in resilience and mitigation. The resilience metric is the ratio of avoided outage-induced loss of economic output to a potential (or counterfactual) total economic output in a baseline condition. Their approach deals with disruption impacts on the private commercial and industrial sectors of an economy—what they refer to as "business interruption" costs—as opposed to utilities and the physical grid itself (and residential customers and governmental and public entities). They use a simple mathematical example to illustrate and quantify their approach.

Benjamin Hobbs of Johns Hopkins University discussed several innovative elements of the Eyer-Rose framework and analysis: (1) the clarification of the substitutability between preventive (mitigation) and adaptive (resilience-increasing) actions, (2) the categorization of alternative means of improving resilience (static versus dynamic), and (3) the parsimonious mathematical model used to apply the abstract framework. Hobbs also pointed out certain limitations of the Cobb-Douglas model, and suggested several avenues for extending the Eyer-Rose framework, including considering complementarities between mitigation and resilience actions (since the Eyer-Rose model treats them as substitutes), and incorporating multiple decision-makers to more concretely represent the various parties that are involved in making mitigation—resilience decisions in practice.

The general discussion focused both on specific aspects of the Eyer-Rose framework and model and on issues associated with understanding and analyzing widespread, long-term outages that it raised. Several discussants observed that there are important outage impact categories not included in the

[1] The terms "outage", "interruption", "blackout", and "disruption" are used interchangeably throughout this document consistent with the author's manuscripts and discussant's written comments. It has been noted by researchers and practitioners that there can be a distinction between these terms (e.g., outage represents infrastructure that is not functioning at full capacity to deliver power; interruption refers to an electricity service disruption to a customer).

Eyer-Rose model, including the loss of human life, the migration of affected populations and firms, and other longer-term effects (points that Rose readily acknowledged). In the same vein, one participant emphasized that future widespread, long-duration outages may exceed the scale and scope of those experienced previously, and that there may be a need for fundamentally different analytical methods to address them. Several methodological issues were also discussed, including the aggregate data and statistical method that Eyer and Rose used to estimate business losses, and the relative merits of survey methods for this purpose, and the details of the Cobb-Douglas model.

Topic 2: "Estimating Residential Customers' Costs of Large, Long-Duration Blackouts"

Authors: *Sunhee Baik, Selin Sirinterlikci, Jun Woo Park, Alexander Davis, and M. Granger Morgan (Carnegie Mellon University)*
Discussant: *Bernard Neenan (Energy Resource Economics)*

Sunhee Baik, Granger Morgan, and Alexander Davis of Carnegie-Mellon University (CMU) presented results of a previously completed survey of residential electricity customers' willingness-to-pay (WTP) to receive limited service during a 24-hour, summer-day blackout. The study was designed to address the lack of research on household WTP during a large, long-duration power blackout as opposed to traditional studies of shorter-term blackouts (i.e., less than 24 hours). The key methodological innovation in the survey was that it took account of limited knowledge and bounded rationality—customers were given information and guidance in order to develop an understanding of the outage scenario and of their own electricity usage and how it would be affected. Face-to-face interviews were conducted, and the CMU team developed a web-based survey tool to facilitate further research on residential resilience WTP.

Bernie Neenan of Energy Resource Economics, LLC, found the CMU approach to residential resilience valuation promising while pointing out several limitations and shortcomings. He suggested several avenues for improvements and extensions to address these concerns: (1) expanding the survey to include additional outage scenarios and electricity service attributes, (2) shortening the survey and making it more concise, and (3) collaborating with other researchers, as well as with utilities and regulators to share information and connect academic research to actual practice.

During the general discussion, a number of participants commented on the WTP concept, including its empirical validity and its suitability for use in surveys from the perspectives of utilities and regulators, as well as on the role of bounded rationality .[2] Concerns were raised regarding the plausibility of 20-ampere service as a rationing scheme during the restoration period following a blackout, given that utilities do not use that scheme (instead, rotating outages are more commonly used). It was also suggested that using existing utility data on households' intra-day usage patterns might be part of an alternative to the WTP survey approach, by facilitating direct empirical measurement of households'

[2] The term *bounded rationality* refers to consumers' and firms' limits in understanding and processing information required to make complex economic decisions.

actual choices and practices. There were also comments on the practicality of this specific survey instrument—including its length—and on the influence of the survey solicitation method (phone, mail, online) when eliciting responses. Other topics raised by participants included the justification for using 24 hours as a threshold for classifying outages, in terms of resilience as opposed to reliability (with 60 hours proposed as an alternative), and the possibility of expanding the research to study other types of service interruptions, including water or other utilities.

Topic 3: "Economic Consequence Analysis of Electric Power Infrastructure Disruptions: An Analytical General Equilibrium Approach"

Authors: *Ian Sue Wing (Boston University) and Adam Rose (University of Southern California)*
Discussant: *Tim Allison (Argonne National Laboratory)*

Ian Sue Wing of Boston University and Adam Rose of USC developed a simple applied general equilibrium model to estimate aggregate economic consequences of large-scale electric power infrastructure disruptions. The model is sufficiently simple that it can be solved analytically and can provide quantitative output. This modeling strategy is deliberate and addresses the fact that full-scale computable general equilibrium (CGE) models (in general and applied to electricity disruptions) are challenging to build, parameterize, and use, and are subject to the "black box" problem. That is, it can be difficult (or impossible) to fully understand their drivers and to interpret their numerical outputs. In addition, their approach is in part motivated by the fact that it is extremely difficult to integrate power system and economic models to study disruptions (among other topics). The Sue Wing-Rose model aims to provide credible first-order results in a tractable and transparent framework that, in contrast to full CGE models, can be subject to thorough and comprehensible sensitivity analysis. The researchers noted it would be applicable for disruption lengths lasting up to one month. The study included a quantitative analysis of a hypothetical widespread, long-duration power interruption caused by an earthquake in the San Francisco Bay area.

Tim Allison of Argonne National Laboratory discussed the study, noting that it was valuable work. He discussed the tension between the need for model detail in analyzing disruptions and the scarcity of data needed to support such detail. He also noted that, while sponsors increasingly demand CGE models for policy analysis, there are concerns about their validity and their costs. He views input-output (I/O) modeling as less expensive, easier to use in practice, and sufficient for at least first-approximation answers to many questions. Notwithstanding data issues, he suggested that increases in model detail on economic factors would be warranted for analyzing long-term disruptions.

Several themes were addressed during the general discussion. A number of participants expressed skepticism at what they considered the implausibly low magnitude of Sue Wing and Eyer's economic loss estimated in the earthquake scenario. Sue Wing indicated that the numerical results reflected the model's lack of sectoral disaggregation, and hence, the lack of interdependencies among them. This led in turn to a discussion of economic metrics. The estimate in question was a standard economic measure of "welfare loss," the "equivalent variation;" Rose pointed out the cost of the hypothetical disruption in terms of lost regional GDP was an order of magnitude greater when estimated using a full-scale CGE model (in another study). There was discussion of the relative merits of simple versus complex models; while there was skepticism about simpler models, one participant pointed out the potential “illusion of precision” problem associated with complex models—i.e., greater detail not necessarily leading to greater validity. Several participants also raised the question of whether, in view of the specialized knowledge, training, and experience required, these types of models could be used to create practical, usable tools for utilities and regulators.

Topic 4: “Using Stated Preferences to Estimate the Value of Avoiding Power Outages: A Commentary with Input from Six Continents”

Author: *Daniel Shawhan (Resources for the Future and Cornell University)*
Discussant: *Riccardo Boero (Los Alamos National Laboratory)*

Daniel Shawhan of Resources for the Future and Cornell University presented extensive comments on how to use stated-preference methods to estimate the value of avoiding electric power outages, with a particular focus on the methods that prevail in the United States, as described in a draft outage valuation guidebook for utilities. This guidebook is currently being developed by Nexant, Inc. and Lawrence Berkeley National Laboratory. Some of the comments are from 16 stated preference valuation researchers and practitioners on six continents. The comments address the elicitation format, the scenario posed in the question, the use of a battery backup scenario in particular, the effects of auxiliary questions, the value of describing the geographic scope of the outage, testing for and reducing response bias, the possibility that studies may be designed to produce high or low values, special considerations for valuation of long-term outages, and several other best practices, suggestions, and concerns.

Discussant Riccardo Boero of Los Alamos National Laboratory was critical of the underlying WTP concepts within the guidebook that was reviewed in Shawhan’s paper. His main points were that the underlying validity of the willingness-to-pay concept was open to question, that considerations of risk and uncertainty should incorporated into the survey, (including bounded rationality factors such as framing and loss aversion—from prospect theory),[3] and that, contrary to standard theory, the willingness-to-pay (i.e., the cost of the lost electrical service) and the customers’ avoided (loss of service) cost are not equivalent.

The general discussion addressed some of the discussant’s comments, as well as Shawhan’s expert elicitation on the LBNL/Nexant guidebook. It was suggested that customers should not be asked isolated, hypothetical questions about a single power outage, and that, instead, more information and

[3] *Prospect theory* is a theory of decision-making based on principles and findings of cognitive psychology, developed as a partial alternative to the classical economic model of consumer choice. *Framing* refers to the influence of individuals’ understanding of a problem and its context on their choice strategies, and *loss aversion* refers to their gauging gains and losses of a potential decision in terms of their current situation, rather than—as in economics’—in terms of some objective ranking.

context must be provided in order to elicit meaningful responses. For example, it was pointed out that omitting information about how widespread the outages are (a handful of residences in a neighborhood versus an entire metropolitan region) in the surveys could be problematic. There was discussion of the pragmatic value and use of WTP survey studies in practice from the standpoints of utilities and regulators. Several participants stated that there is skepticism among some regulators about the validity or usefulness of such studies. By contrast, several other participants provided examples of WTP and related surveys that are being used by utilities—and it was noted that there are regulatory dockets and proceedings where these approaches are being used and accepted by regulators. Other topics included additional hypothetical back-up electricity supply options that the survey might present to respondents, and the differences between nationally conducted surveys versus surveys sponsored by individual (or small collections of) utilities.

Topic 5: "Evaluating Methods of Estimating the Cost of Long-Duration Power Outages"

Author: *Jeffrey Roark (Electric Power Research Institute)*
Discussant: *Mark Weimar (Pacific Northwest National Laboratory)*

Jeffrey Roark of the Electric Power Research Institute (EPRI) described recent work on valuing resilience, which assessed and compared different economic methods and techniques for resilience valuation: customer damage functions (CDFs), discrete choice experiments (DCEs), macroeconomic modeling (I/O and CGE), and analysis of information collected by insurance companies. Each approach was found to have both advantages and limitations. CDFs might be limited by customers' inexperience with widespread, long-duration power outages (as opposed to more familiar short-term outages). DCEs may be preferable because of their well-established theoretical basis and capacity for taking account of various aspects of longer-duration and scale outages. I/O modeling is a useful pragmatic methodology, although it does not completely address all the dimensions of resilience. In particular, it does not capture the ability of households and firms to adapt to power outages and thereby mitigate their impacts. CGE models in principle provide for comprehensive and consistent economy-wide analysis of widespread, long-duration power outages, including adaptation. In addition and notably, they are also subject to stringent data requirements as well as uncertainties in the values of key parameters. Insurance-based data analysis, while possibly useful as an adjunct to other methods, was judged to be not well-suited for resilience analysis, because—in addition to being proprietary and thus difficult to obtain—such analyses are likely not fully representative of all segments of customer populations and cover only a subset of possible damages and costs.

Mark Weimar of the Pacific Northwest National Laboratory discussed perspectives on the various methods. He argued that, when adequate data are available, CDFs are likely to be more accurate than DCEs, with the latter being a back-up option in the absence of WTP survey information. He agreed that CGE modeling is in general the preferred macroeconomic method because of its capacity to represent customers' adaptive behavior (i.e., resilience, mitigation) in the face of power outages, while also acknowledging the usefulness of I/O for practical reasons, particularly ease-of-use, relatively low expense (compared to CGEs), and validity for estimating first-order direct impacts. Weimar concurred with EPRI's conclusion on the limitations of using insurance data for resilience analysis.

Macroeconomic modeling was one focus of the general discussion, both pertaining to Roark and Weimar's remarks and the earlier Sue Wing-Rose presentation and discussion. One topic was the relative merits of CGE and I/O models, particularly given the trade-offs between pragmatic considerations such as usability and cost, where I/O models have an advantage, and completeness of the representations of economies and the capacity to analyze resilience mechanisms, a strength of the CGEs. The value of relatively simpler models was also reiterated. In addition, the importance of CGE sensitivity analysis was mentioned; it was pointed out that the single most important assumption in determining CGE results was capital mobility among sectors. Institutional considerations of macroeconomic resilience analysis were also raised, including stakeholders' degrees of acceptance of the different models. In this context, several participants remarked on special aspects of resilience-focused decision-making in contrast to traditional reliability-only decision-making, including the value of information to different parties and the fact that some resilience choices and decisions are of a societal nature and not simply applicable to energy/utility systems.

Topic 6: "Data Landscape: Challenges and Opportunities"

Authors: *Josh Schellenberg, Myles Collins, Michael Sullivan, Shannon Hees, and Stephanie Bieler (Nexant)*
Discussant: *Vanessa Vargas (Sandia National Laboratories)*

Broader data challenges in the economic analysis of widespread, long-duration power interruptions were assessed by a Nexant, Inc. team led by Joshua Schellenberg and Myles Collins. Their study focused on non-residential—i.e., commercial and industrial (C&I) sectors—because residential losses from such interruptions will generally be a small fraction of overall losses, particularly when accounting for indirect impacts among businesses. They assessed data issues specific to making resilience investments to minimize risks of widespread, long-duration power interruptions to critical infrastructure facilities, using the Federal Energy Management Administration's benefit-cost analysis method as an example.

Nexant discussed how and why survey methods can be used to estimate C&I customers' WTP to avoid interruption impacts, while also pointing out that they are not designed to assess indirect costs, and also noting that there are several sources of survey error. Data issues with regional economic modeling of widespread, long-duration power interruptions were also reviewed, emphasizing the absence of sufficiently granular data required to support the modeling, as well as the inconsistencies among (and limited availability of) information on indirect costs in relation to interruption magnitude and frequency. Nexant also noted data limitations for forecasting interruption scenarios and the probabilities of outcomes both with and without resilience investments, in order to gauge their value. Nexant's recommendations were to (1) improve critical facilities widespread, long-duration power interruptions impact evaluation; (2) conduct nationwide C&I WTP surveys with representative samples; (3) explore the use of regional economic modeling of interruptions in a regulatory context to improve their accuracy and help utilities and policy-makers understand ways of mitigating interruption impacts; (4) examine the use of survey data as a complement to modeling; and (5) increase sharing among utilities of data on extreme weather impacts and the performance of resilience investments.

Discussant Vanessa Vargas of Sandia National Laboratories (SNL) generally endorsed Nexant's findings while pointing out practical challenges to implementing its recommendations. She supported further research on valuing avoided impacts as worthwhile and feasible. She promoted modeling work done by SNL and survey research conducted by Argonne National Laboratory as examples of combining survey data with regional economic models to analyze widespread, long-duration power interruptions. At the same time, Vargas noted that increased effort should be devoted to further developing the economic models for resilience analysis, and also suggested that the models should be capable of analyzing multiple impact categories, not just electricity-related impacts. She suggested that both technical (e.g., sampling-related) issues and resource constraints might hinder the development of national-level surveys. Vargas also suggested that, while clearly desirable, information-sharing among utilities was likely to be hindered by coordination difficulties, including a potential reluctance to release proprietary information.

In the general discussion, several of Nexant's findings were endorsed, such as the importance of better information on critical facilities. The value and validity of surveys for resilience analysis was discussed, and the relative usefulness of survey information versus economic modeling was debated. Also discussed was the credibility of using and communicating different economic cost metrics to non-specialist stakeholders. Other topics discussed included the merits of conducting a national survey (e.g., that would include some questions related to outage costs that individual utilities would be adverse to asking their customers, such as those associated with long-duration, widespread power interruptions), what different (or additional) questions might be included in a national-level survey to inform regional economic models, and how national survey data might be directly incorporated into CGE modeling of disruptions.

I. Mitigation and Resilience Trade-offs In Electricity Outages

Authors: Jonathan Eyer and Adam Rose
Affiliations: Center for Risk and Economic Analysis of Terrorism Events (CREATE) and Sol Price School of Public Policy, University of Southern California

1. Introduction

The issue of electricity reliability is a serious one because this utility service is so critical to human health and well-being. Moreover, the trend of electricity dependence and outages are both on the rise (Eto et al., 2012). Reliability has been widely studied, and technologies and market innovations have been developed and implemented to improve it. Nearly all of these solutions, however, focus on the supply-side by reducing the frequency and magnitude of the initial outage. For example, by identifying and addressing weaknesses in critical nodes of electricity systems, reliability of electricity grids during a cascading failure can be greatly enhanced (Chang and Wu, 2011). Also, electricity systems can be designed to recover more quickly from unplanned outages.

What is often overlooked is the behavioral response on the customer side to partial or complete electricity outages. These basically involve tactics to cope with electricity shortages and have been brought under the heading of resilience (Rose et al., 2007; Greenberg et al., 2007). From an economic perspective, resilience pertains to actions taken to use resources as efficiently as possible to maintain production in the face of a disruptions of critical inputs (Rose, 2004; 2017). It is actually a process where resilience capacity can be built-up in advance to be implemented when needed (inherent resilience), as well as various improvisations once the disruption has begun (adaptive resilience). [1] Prime tactics in the electricity arena to minimize business interruption (BI) are: conservation, backup generators, distributed generation in general, use of alternative energy sources, relocation, and production rescheduling. Formal modeling at the microeconomic level has been done in the context of economic production theory to analyze the optimal mix of tactics or create an overall strategy (Rose and Liao, 2005; Dormady et al., 2017a). Analyses have been undertaken to examine the effectiveness of these tactics at the level of the individual business and the broader supply-chain implications in

[1] Dozens of definitions of *resilience* have been offered along several dimensions. One important distinction is between definitions that consider resilience to be any action that reduces risk (e.g., Bruneau et al., 2003; USEOP, 2013), including those taken before, during and after an unforeseen event, such as a power outage, and those that use the term narrowly to include only actions taken after the event has commenced, acknowledging, however, that resilience is a process. The latter definition does not ignore pre-event actions, but prefers to refer to them as *mitigation*, and emphasizes that the intent of these actions is to make a system more resistant, robust or reliable (in standard engineering terminology). Our definition simply chooses to focus on the basic etymological root of resilience, "to rebound", and thus emphasizes system or business continuity in the static sense and recovery in the dynamic one (see also Greenberg et al., 2007). The distinction between reliability (as promoted by mitigation) and resilience is poignantly stated in a recent NRC report: "Resilience is not the same as reliability. While minimizing the likelihood of large-area, long-duration outages is important, a resilient system is one that acknowledges that such outages can occur, prepares to deal with them, minimizes their impact when they occur, is able to restore service quickly, and draws lessons from the experience to improve performance in the future" (NRC, 2017, p. 10)

relation to the Northridge Earthquake power outages, the post-regulation electricity shortages of the early 2000's, and simulated disasters such as a terrorist attack (Rose and Lim, 2002; Rose et al., 2005; Rose et al., 2007a). Many resilience tactics have already been implemented, and insurance companies have been known to reimburse policy-holders for the purchase of back-up generators (Eto et al., 2001). More recently, progress has been made in actually measuring the cost, in addition to the effectiveness of various resilience tactics (Dormady et al., 2017b).

A critical gap in our understanding of how to cope with electricity disruptions is the optimal mix of pre-event activities (generally categorized as mitigation) and post-event activities (resilience). As electricity reliability is usually couched in terms of mitigation, we can also refer to this as the "reliability-resilience trade-off." [2] The purpose of this White Paper is to develop an analytical model to examine these trade-offs under various conditions relating to characteristics of individual mitigation and resilience tactics, matters of timing, and the probability of outages. More specifically, we develop and calibrate a theoretical model in which expected BI from electricity outages can be decreased using ex-ante utility mitigation investments in electricity reliability that reduce the likelihood and/or magnitude of an outage, ex-ante customer investments in inherent electricity resilience that reduce the need for electricity in the event of an outage, ex-post customer adaptive resilience that reduces the BI from losing electricity, and ex-post dynamic resilience that reduces the duration of the outage, and hence also reduces BI. In order to calibrate the model, we identify a representative set of actions from each of these broad categories (strategies) and use the benefit-cost ratio of each strategy to reflect the total expected BI loss reduction from an electricity outage as a function of spending on each. By minimizing the sum of total expected losses and expenditures on risk reduction strategies, we calculate the optimal mix of risk reduction strategies for a given level of total expenditure or a target level of risk reduction.

2. Overview of Strategies

We specify a set of risk reduction strategies and the pathway through which they reduce total losses from an outage in Table 1. We define this set to include two types of mitigation strategies— those intended to reduce the magnitude of outages and those meant to lower the frequency of outages – and three types of resilience –inherent static, adaptive static, and dynamic. In each case, there are a range of different attributes of the risk reduction strategy. We note whether a particular strategy reduces the duration of outages, the frequency of outages, the duration of the recovery of business activity, or the speed[3] of recovery of business activity.

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[2] Keogh and Cody (2013; p. 1) have suggested that the term "resilience" might be considered as covering both "robustness and recovery characteristics of utility infrastructure and operations, both of which avoid or minimize interruptions of service during an extraordinary and hazardous event." As such, it is intended to be broader than the term "reliability", in that they do not consider reliability to be sufficiently meaningful to handle large-scale disruptions. However, we contend that this juxtaposition is confusing, and prefer to refer to reliability as a goal of pre-event mitigation and resilience as activities to reduce losses once the event has commenced.

[3] "Speed" here is short-hand for the entire time-path of the recovery. This has two important dimensions: the shape of the entire time-path and its duration. Jump-starting the recovery and shortening its duration can both reduce BI losses, though the former is likely to have the greater effect (see Xie et al., 2018).

Table 1. Strategies for Reducing BI

	Mitigation - Frequency	Mitigation – Magnitude	(Adaptive) Dynamic Resilience	Adaptive Static Resilience	Inherent Static Resilience
Example	Hardened Transformer	Smart Meters	Dispatching Replacement Equipment Quickly	Production Re-Routed to Non-Affected Areas	Purchase & then Use Backup Generator
Entity	Utility	Utility	Utility	Customer	Customer
Affects Magnitude		X			
Affects Frequency	X				
Affects Duration of Recovery			X		
Affects Speed of Recovery			X	X	X
Public Good or Private Good	Public	Public	Public	Private	Private
Period when Expenditure Takes Place	Before Outage	Before Outage	After Outage Begins	After Outage Begins	Before Outage
Period when Implementation Takes Place	At Onset of Outage	During Outage	After Outage Begins	After Outage Begins	After Outage Begins
Time Periods in Analysis	At least 1	At least 1	At least 2	At least 1	At least 2

This paper presents a theoretical model in which planners select an optimal portfolio of mitigation and resilience in order to minimize expected electricity outage losses. We explore a range of models in which mitigation and resilience can reduce BI losses. In each case, we assume that mitigation and inherent static resilience require expenditures before it is possible to know whether or not an outage will occur within a given timeframe, while adaptive static resilience and dynamic resilience are undertaken ex-post. We will develop this framework in both one-period and multi-period frameworks, and employ a Monte Carlo simulation centered on the uncertainty in the efficacy of mitigation and resilience.

3. Baseline Theoretical Model: Tradeoff Between Mitigation (Reliability) and Resilience

3.1 Background

In our model, planners seek to minimize the sum of expected losses, mitigation expenditure, and resilience expenditure. Damages occur only if an outage takes place, which happens with probability P. Losses are a function of mitigation and resilience expenditures as well as an underlying parameter that reflects the inherent disaster risk. We assume that planners have decided on a targeted overall expenditure level for disaster loss reduction.[4, 5]

Mitigation tactics -- such as installing stronger transformers and replacing existing solar inverters with technologically-advanced smart inverters -- reduce the likelihood of a major outage, while advanced metering infrastructure can reduce the duration of an outage. Resilience tactics, such as shifting production to unaffected areas or substituting alternative production inputs, also reduce the magnitude of disaster damages. There are two key distinctions between mitigation and resilience that influence the optimal mixture of the two tactics. First, most inherent and all adaptive resilience only occurs, and resilience costs are typically only incurred, if an outage takes place. Mitigation, on the other hand, is paid for up-front and costs are incurred even if an outage does not strike.

The planner's general problem is to minimize:

$$\min_{m,r} PD(\gamma mr) + P\, p_r r + m p_m \;\; s.t.\, P\, p_r r + p_m m = c$$

We denote mitigation and resilience allocation quantities with m and r, respectively. p_r and p_m are the price of resilience and mitigation per unit, and the parameter γ is the underlying risk exposure.[6] c is the level of expenditure to be allocated towards risk reduction.

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[4] This problem could also be formulated based on minimizing expenditure given a targeted level of loss reduction. The resulting optimal levels of mitigation and resilience would be equivalent to the model that we present.

[5] There are several alternative ways to measure losses from electric power outages. One of them is the concept of "value of lost load" (VOLL), and another is System Average Interruption Duration Index (SAIDI) (see Keogh and Cody, 2013). Economists have measured it in several ways, such as expenditures on back-up generators (e.g., Matsukawa and Fujii, 1994; Beenstock et al., 1997). In this analysis, we use the more general concept of business interruption, typically measured in terms of a decrease in gross output or GDP. See Sanstad (2015) for a discussion of these and other metrics. A distinction is often made between "direct" and "indirect" losses. The former term is typically used to refer to losses in revenue of the electric utility itself or losses in output of its direct customers. The term "indirect" includes numerous considerations, such as increased crime, but is primarily used to refer to downstream supply-chain losses to customers of those directly affected by the outage, and are generally referred to as multiplier or general equilibrium effects (see again Sanstad, 2015).
Note that our modeling approach is sufficiently general to cover these various alternative definitions of losses.

[6] A larger γ parameter indicates greater disaster damages at all levels of mitigation and resilience.

Note that in the budget constraint the expenditure on resilience, p_r*r, is multiplied by the probability of an outage, P. This is because resilience expenditure will only take place when the outage occurs (with probability P). The budget constraint can therefore be conceptualized as holding only in expectation. When an outage takes place and resilience expenditures occur, spending will exceed c. When an outage does not take place and resilience expenditure does not occur, spending will be below c.

We define the loss function in a Cobb-Douglas specification, i.e. $D(\gamma, m, r\ ) = \gamma m^{\alpha} r^{\beta}$, where α and β are elasticity parameters reflecting the efficacy of the loss reduction strategies. An alternative formulation would be a linear production function, where mitigation and resilience are purely additive, and which implies the two are perfect substitutes. However, we have pursued a Cobb-Douglas (power function) formulation for two major reasons.

First, the linear production function is likely to result in corner solutions in an optimization problem (all one strategy or the other). Second, the linear production function implies a constant marginal product. This is inconsistent with the existence of diminishing returns that have been found to be prevalent in empirical analyses of both mitigation and resilience. For example, studies indicate a declining schedule of benefit-cost ratios (BCRs) for mitigation alternatives, as measure of efficacy (Rose et al., 2007). While empirical analyses of resilience are still in their infancy, preliminary indications are that BCRs vary across resilience tactics, such as conservation or substitution for critical inputs, use of inventories and excess capacity for business relocation. The constant marginal rate of technical substitution associated with the linear production function would require either constant marginal products or perfectly offsetting percentage changes in marginal products of the two inputs (risk reduction strategies) so that the ratio of the two remains constant.

There are several notable shortcomings of the Cobb-Douglas framework that should be considered when interpreting these results. Most notably, the cost shares for each risk reduction strategy are constant and entirely determined by the relative exponential parameters. This specification also precludes the possibility of corner solutions (i.e., using only either mitigation or resilience). While electricity-oriented mitigation expenditure may in fact be zero for consumers, it is unlikely that corner solutions will exist when viewed from the meso- or macro-level. Similarly, the Cobb-Douglas formulation suggests that if the expenditure target is equal to zero that damages will be infinite. Again, while particular customers may not allocate expenditure towards risk reduction, this is unlikely to be the case at an aggregated level.

3.2 Analytics of One-Period with Exogenous Probability of Damages

First, we consider the simplest case: a single period in which we analyze the trade-offs between reliability and resilience, where the probability of an outage is exogenous with respect to the mitigation to promote reliability and resilience to reduce business interruption. In essence, the model minimizes the allocation of expenditure across these two broad strategies. More specifically, this case examines the trade-off between mitigation that reduces the magnitude of the loss from the outage and adaptive resilience that reduces the ensuing BI. Adaptive resilience refers to customer actions that result from improvisation after the outage begins, with no pre-outage expenditure. Examples would include: conservation, re-routing production to branch plants that have electricity, making up lost production at a later date,[7] etc. This can be treated as a one-period model because of the anticipation of the amount of adaptive resilience, which itself takes place in only one period (in contrast to the 2-period nature of inherent resilience).

Given our Cobb-Douglas framework in which disaster damage is given by $D(\gamma, m, r\ ) = \gamma m^{\alpha} r^{\beta}$, where γ is the level of outage damages given current levels of mitigation and resilience (which we normalize such that each is equal to 1.0). For α and $\beta < 0$, an increase in m or r reduces net losses. Again, because we are considering changes relative to the current expenditure levels (i.e., m=1, r=1), the cost of mitigation and the cost of resilience, p_m and p_r, respectively, is equal to *current* expenditure on these tactics, and the expenditure constraint, c, is the expected amount that is to be spent on mitigation and resilience.

The planner's problem is given by:

$$\min_{m,r} P\ \gamma m^{\alpha} r^{\beta} + P\ p_r r + p_m m \qquad s.t. P\ p_r r + p_m m = c$$

Solving this cost-minimization problem yields the optimal level of mitigation:

$$m^* = \frac{c\alpha}{p_m(\beta + \alpha\ )}$$
$$r^* = \frac{c\beta}{P\ p_m(\beta + \alpha)}$$

Note that both the optimal level of mitigation, m*, and the optimal level of resilience, r*, are functions of each exponential parameter, α and β, as well as the budget constraint. Only resilience is dependent on the frequency with which a disaster occurs.

The invariance of each risk management alternative to the price of the other options is driven by the assumption that damages are determined according to a Cobb-Douglas function. This functional form assumes a constant elasticity of substitution (equal to unity). The functional form also calls for the share, but not the absolute level, of total expenditure for each input (strategy) being driven by the Cobb-Douglas parameters. The optimal level of expenditure on each risk management alternative is strongly affected by the benefit-cost ratios in relation to their marginal productivities, and the absolute levels of mitigation and resilience are determined by their costs. Similarly, the relationship between the probability of an outage and adaptive resilience is a result of the fixed expected expenditure on resilience. As the probability of an outage decreases, the amount of adaptive resilience rises in order to hold expected expenditure constant. Note, however, that this suggests lower overall losses from outages, in part, because adaptive resilience expenditures are less likely to be needed.

[7] This tactic would best be modeled with 2 periods following the onset of the outage.

By taking the derivative of m* and r* with respect to each of the parameters, one can show the effect of parameter changes on optimal levels of mitigation and resilience. The set of these partial derivatives are given below. The probability of a disaster P must fall between 0 and 1, and the parameters α and β must be less than zero if mitigation and resilience reduce losses:

$$\frac{\partial m^*}{\partial c} = \frac{\alpha}{p_m(\alpha + \beta)} > 0$$
$$\frac{\partial m^*}{\partial \alpha} = \frac{c\,\beta}{p_m(\alpha + \beta)^2} < 0$$
$$\frac{\partial m^*}{\partial \beta} = -\frac{c\alpha}{p_m(\alpha + \beta)^2} > 0$$
$$\frac{\partial r^*}{\partial c} = \frac{\alpha}{p_r P(\alpha + \beta)} > 0$$
$$\frac{\partial r^*}{\partial \alpha} = -\frac{c\,\beta}{p_r\, P(\alpha + \beta)^2} > 0$$
$$\frac{\partial r^*}{\partial \beta} = \frac{c\alpha}{p_r\, P(\alpha + \beta)^2} < 0$$

Both the optimal level of mitigation and the optimal level of resilience are increasing in the budget constraint, c. The optimal level of each tactic is decreasing in its own exponential parameter (e.g. the optimal level of mitigation is decreasing in α). This occurs because of the underlying structure of the damage function. Note, for example, that if α were to equal -1, the exogenous level of damages, γ would be multiplied by 1/m. If instead, α were to equal -0.5, γ would instead be multiplied by $\frac{1}{\sqrt{m}}$. Similarly, the optimal level of each tactic is increasing with the other tactic's exponential parameter (e.g. the optimal level of mitigation is increasing in β). As a given tactic becomes less effective at reducing damages, the alternative tactics become relatively more attractive by the assumption of substitutability between the two tactics.

As a numerical example, suppose that an entity would experience outage costs of $100 million if a disaster struck and there was no mitigation or resilience. Further suppose that an electricity service disruption occurs with probability P = 0.25, and that the entity is currently spending $10 million on mitigation and $5 million on resilience. The entity wishes to increase its risk reduction expenditure by 10% to $16.5 million total.

We can parameterize the values α and β based on beliefs about the marginal effectiveness of remaining mitigation and resilience strategies. Suppose, for example, that the next best remaining mitigation tactics (given the existing level of $10 million in mitigation) provides benefits in relation to costs of 4:1, and the best remaining resilience tactics provides benefits of 5:1. We would require α such that a 10 percent increase in mitigation expenditure (a $1 million increase) results in a reduction in disaster losses of $4 million. Similarly, we require β such that a 20 percent increase in resilience expenditure results in a reduction in disaster losses of $5 million. In each case, we hold the level of the alternative risk reduction at current levels. The resulting values are $\alpha = -0.428$ and $\beta = -0.281$.

The optimal mitigation and resilience levels are m=0.996 and r = 1.308. The interpretation here is that current levels of mitigation should be decreased slightly from the assumed baseline of $10 million to $9.96 million, while resilience levels should be increased from the assumed baseline of $5 million to $6.54 million. Note that total expenditure meets the new expenditure goal of $16.5 million. Electricity outage losses have been reduced from the $100 million baseline to $92.89 million. Expected losses have fallen from $25 million to $23.2 million.

There is, of course, uncertainty in each of the assumptions underlying the parameterization. To investigate the sensitivity of the results to these assumptions we conducted a Monte Carlo analysis by assuming that each key parameter is a random variable. We took 10,000 draws of each of variable and re-evaluated the optimal level of mitigation and resilience according to the solution derived in the analytical model.

In Figure 1, we show the correlation between mitigation and adaptive resilience in turn with: 1) the BCR of adaptive resilience, 2) the BCR of mitigation, 3) the probability of an outage, and 4) the risk reduction expenditure target. The primary discernible patterns are the relationships between adaptive resilience and the probability of an outage, and between mitigation and the BCR of mitigation. The former occurs because the Cobb-Douglas specification implies the share of expected expenditure allocated to adaptive resilience remains constant regardless of how frequently adaptive resilience actually takes place. The BCR of mitigation has a relatively strong impact because the BCR of mitigation tends to be relatively low, resulting in a larger alpha parameter.

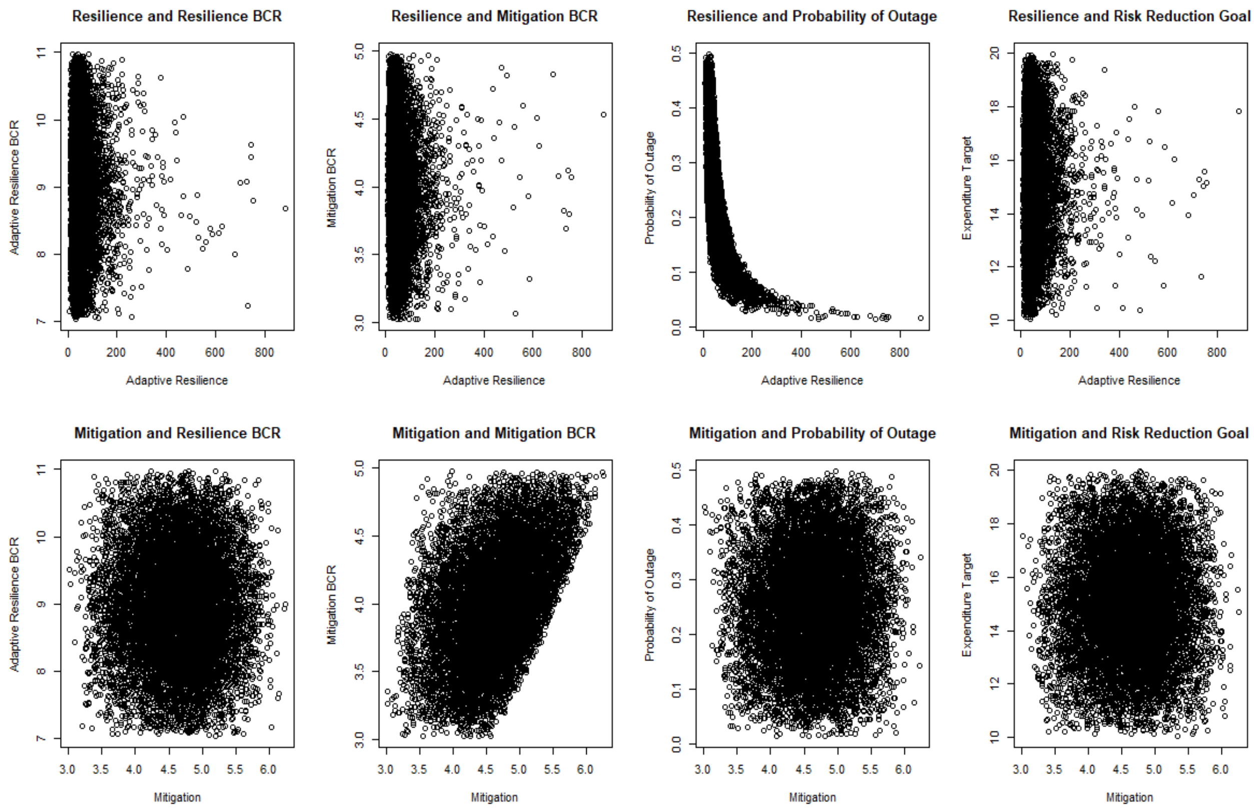

Figure 1: Sensitivity of Mitigation and Adaptive Resilience to Parameter Assumptions

4. Refinements of the Baseline Model

The baseline model can be modified to represent any given combination of mitigation and resilience tactics.

For example, in the case of comparing the optimal portfolio of mitigation to reduce outage frequency and dynamic resilience to recover in accelerated manner, the probability of an outage would need to depend on ex-ante mitigation expenditure, while BI would need to occur for multiple periods with the duration and magnitude of BI in post-outage periods dependent on resilience.

The social planner's problem in this case would be:

$$\min_{m,r_a,r_d} P(m)[\gamma m^{\alpha} r_a^{\beta}] + P(m)\, I(r_d = 0)\, D_2 + p_m m + P(m)\left[p_{r_a} r_a + p_{r_d} r_d\right]$$

$$s.t.\, p_m m + P(m)\left[p_{r_a} r_a + p_{r_d} r_d\right] = c$$

Note that now BI occurs in two periods. BI in the first period is determined by mitigation expenditure and resilience expenditure. BI in the second period, however, is determined by whether or not dynamic resilience takes place. The probability of an outage is determined by the amount of mitigation that is undertaken. This not only affects the expected BI due to electricity outages but also the expected expenditure on resilience (because resilience expenditure only takes place in the event of an outage).

In Table 2 we present a set of cases that provide a robust understanding of the various risk management options and how they would be incorporated into a model of optimal risk strategies.

Table 2. Modifications to Base Case Model for Each Strategy

	Mitigation with Fixed Probability	Mitigation with Fixed Magnitude	Dynamic Resilience	Adaptive Resilience	Inherent Resilience
I. Base Case	X	X		X	
II. Include Inherent Resilience	X	X		X	X
III. Include Dynamic Resilience	X	X	X	X	
IV. Make Probability Endogenous	No	X		X	
V. Full Case (combine II, III, IV)	No	X	X	X	X

Case II. Include Inherent Resilience

Some resilience strategies require ex-ante expenditures. For example, while portable generators can reduce the amount of time that a business goes without power during an outage, the generator, and often the fuel, must be purchased beforehand. Such strategies are referred to as inherent resilience.

In order to incorporate this type of resilience, we introduce a new component to the damage function. Like mitigation, inherent resilience is paid regardless of whether an outage takes place. The augmented social planner's problem is thus:

$$\min_{m,r_a,r_i} P\,\gamma m^{\alpha} r_a^{\beta} r_i^{\eta} + P\,p_r r_a + p_r r_i + m p_m$$

$$s.t.\;\; P p_r\, r + p_r r_a + \; p_m m = c$$

where the a and i subscripts of r refer to adaptive and inherent types of resilience, respectively.

We again utilize the fact that the ratio of the marginal productivities must equal the ratio of the prices of the loss reduction strategies, but now exploit two additional such expressions (the ratio of mitigation to inherent resilience and the ratio of mitigation to adaptive resilience).

Inherent resilience in this case is similar in nature to mitigation -- it occurs with certainty and yields benefits according to its underlying parameter. The major difference, of course, as noted earlier in the paper, is that mitigation is undertaken by the utility and most resilience is undertaken by its customers. By substituting these values into the budget constraint, we find:

$$m^* = \frac{c\alpha}{p_m(\beta + \alpha + \eta\,)}$$

$$r_a^* = \frac{c\beta}{Pp_{r_a}(\beta + \alpha + \eta\,)}$$

$$r_i^* = \frac{c\eta}{p_{r_i}(\beta + \alpha + \eta\,)}$$

The key results are largely unaffected by the introduction of inherent resilience. The optimal allocation of each risk management option increases as its associated parameter falls (becomes more negative) and decreases as the parameters for the other risk management options fall. Because inherent resilience expenditures in this model formulation occur with certainty (rather than occurring only if an outage takes place, as is the case with adaptive resilience), the optimal allocation of spending on mitigation and inherent resilience is essentially identical. Indeed, inherent resilience can be perceived as a form of mitigation.

In Figure 2, we present the results of a Monte Carlo analysis with the inclusion of inherent resilience. The primary relationships remain unchanged. It is important to note the similarity between mitigation and inherent resilience (rows 2 and 3). The variations in these risk strategies are similar because the level of ex-ante inherent resilience expenditure is modeled identically to that of mitigation in the confines of our model.

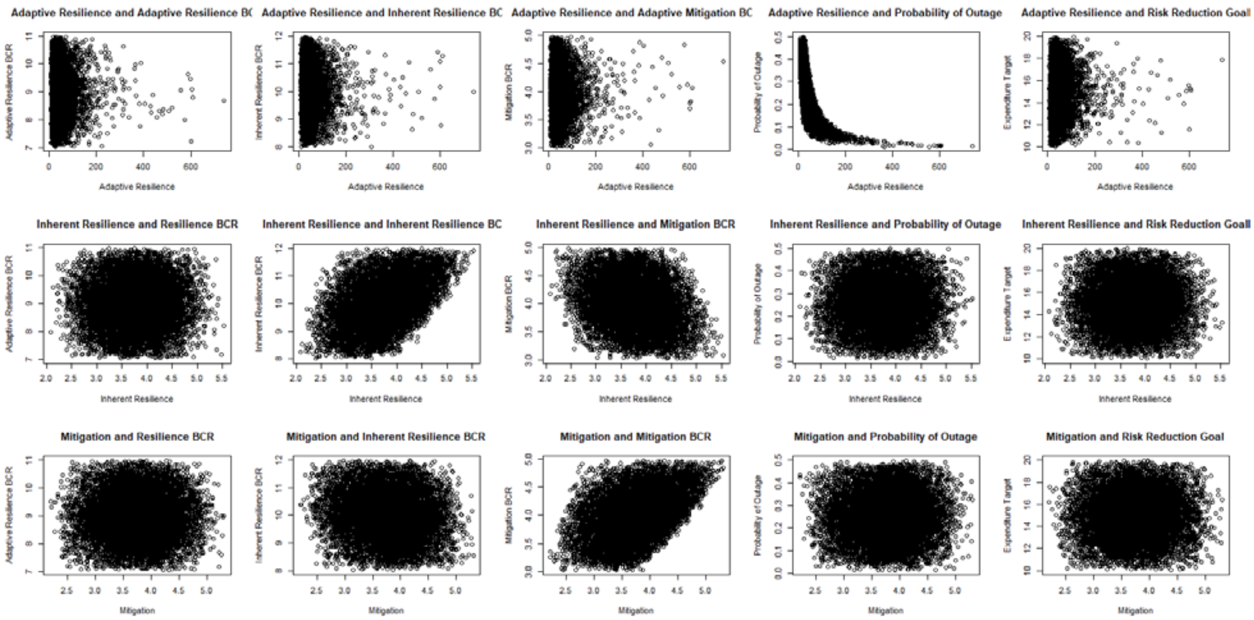

Figure 2: Sensitivity of Mitigation, Inherent Resilience, and Adaptive Resilience to Parameter Assumptions

Case III. Include Dynamic Resilience

We also consider the possibility of dynamic resilience. Dynamic resilience takes place after an outage and reduces the duration of the outage, thereby reducing the losses incurred. In this case, we treat subsequent damages as binary. If dynamic resilience is undertaken, then damage will not occur in the second period, but if dynamic resilience does not take place, then there will be damages in a second period. In our initial formulation, dynamic resilience can only take on a value of zero (there is no dynamic resilience, and losses occur in the second period) or one (there is dynamic resilience, and no second period losses occur).

The optimization problem for the social planner in this case is:

$$\min_{m, r_a, r_d} \ \gamma m^{\alpha} r_a^{\beta} + I(r_d = 0) * D_2 + P\, p_r r_a + P * \ I(r_d = 1) * p_d + p_m m$$
$$s.t. \quad P p_r \, r + P p_d * I(r_d = 1) + p_m m \ = c$$

The key difference between this formulation and the Base Case is the introduction of an indicator function I(.), which takes on a value of one only if the associated conditions are met. For example, if there is no dynamic resilience allocation $I(r_d = 0)$, then D2 is added to the baseline losses, but, if dynamic resilience takes place, $I(r_d = 0)$ is false and takes on a value of zero.

This results in two optimization problems: one in which dynamic resilience takes place, and one in which dynamic resilience does not take place. The final allocation decision is determined by whether expected losses are higher with or without dynamic resilience.

First, we consider the scenario in which dynamic resilience does not take place (i.e., r_d =0). In this case the problem reduces to the Base Case because no dynamic resilience expenditure takes place and the additional damage is additive.

$$m^* = \frac{c\alpha}{p_m(\beta + \alpha)}$$

$$r_a^* = \frac{c\beta}{Pp_{r_a}(\beta + \alpha\,)}$$

$$r_d^* = 0$$

If dynamic resilience does take place, mitigation and adaptive resilience allocations are reduced through the mechanism of the budget constraint. The optimal levels of mitigation and adaptive resilience (contingent on paying for dynamic resilience) can again be calculated using the ratio of marginal products and the ratio of the prices.

The optimal risk reduction levels are:

$$m^* = \frac{(c - Pp_{r_d})\alpha}{p_m(\beta + \alpha)}$$

$$r_a^* = \frac{(c - Pp_{r_d})\beta}{Pp_{r_a}(\beta + \alpha\,)}$$

$$r_d^* = 1$$

The social planner will compare the expected total damages in each case and choose whether or not to pursue dynamic resilience as a risk reduction strategy. In the former case, the total expected expenditure is:

$$\text{Expenditure} = P\,\gamma \left(\frac{c\alpha}{p_m(\beta + \alpha)}\right)^{\alpha} \left(\frac{c\beta}{Pp_{r_a}(\beta + \alpha\,)}\right)^{\beta} + D_2 + P\,p_r \left(\frac{c\beta}{Pp_{r_a}(\beta + \alpha\,)}\right) + p_m \left(\frac{c\alpha}{p_m(\beta + \alpha)}\right)$$

If, on the other hand, dynamic resilience takes place, total expected expenditure is:

$$\text{Expenditure} = P\,\gamma \left(\frac{(c - p_{r_d})\alpha}{p_m(\beta + \alpha)}\right)^{\alpha} \left(\frac{(c - p_{r_d})\beta}{Pp_{r_a}(\beta + \alpha\,)}\right)^{\beta} + Pp_d + P\,p_r \left(\frac{c\beta}{Pp_{r_a}(\beta + \alpha\,)}\right) + p_m \left(\frac{c\alpha}{p_m(\beta + \alpha)}\right)$$

Whether or not it is optimal to allocate resources to dynamic resilience depends on several key components. First, as the price of dynamic resilience increases, the likelihood that dynamic resilience is in the optimal risk reduction set decreases. Similarly, as the damage in subsequent periods decreases, the likelihood that dynamic resilience will take place falls. This extends to the case of dynamic resilience affecting multiple periods, as well. If losses from an outage are expected to continue for multiple periods or if losses are viewed as a continuous flow, these damages can simply be aggregated into a single net present value of losses that can be offset with dynamic resilience.

The attractiveness of dynamic resilience also decreases with the efficacy of mitigation and adaptive resilience. Because we assume a fixed budget constraint, allocating additional expenditures to dynamic resilience limits the amount of mitigation and adaptive resilience that can take place. If these alternative risk reduction options yield large enough benefits, the social planner would prefer to absorb the losses in later periods in order to reduce damages in the main outage period.

We again present a Monte Carlo analysis in Figure 3. Dynamic resilience introduces additional complexity into the model. It should only take place when its cost is relatively low or when the losses from the outage in subsequent periods are relatively high. If dynamic resilience is justified, the total amount of mitigation and adaptive resilience declines because funding must be allocated to pay for the dynamic resilience. This complicates the formulation of the optimal level of mitigation and adaptive resilience by inducing relationships between these risk management strategies that do not exist in the simple Cobb-Douglas formulation. For example, mitigation expenditure is not correlated with the cost of adaptive resilience in the base case, but they are related when dynamic resilience is introduced because the cost of adaptive resilience influences the attractiveness of dynamic resilience.

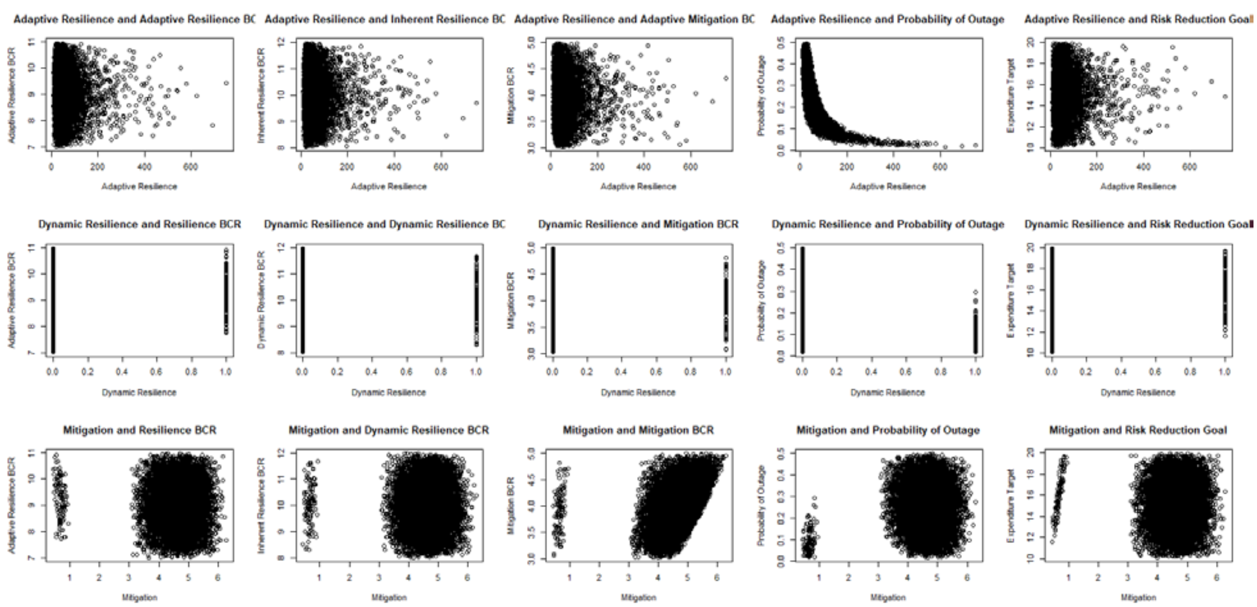

Figure 3: Sensitivity of Mitigation, Dynamic Resilience, and Adaptive Resilience to Parameter Assumptions

Case IV. Include Endogenous Probability of an Outage

We also consider a case in which the likelihood of an outage is not strictly exogenous. Some ex-ante mitigation strategies could reduce the probability that an outage occurs rather than just reducing the losses from the outage.

The social planner's problem in this case is:

$$\min_{m,r_a} P(m)\,\gamma m^{\alpha} r_a^{\beta} r_i^{\eta} + P\, p_r r_a + p_m m$$
$$s.t.\ P(m) p_r r_a + \ p_m m = c$$

The distinction between this scenario and the base case is that the probability of an outage, P, is now dependent on the level of mitigation, m. For simplicity, we assume that the marginal reduction in the likelihood of an outage for an increase in mitigation is constant (i.e., P(m) = (a-m)/b where a < b are constants).

There is no closed-form analytical solution for the social planner's problem. We instead turn to a numerical solution. We draw 10,000 combinations of each of the associated parameters for the social planner's problem and use a non-linear optimization algorithm to calculate the optimal combination of mitigation and resilience for each set of variables.

Figure 4 presents the correlation between the optimal levels of mitigation and adaptive resilience and several key parameters.

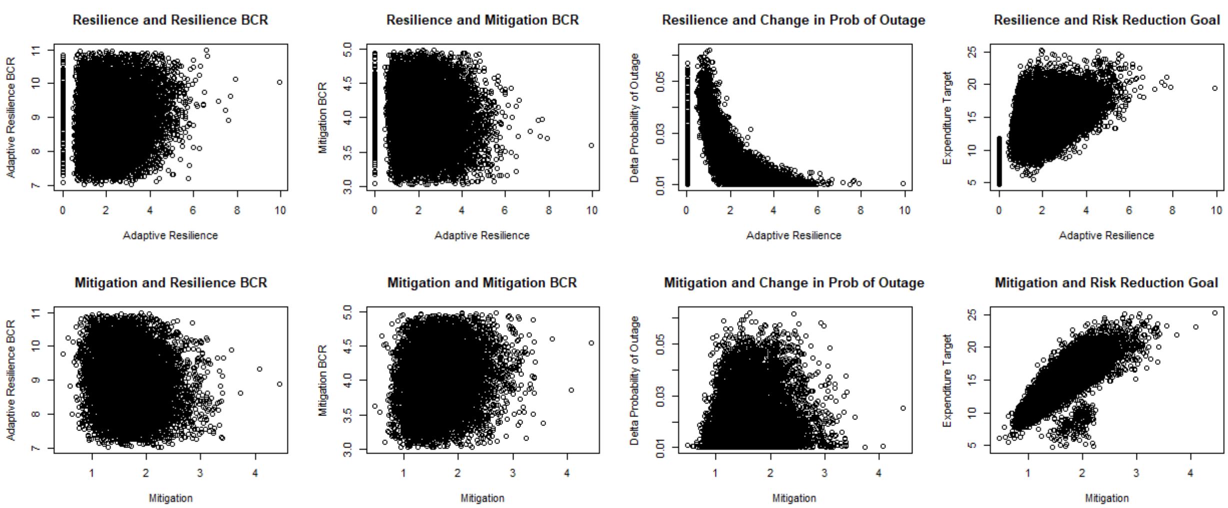

Figure 4: Sensitivity of Mitigation, Dynamic Resilience, and Adaptive Resilience to Parameter Assumptions

A graphical analysis of parameter correlations reveals the effects of resilience and mitigation BCRs are similar to the base case. This is not surprising because the cost shares are still driven by the Cobb-Douglas parameters.

The introduction of outage probability that is endogenous to the level of mitigation results in a marginal reduction in the attractiveness of resilience and a marginal increase in the attractiveness of mitigation. As the change in probability of occurrence of an outage associated with an increase in mitigation falls to zero (i.e., as the probability of an outage becomes exogenous), the optimal level of resilience increases. Similarly, when a change in mitigation results in a large reduction in the likelihood of an outage, the social planner chooses to reduce resilience expenditure and substitutes toward mitigation. For some parameter combinations, it is optimal for the social planner to spend as little as possible on resilience in order to shift expenditure to mitigation.[8]

Similarly, as the change in probability of an outage associated with mitigation increases, the optimal level of mitigation expenditure increases. Because we constrain the probability of an outage to be greater than or equal to zero there is a quadratic relationship between the change in outage probability and the optimal level of mitigation. If mitigation is sufficiently effective at reducing the probability of an outage, the probability of an outage reaches its computational minimum before spending targets are met. This condition is unlikely, however, because it requires the probability of an outage to be highly responsive to mitigation, the baseline probability of an outage to be low, and a high spending constraint.

Case V. Full Case

This case could be analyzed in a 2-period model, with the first period including consideration of both mitigation and the initial expenditure aspect of inherent resilience and the second period representing the implementation of the inherent resilience. However, again, to trace the time-path of recovery more fully would require at least a 3-period analysis.

5. Conclusion

This study created a framework for assessing tradeoffs between various risk management tactics and applied this framework to consider mitigation, adaptive resilience, inherent resilience, and dynamic resilience. We have derived the conditions for optimizing the mix of various combinations of risk reduction strategies. We have also run sensitivity tests to gain further insight and test the robustness of the results.

The key conclusion from this paper is the relationship between the relative marginal benefits of each risk management strategy and their relative marginal costs. While the Cobb-Douglas functional form resulted in a number of simplifying assumptions (e.g., constant elasticity of substitution between each combination of two strategies), this relationship will not change. If the loss function were relaxed by treating adaptation and resilience as additive or by relaxing the assumption of constant elasticity of substitution, the relationship between optimal levels of risk management alternatives would obviously change. However, the conclusion holds that policy makers should holistically consider the relative benefits each risk management strategy. Policy makers who pursue extensive levels of mitigation may be over-mitigating if there are still alternative risk management strategies such as resilience that will produce a larger marginal benefit.

There are several important extensions of this paper that should be considered. First, it would be useful to relax the assumption of the Cobb-Douglas damage function and to instead rely on fully specified production functions for mitigation and resilience. There is little empirical research on the complementarity of mitigation and resilience, though. It would also be useful to consider a distribution

[8] We constrain the numerical optimization problem to strictly positive amounts of resilience because our specified damage function would result in zero costs from an outage if either mitigation or resilience were set to zero.

of outage types in order to better reflect the range of potential outages. This could be achieved by allowing for heterogeneous γ parameters that are drawn from a probability distribution. Finally, this paper assumed a single benevolent social planner sets the levels of mitigation and resilience in order to minimize total expected damages, subject to an expenditure constraint. While this assumption allows mitigation and resilience to be aggregated across heterogeneous actors (e.g., utilities and consumers), in reality different actors make their optimization decisions separately and with uncertainty about other actors' decisions. It would be useful to reconsider the mitigation and resilience tradeoff in the context of a game-theoretic model, with consumers and utilities purchasing mitigation and resilience as public and semi-public goods.

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Discussion of "Mitigation and Resilience Tradeoffs In Electricity Outages"

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The organizers of this meeting are to be congratulated for promoting careful analysis of the value of resilience, especially with respect to large-scale electric power outages.

Basic Framework

The proposal has several innovations:

- An abstract framework that clarifies the substitution roles of different types of alternatives (it points out the essential substitution relationship between preventive and corrective control actions, as a power engineer would call them;[9] the authors term them "inherent resilience" and "adaptive resilience").
- A useful if not exhaustive categorization of alternatives for improving resilience of power systems (real alternatives don't fall quite so neatly into these bins; for instance, there are many important *ex ante* investments that increase the range of adaptive possibilities or lower their costs. For instance, a consumer could buy an emergency generator, and then incurs fuel costs if the outage hits-- this doesn't fall neatly into the inherent or adaptive resilience categories.)
- A parsimonious model of their effect on resilience based on the Cobb-Douglas model, showing how the different types of options interaction. By embedding that "production function" for outage costs within an optimization model, the effects of some alternative assumptions on the optimal mix of options subject to a budget constraint are explored.

The paper is a good reminder that the benefits of one type of measure to improve resilience depend on how much investment has been made in other measures, and that the problem needs to be considered from a whole system perspective. This yields important conclusions such as:

- "For some parameter combinations, it is optimal for the social planner to spend as little as possible on resilience in order to shift expenditure to mitigation."
- "Policy makers who pursue extensive levels of mitigation may be over-mitigating if there are still alternative risk management strategies such as resilience that will produce a larger marginal benefit."

[9] E.g., J. Giri, M. Parashar, R. Avila-Rosales, and D. Wilson, "The Case for Using Wide-Area Monitoring and Control to Improve the Resilience and Capacity of the Electric Power Grid," in Real-Time Stability in Power Systems, pp. 235-278, Springer, 2014, Cham.

Policy makers, regulators, and others need to be reminded of these fundamental points.

The Cobb-Douglas model has some well-known limitations, some of which the authors acknowledge.

(1) For the basic analysis, the C-D form results in a constant expenditure share (e.g., 30%/70%) regardless of the budget size. The relative shares are driven by the exponent values in the function, and relative prices. The optimal amount is never zero of a particular measure, unless the overall budget is zero.
(2) However, in real situations, there are many "corner solutions" in which the optimal investments are zero. Consider for instance the vast majority of customers who invest zilch in emergency generators or other "corrective" actions (unless a few dollars for flashlight batteries is counted). (More on corner solutions below.)
(3) With the negative exponents assumed here, zero budget results in infinite outage costs.
(4) "First, most inherent and all adaptive resilience only occurs, and resilience costs are typically only incurred, if an outage takes place." This is not accurate. In the real world, there are also complementary relations. In order to be able to modify production quickly, or shift it to other locations, control systems need to be invested in, inventories stocked in multiple places, etc. For instance, HP is spending to have better systems for allocating its computational loads among servers around the world. Thus, investments buy more flexibility to respond, with costs incurred both before and after events. The model could be easily expanded to evaluate investments that reduce the costs of, or otherwise facilitate adaptation

Extensions

Here are some ways that the work could be extended to yield more insights about particular types of measures and optimal mixes.

The budget is actually on expected (probability weighted) expenditures. Given the reality of risk-averse decision making, a generalization would be a chance constraint (e.g., a constraint saying that there is a 90% chance that the expenditures will be M or less).[10] This is only useful if the model is elaborated so that there is a distribution of potential outages durations and severities.

This is a "cost effectiveness" analysis-- given a budget, what is the best way to spend it to reduce expected outage costs as much as possible. A broader phrasing is as a benefit-cost analysis, which would ask what is the optimal level of the budget *c*? The resulting problem would still have the same first order conditions for the optimal mix of measures, but there would be an additional condition for the optimal budget that will relate the optimal budget to the "VOLL" (which is gamma in their first equation). This gets more interesting if there is a diversity of customers, as noted below.

Alternatively, a multiobjective framework may be more useful in which the benefits attained are traded off against the budget.

[10] A. Charnes and W.W. Cooper, "Chance-constrained programming," Management Science, 6(1), 73-79, 1959.

It would be interesting to attempt to parameterize the models based on actual technological alternatives to explore the nature of optimal mixes of different measures, e.g., storage/PV or emergency generators for consumers, versus undergrounding of lines or less drastic measures to reduce the probability of distribution outages. Alternatively, one could formulate optimization models based on actual technological relationships (e.g., nonlinear integer programs). What do actual production functions for resilience look like (I suspect that they are very un-Cobb Douglas)?

To achieve the optimal solution, there would have to either be coordination among the parties (*a la* Coase[11]) or a benevolent utility with perfect information about customer costs and options who could also (somehow) control consumer resilience-related investments. However, there are market failures -- imperfect information, incomplete markets for risk etc. – that prevent such perfect coordination or benevolent planning. So it would be interesting to consider this as a multiparty problem, in which the utility may have a budget and private customers with a diversity of incomes and valuations of outages control their corrective decisions. What information does a utility need to decide on the "right" level of the budget? What is the inefficiency of having the wrong information? Utilities may have budgets, but consumers are likely to balance the marginal costs and benefits of different preventative and corrective measures, so the models for each party may differ in their fundamental form.

With multiple parties with different valuations (VOLL), then the problem becomes one of allocating a budget among measures that benefit all consumers, versus measures that benefit subsets of consumers, versus consumer actions themselves. Given the information and other market failures, this framework could be used to explore inefficiencies that result from these market failures. Then decision makers who are responsible for preventive actions ("inherent resilience") will need to take into account how consumers react (corrective actions, "adaptive resilience").

This framing naturally leads to Stackelberg-type (leader-follower) games in which a "leader" makes investments, and "followers" then make their choices, and the leader's objective may include benefits to all parties.[12] (See figure below.) The result can be "second best" policies (given the presence of the market failure, what is the social welfare-maximizing action of the leader,[13] which will be in general yield less net benefits than the "first-best" solution, which is not feasible given that the leader does not control the actions of the followers).

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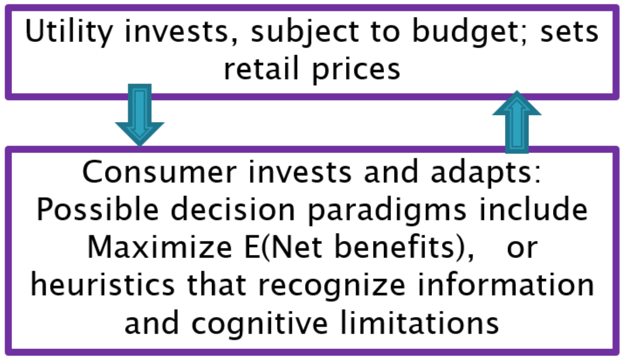
[11] R. Coase, "The Problem of Social Cost". Journal of Law and Economics. **3** (1): 1–44, 1960.

[12] An example of this framework, in which a leader-follower analysis is conducted of the game between utilities and consumers (however, in the context of optimizing energy efficiency) is B.F. Hobbs and S.K. Nelson, "A Nonlinear Bilevel Model for Analysis of Electric Utility Demand-Side Planning Issues," Annals of Oper. Res., 34, 1992, 255-274. For more on the formulation and solution of leader-follower games, see pp. 118-120, Ch. 6, and Section 7.4 of S.A. Gabriel, A.J. Conejo, J.D. Fuller, B.F. Hobbs, and C. Ruiz, Complementarity Modeling in Energy Markets, Springer-Verlag, 2012.

[13] R.G. Lipsey and K. Lancaster, "The general theory of second best," The Review of Economic Studies, 24(1), 1956, pp.11-32.



This would also allow a richer analysis of options that require coordination/agreements between leaders and followers. For instance, resilience can be improved if a customer can access more than one feeder (the feeders are utility expenses, but the customer's switching equipment is a customer expense). Transaction costs involved in Coasian-type bargaining (e.g., in which one party pays another to do something beneficial for the first party) are interesting. A Coasian framework would also address interesting questions about property rights (do consumers have a right to power with a certain reliability, and utilities would have to bribe or compensate them to accept less, or to install corrective/adaptive measures? Or do consumers have to pay utilities to induce them to install preventative/inherent measures?)

Another direction would be the design of mechanisms that induce revelation of private costs (such as Chao et al.'s priority pricing,[14] where consumers sort themselves into groups based on their revealed willingness to pay for reliable power), and simulating them in a multiparty version of this model.

Extreme outages have unknown probabilities, due to lack of historical data and evolving technologies and challenges. This is a challenge for frameworks that require probabilities. (As Billinton and Allan often reminded us,[15] reliability models for power systems are useful for qualitative insight and ordinal comparisons of alternatives, but the precise indices such as LOLP or EUE cannot be interpreted as cardinal numbers, since there are too many assumptions such as component independence that are large simplifications, and too many parameters that are poorly known.) What alternative decision making frameworks might be useful? E.g., if different market parties have differing beliefs about probabilities, and markets for risk are incomplete? Or how about robust decision making[16] or robust optimization?[17] These are very distant from the authors' framework, but it is interesting to contemplate how that framework might be extended to deal with such profound uncertainties.

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[14] H.P. Chao, S.S. Oren, S.A. Smith and R.B. Wilson, "Priority Service: Market Structure and Competition" The Energy Journal, Special Issue on Electricity Reliability, vol. 9 (1988), pp. 77-104.

[15] R. Billinton and R.N. Allan, Reliability Evaluation of Engineering Systems, New York: Plenum Press; 1992.

[16] R.J. Lempert, S.W. Popper, and S.C. Bankes, Robust Decision Making: Coping with Uncertainty. The Futurist, 44(1), 2010.

[17] W. Yuan, J. Wang, F. Qiu, C. Chen, C. Kang, and B. Zeng, "Robust optimization-based resilient distribution network planning against natural disasters," IEEE Transactions on Smart Grid, 7(6), pp. 2817-2826, 2016.

II. Estimating Residential Customers' Costs of Large Long-duration Blackouts

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Abstract

America's dependence on reliable electric power, and our individual and collective vulnerability to power disruption, continues to grow. While it would be technically possible to make changes that could sustain many critical electricity-dependent services during widespread and long-lasting outages, implementing smart grid technologies, distributed generation resources, or other technologies to do that would require incremental investment with benefits that, in many cases, are uncertain and difficult to quantify.

We previously completed a study that employed face-to-face interviews to assess the willingness-to-pay of residential customers to receive backup service during a hypothetical 24-hour outage on a hot summer day. In that study, we observed consumer surplus associated with providing partial electric backup service (i.e., the respondents' willingness-to-pay per kWh was significantly higher for low-amperage backup service than for full service) and the assessed value of the first few kWh significantly increased as respondents received additional information and came to better understand the outage and its consequences.

In order to explore respondents' willingness-to-pay under a variety of scenarios in different locations more efficiently, we have developed a generalizable web-based survey framework that a researcher or decision-maker can use to design their own outage scenarios and elicit residential customers' willingness-to-pay for reliable electric services in those settings. Here, we report on the web-based tool we have built and the experimental design of the study we have initiated to obtain informed judgments from individuals about their economic and social preferences for a low-amperage electric backup service in the event of a large power outage of long duration. In this first implementation, we have used two hypothetical outage scenarios, both of which result in a 10-day outage during freezing winter weather; we are currently recruiting a representative sample of Northeastern residents (a subset of whom have previously experienced a long outage) and examining several research questions. Now that the tool exists, future applications can easily explore other outage scenarios and durations.
The web-based survey framework should help researchers and decision-makers explore preferences for reliable electric services under a variety of scenarios and allow users to construct an outage damage function for residential customers. Results from such studies should serve as one input to decisions about when and whether upgrades to advanced distribution systems might be justified on economic and social grounds in at least some regions of United States where the relative probability of outages is high and the population and local and regional governments are risk averse.

1. Introduction

American society depends on electric power for many individual, household, and commercial activities, making our individual and collective vulnerability to power disruption a key question for policy analysis. Most power outages are local (IEEE Working Group on Distribution Reliability, 2015), but widespread and long-duration outages (WLD-outages) do occur, and impose considerable private and social costs. Examples include the ice storm that hit Southern Québec, Ontario, and Northern New York in 1998 and the extensive outages along the Southeast United States and Caribbean affected by Hurricanes Harvey, Irma and Maria. In the past, such outages have been caused by extreme weather events and operatonal errors, but in the future they could also result from other causes such as large solar mass ejections (McMorrow, 2011) or terrorist attacks (National Research Council, 2012).

Given the proliferation of modern "smart" technology and distributed generation (DG), today, with some modest distribution system upgrades, it would be possible to provide at least limited service to some customers and sustain critical services in the event of large-scale power outages (Narayanan and Morgan, 2012). While past work has demonstrated that there exists substantial consumer surplus associated with the first bit of electricity (Baik, Davis and Morgan, 2018), the assessed amount of that surplus can be expected to depend on three factors: 1) the nature (and perhaps the cause) of the blackout; 2) the extent of backup service coverage; and, 3) the degree to which decision-makers understand the extent and consequences of the blackout.

Previously, we developed and demonstrated a set of improved methods to assess informed judgments by residential customers about the cost of WLD-outages (Baik, Davis and Morgan, 2018) and performed a first order assessment of when incremental investments to upgrade a distribution system become cost-effective (Baik, Morgan and Davis, 2018). Building on that work, we have now developed a web-based survey framework that is designed to elicit the value of reliable electric services in the event of WLD-outages caused by existing and emerging threats to the major electric power system. In the first application of the web-based tool, we have posited two outage scenarios: a massive solar storm and a terrorist attack. Once results have been obtained, we will explore how they might be used as an input to determine the level of investment in system upgrades that might be justified on economic and social grounds.

2. Previous Studies on Value of Electric Service Reliability

Since the mid-1980s, electric utilities have conducted a number of studies to assess customer costs for power outages lasting for a few hours. Utilities and public utility commissions (PUCs) have used these results to justify reliability levels and associated investments. To estimate customer outage costs, most studies use one of four methods. The first uses revealed preferences, where respondents are asked how much they have paid for backup equipment or other mitigating services to avoid power outages. For example, Caves, Herriges, and Windle (1992) infer industrial customers' interruption costs from what are known as Interruption and Curtailment (I/C) programs, which provide special discounted electricity rates for commercial and industrial customers in return for curtailing usage on request, or allowing a utility to occasionally interrupt electrical service. This approach only reveals meaningful preferences if customers have accurate expectations about the probabilities and costs of outages, two key parameters that are difficult for researchers to estimate, making it unlikely that they are common knowledge (Manski, 2004). Also, most residential and commercial customers do not use backup generation or interruptible contracts even though they experience interruption costs. In a recent study conducted by Burlingame and Walton (2013), the monetary losses experienced by each customer group were added up on a daily basis and these costs were then extrapolated for periods up to a week. While the method would be useful to obtain upper bounds, not all monetary losses occur in an outage (for instance, in some regions may have backup power for water and sewer system, and some people who are not employed or can get paid during outages do not need to worry about their lost income). Perhaps more important, this method does not include non-monetary losses, such as inconvenience, that for residential customers may dominate.

Second is the stated preference method, which asks respondents to state their maximum willingness-to-pay (WTP) to avoid a given interruption (Sullivan and Keane, 1995; Chowdhury *et al.,* 2004), uses yes-no questions to given bids and assesses the dollar value at which respondents switch from "yes" to "no" (Kim, Nam and Cho, 2015), or asks respondents to choose between scenarios with varying levels of reliability and associated prices (i.e., choice modeling, discrete choice experiments, or conjoint analysis). For example, Baarsma and Hop (2009) use conjoint analysis to assess the trade-off between changes in outage frequency, duration, day of the week, part of the day, season, warning in advance, and changes in electricity bill. London Economics (2013) uses choice experiments to assess the trade-off between outage duration, season, time of day, day of week, and one-time WTP or willingness-to-accept (from £1 to £15). This method is a bottom-up approach and generates results without relying on other data, such as historical data on backup power installation costs. Nonetheless, interruption costs from the hypothetical outages are highly subjective, and individuals may not fully understand the consequences of an outage.

The third approach, called the production function method, produces estimates based on macroeconomic data (for example, gross domestic product or the average annual income per household), which is useful when there are limitations in the availability of data (such as data on customer tradeoffs between reliability and price; Woo and Pupp, 1992) and resources (such as time and money because the analysis only requires a small quantity of easily obtainable data; Van Der Welle and Van Der Zwaan, 2007). For example, Munasinghe (1980) calculates the value of foregone leisure, which he estimates as the product of after-tax earning rate (per hour) and outage duration, to estimate residential customers' outage costs. Similarly, de Nooij, Koopmans and Bijvoet (2007) calculate the value of leisure time by multiplying the average gross hourly wage rate after tax, outage duration, and the percentage of households that are expected to lose their leisure time. Stevie *et al.* (2014) develop econometric load forecasting models for three electric customer groups (for instance, residential customers' demands are roughly estimated by their electricity price, income, weather and other variables) to calculate the value of electric service to the customer. But such macroeconomic estimates are generally too broad because studies: 1) simply divide direct costs of production (for example, annual GDP per capita or average annual income after tax) by annual electricity consumption, 2) do not consider interruption attributes such as timing of outages, and 3) and only consider a few sources of cost when they estimate the costs (i.e., they do not include other monetary losses such as repairing damaged equipment, lost income, and other non-monetary losses such as lost free time and inconveniences).

Finally, the fourth method involves case studies of historical blackouts and outages. For example, Corwin and Miles (1978) estimate economic and social impacts of the 1977 New York City blackout. While such an approach can provide important qualitative results, quantitative analysis is difficult because of the limited data available from rare outages. Moreover, because future large outages may not be the same as past ones, historical data may not reflect future outcomes.

While it is relatively straightforward to estimate the economic costs of blackouts for industrial and commercial customers (although assessing subsequent business rebound after an outage can be more challenging), the *soft costs* experienced by residential households (e.g., not being able to use the air conditioner on a very hot day) are more difficult to quantify. Instead, many past studies have asked residential customers about their WTP or willingness-to-accept to avoid hypothetical outages. These studies typically deal with outages of a fixed duration lasting just a few hours for particular regions (for example, only surveying customers in the Midwest United States who are served by the MidAmerican Energy company, Chowdhury *et al.,* 2004). They examine specific customer mixes (for example, only residential customers; Carlsson, Martinsson and Akay, 2011; Hensher, Shore and Train, 2014; Ozbafli and Jenkins, 2016). Also, they focus on specific outage scenarios, mostly brief outages. For instance, Carlsoon, Martinsson and Akay (2011) consider planned outages lasting for 1, 4, 8, and 24 hours and unplanned outages lasting for 2-6 hours.

To generalize these results, researchers have conducted meta-analyses of previous studies every 5 years, extending the effort over time to include more participating companies, and deriving additional customer outage models (Lawton *et al.,* 2003; Sullivan, Mercurio and Schellenberg, 2009; Sullivan, Schellenberg and Blundell, 2015). These studies estimate customer damage functions that can be applied to estimate interruption costs for a given season, day of week, timing of interruption, duration, geographical region, and customer type.[1] However, the details of these studies are not publicly available (Sullivan, Mercurio and Schellenberg, 2009). Previous studies of the sort that have been summarized by Sullivan and Keane (1995) suffer from several shortcomings. First, to the best we have been able to determine, they have not involved any systematic effort to help respondents fully understand and consider the various implications of the hypothetical outages –impacts and outages that they may not have experienced or previously considered. Second, the surveys appear to have done little to minimize cognitive biases (Mitchell and Carson, 1989; Schulze *et al.,* 1996; Cameron *et al.,*

[1] Freeman, Sullivan & Co. and Lawrence Berkeley National Laboratory recently update the Interruption Cost Estimate calculator for reliability planning (available at http://icecalculator.com). Using the tool, electric reliability planners, government organizations, or other relevant authorities can roughly estimate their interruption costs by entering reliability inputs (e.g., SAIFI and SAIDI/CAIDI), numbers of residential and non-residential customers, and state. However, the details of the models are not open to public.

2002). Third, these surveys considered only relatively brief outages (from momentary to several hours). The costs per kW of lost services during longer duration outages –many hours, several days, or even weeks –are likely to be much different than the costs of brief outages, so simply scaling up the results is not appropriate. Fourth, past valuation methods have only considered the difference between full backup service and no service. However, for most customers, the unit value of the first small amount of electricity (for critical electric appliances and services such as a few lights and refrigeration or heating) is likely to be worth significantly more than the value of the last increment consumed (for non-critical electric appliances and services). These issues must be addressed to adequately estimate the value society places on avoiding low probability, WLD-outages.

Finally, we should note that discrete choice modeling has been used to estimate consumers' preferences for electricity services (for example, for understanding residential customers' preferences for electric service plans (Neenan *et al.*, 2016) and improved electricity services (Huh *et al.,* 2015)). However, we do not consider the use of discrete choice modeling to be appropriate to the problem of assessing the cost of long outages. ***First***, we believe that peoples' preferences for reliable electric services are uncertain and incomplete when they only bring to bear their prior knowledge, thus it is difficult to use a single cardinal utility function to incorporate the preference uncertainty because the utility function is not deterministic. Respondents are probably able to judge rather accurately how they value a Cadbury chocolate candy bar versus a KitKat bar, but without a great deal of assistance to think things through, most have very little basis to judge the relative costs of a 3-day mid-week outage with outdoor temperatures averaging 29°F *versus* an 8-day outage during a cold spell with outdoor temperatures averaging 12°F.

Second, under the discrete choice study settings, researchers need to abstract away significantly from what will actually happen during a blackout when presenting various scenarios. In working through many scenarios, none can be described (or absorbed) in detail; for instance, a survey cannot provide detailed information about what would be available with 20A vs 40A service and what social services are available after 1 day vs 4 days within a reasonable amount of time. Finally, in all such cases, unless respondents receive help in understanding more about the consequences of outages and backup services, their preferences and values are almost certainly uncertain and incomplete. Thus, abstracting away significantly from what will actually happen in the blackout and presenting a number of scenarios (with likely learning effects during the experiment) may lead to mechanical and uninformed responding rather than enlightening people about their world and their preferences in relation to that world.

Third, respondents' value of reliability is determined by many factors (not only by interruption-related factors but also by customer-related factors such as respondents' perceived level of reliability and their demographic characteristics), and there may exist behavioral incoherence (e.g., making choices using lexicographic semi-orders or heuristics). In such cases, differences across people will be washed out by aggregating over individuals to produce a single average utility function - for example, if 50% of people make their choices only based on price whereas the other 50% make their choices only based on the amount of power, the average will end up implying precise tradeoffs in aggregate that none of the participating individuals is willing to make. Thus, using the resulting estimated cardinal utility function over an attribute space would be implausible and unverifiable in the case of value of reliable electric services during WLD-outages.

3. The Value of Assuring Some Electric Service from Pittsburgh Residential Customers against a Large-scale Outage of 24 Hours[2]

3.1 Overview of Our Previous Survey Design

To address these key issues, we developed a survey framework that helps residential customers think carefully about a specific WLD-outage and systematically reflect on how much they value full and partial backup service during that outage (Fischhoff, 1991; Baik, Davis and Morgan, 2018). The approach, illustrated below in Figure 1, is designed to help respondents understand what services would and would not be available in their homes and communities, their personal load profiles as a function of time of day (under normal circumstances or with full backup service), the domestic (or critical) loads they could operate with partial backup service (under limited availability), and the economic losses they might suffer. The framework also allows respondents to express uncertainty in their preferences.

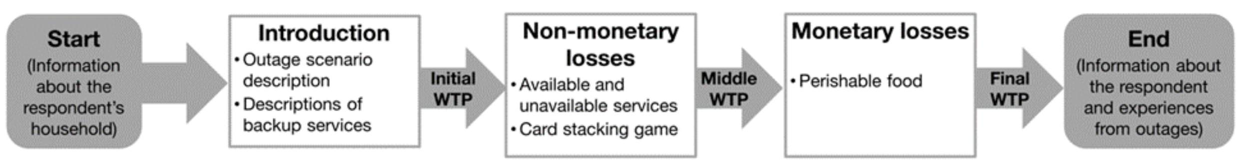

Figure 1. Overview of the face-to-face survey elicitation design indicating the information and exercises that we provided in three different stages, and showing when we pose questions about willingness-to-pay (WTP)

Using the elicitation framework, we tested the two main hypotheses: whether providing more information about a hypothetical outage and its various aspects of inconvenience and economic losses can help respondents better understand and express their preferences, and whether there exists consumer surplus thatould affect the cost-effectiveness of distribution system upgrades. In this study, we focused only on services for individuals and compared WTP for 20 Amps partial backup service and full backup service. While this first study was developed using a specific outage scenario and duration, the approach could be readily modified to explore a variety of other outage scenarios and durations.

Compared to the other survey designs, our framework has four major advantages: 1) the framework can inform respondents about the consequences of a blackout in their home (e.g., value of perishable food and frozen water pipes) and communities (e.g., shopping malls, restaurants, grocery stores, and gas stations will not work); 2) the framework can help respondents understand their priorities for

[2] Portions of the text in this section are adapted from Baik, Davis and Morgan (2018) and Baik, Morgan, and Davis (2018).

electric services (e.g., furnace blower or additional lighting) and reflect on their preferences for backup services; 3) the framework can allow the realistic expression of preferences that may be incomplete (i.e., not defined over all states of the world), uncertain (i.e., unable to provide an exact WTP), and heuristic (i.e., focusing only on some aspects of the decision problem); and, 4) the framework can provide decision-makers with numbers that come from more informed and engaged members of the public, reflect the uncertainty in what people want, and can be aggregated in a number of ways to access alternative policies.

3.2 Characteristics of Backup Services during Widespread and Long-lasting Outages and Elicitation Techniques

There are two important elements that need to be carefully considered in the survey design: one is the characteristics of the good or service and the degree of respondents' preference articulations. The other is determining the most appropriate elicitation format. In preference elicitation, decision-makers should be helped to understand the consequences of their choices before they can choose, and elicitation mechanisms should not assume more than is required or verifiable for that task. For significant and unfamiliar choices, respondents should be allowed to express uncertainty in their preferences. Fischhoff (1991) presents a continuum of philosophies to explain these concepts: at one extreme, people are assumed to have full articulated values ('philosophy of articulated values') whereas at the other extreme, people are assumed to lack articulated preferences and values but develop multi-attribute utility functions using the basic attributes ('philosophy of basic values'). In the middle of two extremes, people are assumed to have stable values of moderate complexity, thus the elicited values may be rendered uncertain and incomplete.

The value of a low-amperage backup service during WLD-outages is a good example of eliciting individuals' preferences when they are in the intermediate position. Electric services are the things with which most people are familiar, but not many of them have experienced WLD-outages nor have they previously considered their WTP to avoid such WLD-outages. That means that even though people may have rough preferences, they may have difficulty understanding the given hypothetical outage scenario and its consequences, especially for longer outages. For instance, respondents may know that their batteries last a few hours or days, but they may not know that their water and sewage service may be unavailable after a few days. Similarly, consequences in communities likely also vary over outage duration; for instance, many people may not know that many banks, ATMs, and (private and small) stores will not work immediately, and some critical social services such as police and fire station and TV and radio stations may run out of fuel in a few days. Finally, a low-amperage backup service that allows people to only run a few critical appliances is a novel thing that many people have never thought about before. To that end, we aimed to help people think carefully about the consequences of a blackout and come up with a reasonable expression of their preferences for full and partial backup services during a WLD-outage.

To determine the most appropriate elicitation technique, we started by comparing the traditional elicitation techniques that have been used in previous studies. As discussed in Section 2, studies generally use one of four methods –revealed preference; stated preference; production function method; and case studies of historical blackouts– to estimate customer outage costs. Among these, the stated preference method has been the most widely used for residential customers. The contingent valuation method asks respondents to state their WTP for a hypothetical service or product, asking respondents to make a direct assessment. While stated preference studies have several inherent issues such as hypothetical bias, Arrow *et al.* (1993) argue that a study that is carefully designed and properly conducted may provide a useful input into decision-making processes.

Because contingent valuation studies have several sources of uncertainty (Shaikh, Sun and Van Kooten, 2007), the elicited values of a commodity or service using different elicitation techniques, for example open-ended versus dichotomous choice techniques, can yield different estimates. Cameron *et al.* (2002) also compare elicitation techniques used in contingent valuation studies and argue that each technique has advantages and disadvantages relative to a given good or service. Here, we focused on open-ended technique and dichotomous choice technique, two of the most widely used techniques in value of lost load studies. Previous studies using the open-ended approach in other contexts have posed questions like, "what is the most that you would be willing to pay for a 3.5 ounce Cadbury solid milk chocolate bar?" (Kealy and Turner, 1993). While seemingly straightforward, the method has several well-documented limitations. The most important is that respondents have difficulty providing a precise number, and often do not feel confident with the numbers they do give, especially for things that are not familiar. Additionally, there is no incentive for respondents to provide their actual values. Indeed, they may believe that lower numbers may lead to lower prices. Thus, respondents tend to not respond to the question (because of its difficulty) or to under-report their values (for strategic reasons). In the dichotomous choice approach, respondents are asked "will you be willing to pay $X for the chocolate bar?" (Kealy and turner, 1993). Dichotomous choice can reduce strategic bias if done with an incentive-compatible mechanism (Mitchell and Carson, 1999). However, a respondent's agreement to a specific bid does not necessarily give their maximum WTP; instead a yes for a given bid provides a lower bound on WTP. Thus, the power of the dichotomous choice approach is relatively low (Alberini, 1995), and a larger sample size is required to identify the underlying distribution of WTP and accurately assess where respondents switch from "yes" to "no" (Cameron and Quiggin, 1994). Additionally, respondents may be anchored by the first dollar amount they are asked to accept or reject (called starting point bias), and may have a tendency to agree (called "yes-saying" bias).

As we briefly addressed, we assumed that people have rough preference for reliable electric services during WLD-outages even in the beginning of the study, and that the information and exercises we provide would help them better articulate their values, even if some of them had previously experienced long-lasting outages (because they may not have fully learned which services are and are not available in their communities and which electric appliances are critical and noncritical for them). However, we expected that some of the uncertainty will remain even after providing the information and exercises. This is because respondents may have additional interpretations of the scenario beyond the description provided in the survey (for instance, how cold will it actually be, what if having no TV is enjoyable, and how bad are frozen pipes really). Thus, forcing respondents to condense the uncertainty into a single response may result in inaccurate inferences about collective decision-making (e.g.

concluding that the society would accept the policy even if the society might be unsure).

Because traditional elicitation frameworks do not allow respondents to express their imprecise preferences, we used the multiple bounded discrete choice method, which increases the dimensions of both bid prices and decision responses, instead, because of its four major advantages. First, multiple bounded discrete choice provides a table which allows respondents to vote on a wide range of reference thresholds with more response options, allowing us to gather more data from each respondent and providing a more precise estimate of WTP per respondent[3] (Welsh and Poe, 1998). Second, the method addresses the high cognitive load of the open-ended response mode by only requiring simple "yes" or "no" answers to small ranges rather than the provision of a point estimate over the (infinite) range of positive numbers[4] (Welsh and Poe, 1998; Cubitt, Navarro-Martinez and Starmer, 2015). Third, we allow respondents to express uncertainty in their WTP by including a "not sure" column. Finally, Roach, Boyle and Welsh (2002) compare results from three different elicitation techniques –open-ended technique, dichotomous choice technique, and multiple bounded discrete choice method with three different ranges– and observe that all the results from multiple bounded discrete choice method fall between the estimates from open-ended technique and dichotomous choice technique. We expect that using multiple bounded discrete choice may help avoid both the potential underestimation problem from open-ended technique (due to cognitive loads and strategic bias) and overestimation from dichotomous-technique (due to yes-saying bias), and thus can provide more reliable estimates.

There are some drawbacks to the multiple bounded discrete choice method. For example, Roach, Boyle and Welsh (2002) determine that welfare estimates can be affected by the range of bids (range bias), and Alberini, Boyle, and Welsh (2003) suggest that the order of presentation can have a significant effect. However, Roach, Boyle and Welsh (2002) argue that a carefully designed survey can reduce some of the bid design effects. To that end, we conducted pilot tests to check whether the elicitation question works without providing additional information and whether for our scenario the range ($0 to $75) covers most of respondents' preferences. See Appendix A for the WTP questionnaires that we designed and used in the actual study.

3.3 Survey Results and Preliminary Use of the Elicited Values

We applied this method to a convenience sample of residents in Allegheny County, Pennsylvania. We conducted 73 face-to-face interviews between July and August 2015. These interviews took 1 hour on average. We found that the respondents valued a kWh for backup services they assessed to be high priority more than for those they assessed as lower priority ($0.75/kWh vs. $0.51/kWh) based on their own prior knowledge. As respondents received additional information about the partial (20 Amps)

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3 Discrete choice technique requires a larger sample size to achieve a distribution of WTP because the method asks respondents only one time if they are willing to pay the specified amount and receive the product (or service) or not.

4 Under open-ended format, respondents feel high cognitive loads because they have to answer specific numbers; thus, it generally ends up with a serious underestimation with a high level of uncertainty and higher non-response rates (Mitchell and Carson, 1989).

services available during an outage, this difference increased ($1.2/kWh vs. $0.35/kWh; see Figure 2-A). The respondents' uncertainty about their WTP (the differences between where their judgments switched from “yes” to “not sure” and “not sure” to “no”) decreased as they worked their way through the protocol (full: $11 to $9.0, partial: $13 to $11 on average; see Figure 2-B). This suggests that they progressively understood more about the blackout and backup services, and how much they cared about the services available with the partial backup service. Finally, we tested two important effects that have cast doubt on WTP numbers from contingent valuation studies – scope insensitivity and anchoring (Kahneman *et al.*, 1999), and introduced two conditions to check the consistency of respondents' preferences. Our checks suggested that ~90% of the respondents were consistent and systematic about their preferences and were not biased by their previous WTP responses. While there was no evidence that the respondents were anchored by their previous WTP statements, they demonstrated only weak sensitivity to the magnitude of service provided.

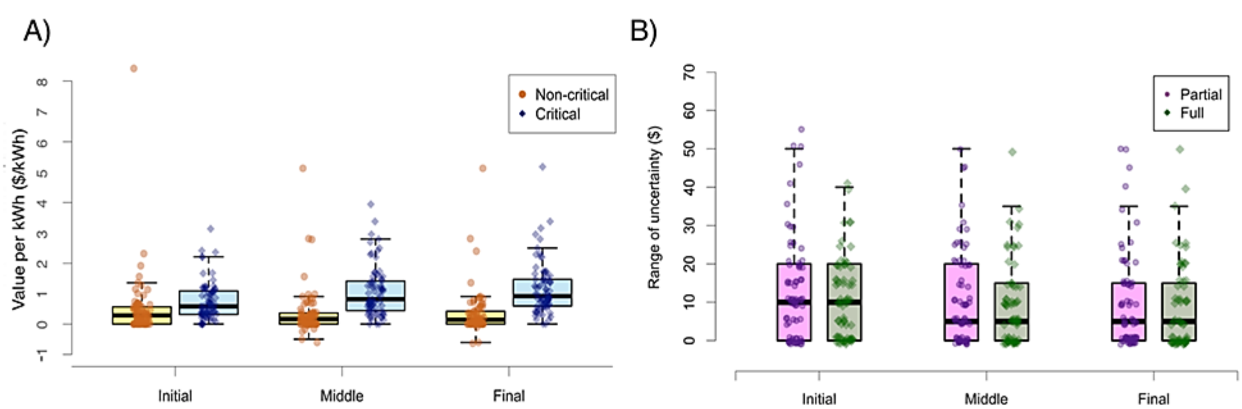


Figure 2. Two main findings from the face-to-face interviews. A) Distribution of the value per kwh to serve lower priority and high priority loads by stage over the course of the study (lower priority demands: left at each stage, high priority demands: right at each stage). B) Distribution of the range of uncertainty in the low-amperage (purple circle) and full (green diamond) backup service with boxplots after dropping the respondents who had WTP higher than $75 at each stage and backup service (partial: left at each stage, full: right at each stage). Both plots are adapted from Baik, Davis and Morgan (2018).

The considerable amount of consumer surplus suggests that a region might be able to substantially reduce interruption costs if, during a WLD-outage, distribution utilities or other relevant parties could find a way to continue to supply at least a small amount of electricity and cover most customers’ bare necessities. Using the values elicited from the survey, in the second paper, we performed a series of order of magnitude calculations (Baik, Morgan and Davis, 2018).[5] Under many circumstances, it appears that implementing the backup service is more cost-effective than buying a small portable generator and storing diesel or gasoline for fueling.[6] As expected, we also found that the service payment needed to

[5] Because we wanted to use the respondents’ preferences after they had gained a full understanding of the outage scenario and its implications, we used the final “sure” WTP values in this analysis.

[6] ~$290 for purchasing a generator and ~$52/outage for gasoline if gasoline costs $3/gallon. See for example http://www.amazon.com/DuroStar-DS4000S-4-Cycle-Portable-Generator/dp/B004918MO2. Accessed 2018 Jan 08.

justify the backup service would be substantially decreased if a region is expected to suffer more frequent and longer widespread outages.

Understanding private WTP is important in assessing the viability of backup service. However, an approach that only provides service to those prepared to pay for it raises issues of social equity. For that reason, we briefly considered two methods to recover the system upgrade costs so that all customers might be served: 1) adding a very small monthly “backup service insurance charge” (<$1/month) to all customer bills, and 2) covering the incremental cost of the upgrade with general tax revenues ($120/household for the lifetime of technologies, which is assumed to be 20 years). While each residential customer would still be responsible for paying for the power during an outage (~$10/day), both methods can be implemented without excessive burden to either residential customers or the region without raising a serious equity issue. Moreover, the backup service would become more feasible and advantageous when considering non-monetary benefits such as decreased injuries and fatalities and equity that we did not include in the assessments.

In sum, we found that there is considerable consumer surplus for small amounts of electricity to power the most important residential loads, and showed that implementing the ability to provide a low-amperage backup service via islanded distribution feeders may make sense in some regions that face a significant risk of WLD-outages. Measurement of that surplus depends on the public having accurate information about blackouts and their consequences.

4. Web-based Survey Framework

4.1 Why Develop a Web-based Survey Framework?

As explained in Section 3, our previous study developed a survey framework that helped residential customers think carefully about a specific WLD-outage and reflect systematically (Fischhoff, 1991) on how much they would value full and partial backup service during that outage. We applied this method to a convenience sample of residents in Allegheny County, Pennsylvania (73 face-to-face interviews conducted between July and August 2015). The face-to-face interviews in our first study worked quite well, but the study had three important shortcomings. First, the method required a great deal of interview time (averaging ~1 hour per interview), so it cannot be readily applied to explore other scenarios. Second, while other scenarios and durations could be studies, this first study only considered an outage of 24 hours on a hot summer weekend when there is no significant chance of loss of life or property. However, the consequences of having almost no backup services for longer periods (e.g., a week or more) are likely to be very different than that of shorter periods (e.g., a day or two), both economically and socially (Apt *et al.*, 2004). As Figures 3-A and 3-B indicate, such outages do occur. Third, in our initial design we focused only on individual homeowners’ WTP to avoid service interruptions to their own homes. In the absence of WTP estimates for supporting neighbors and critical social and private services, in Baik, Davis and Morgan (2018), we explored the issue by making plausible extrapolations from the 24-hour WTP results (varying respondents’ WTP for their private demands by ±20%); however, such analyses could be substantially improved if the actual values were available. In that paper, we also briefly discussed two methods which fully recover the system upgrade costs without raising a serious social equity issue (either by assuming that all the households that are not supported by financial assistance programs for energy bills share the burden equally or by using general tax revenues so that the burden can be distributed in a roughly proportional manner). These are concerns that warrant more careful consideration that we will continue to work on in the future.

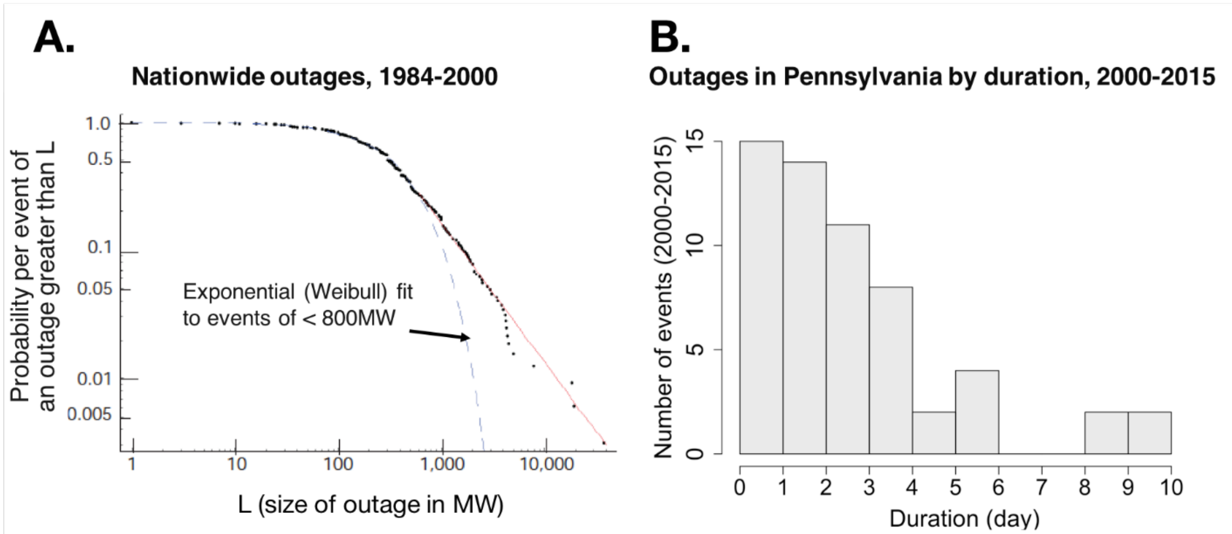


Figure 3. Large blackouts are more common than one might expect. A) Distribution of large blackout in the United States during the period from 1984 to 2000 (data compiled by North American Electric Reliability Corporation, figure reproduced from Talukdar *et al.*, 2003). B) Distribution of large blackouts (outages affecting more than one distribution utility or more than one state) in the state of Pennsylvania during the period from 2000 to 2015 (data compiled by the United States Department of Energy). Plots are adapted from Baik, Morgan and Davis (2018).

To overcome some of these shortcomings, we have developed a web-based interview tool that we believe makes it easier to conduct studies that explore the WTP of residential customers under a variety of scenarios in different locations for WLD-outages of different durations. Online surveys are considered to be cost-effective, time-efficient, easy to use and administer, and able to reach a larger population sample (Krantz and Dalal, 2000; Reips, 2000, 2002; Kraut et al., 2004; Evans and Mathur, 2005; Skitka and Sargis, 2006). At the same time, such surveys also have drawbacks such as low response and completion rates, sampling bias, and issues involving privacy and ethics (Stanton, 1998; Couper, 2000; Best et al., 2001; Nosek, Banaji and Greenwald, 2002; Sills and Song, 2002; Evans and Mathur, 2005; Marta-Pedroso, Freitas and Domingos, 2006).

4.2 Overview of the Web-based Survey Design

To obtain the judgments of individuals about their economic and social preferences for a low-amperage backup service in the event of a large blackout of long duration, we modified our earlier design. We have now completed multiple rounds of pilot testing to minimize the potential influences from the visual and verbal elements (Dillman and Smyth, 2007). The technical specification of the survey platform developed to conduct the survey is provided in Section 4.3.

Figure 4 below summarizes the design of our elicitation approach. Because our previous study revealed a wide range in peoples' WTP due to different electricity use profiles, demographics, and needs, we focused on one scenario for each of the two emerging threats that result in the same consequences: a WLD-outage that lasts long enough during cold winter and impose significant economic and social costs. One of the major differences between the face-to-face survey and the web-based survey is that we dropped the full backup service and we only provide the partial backup service. We removed the full backup service because: 1) the results from our first study already suggested that the value of serving high priority demands was significantly higher than that of lower priority demands, 2) most regions do not have sufficient DG to serve full power to all residential customers during WLD-outages (installing enough DG would be technically feasible but in most cases not economically viable), and 3) the respondents did not display anchoring bias but demonstrated only weak scope insensitivity. Following the changes, we only ask respondents' WTP for the partial backup service, thus, unlike our face-to-face study, we cannot test for scope insensitivity in results from this study. However, scope insensitivity turned out not to be a serious problem in the face-to-face study. We did keep a consistency check for whether the WTP for electricity backup per kWh is greater than or equal to the normal electricity cost ($0.11/kWh).

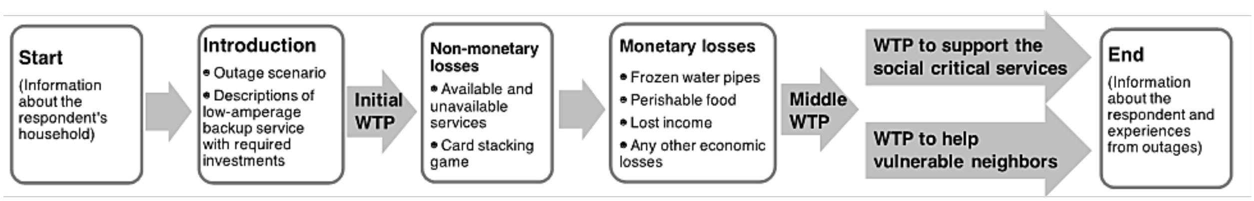


Figure 4. Overview of the elicitation design indicating the information and exercises that we will provide in four different stages (white boxes) and when we pose questions (grey arrows).

In the introduction to the first application of this new tool, we ask respondents to assume that one of the two emerging threats have damaged a number of critical high voltage transformers and caused a WLD-outage across the Northeastern and Midwestern United States and Southeastern Canada during a period of very cold winter weather. This initial scenario states that it will take 10 days for power to be fully restored in the affected regions. We also ask respondents to assume that federal and state governments have declared a state of emergency in response to the event so that they can evacuate severely ill or injured patients or residents with disabilities immediately and distribute essential commodities within few days (see Figure 5 below)

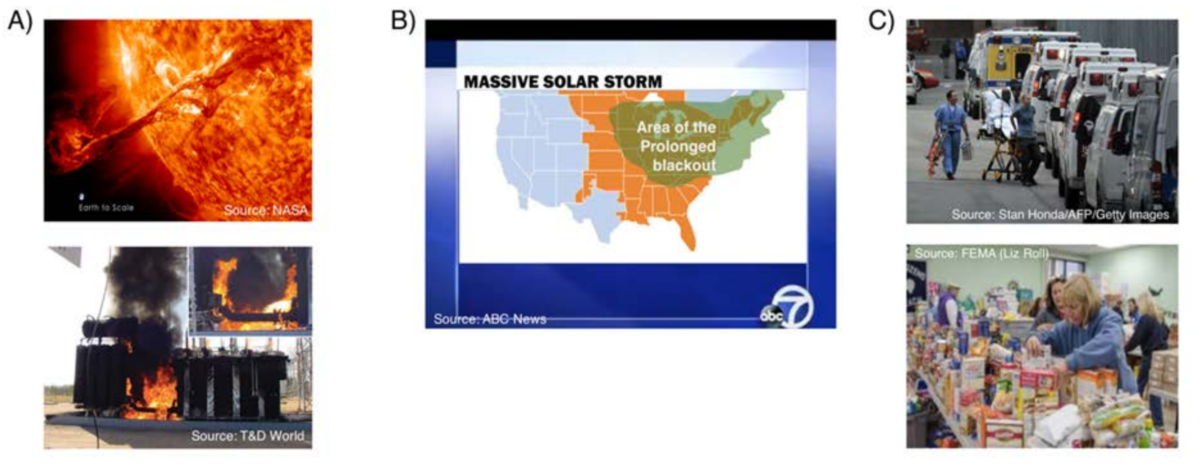
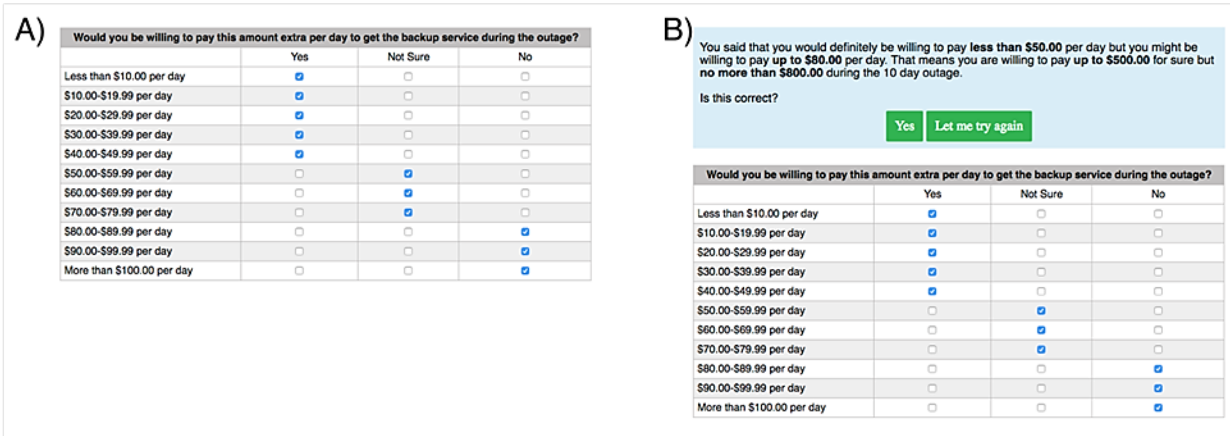


Figure 5. Example images used in the video briefings for our survey instrument for the case of a hypothetical solar storm blackout. A) We tell respondents that there was a massive solar storm that hit the earth during the early morning hours (top) and damaged critical high voltage power transformers (bottom). B) We assume that the event caused a 10-day large regional blackout across the northeastern and Midwestern United States and Southeastern Canada. C) We also tell respondents that federal and state governments have declared a state of emergency so that they can immediately evacuate severely ill or injured patients and residents with disabilities and distribute emergency supplies. The only difference between the solar storm and a second scenario involving a terrorist attack is the cause of the blackout (we assume that the large regional blackout was occurred by a series organized terrorist attacks on electric power system while all the other information remained the same).

After introducing the blackout scenario, our system then explains that people living in the affected region can receive low-amperage backup service through "smart grid" technology. After introducing the scenario and the low-amperage backup service, we ask respondents' WTP to receive the backup service for their own electricity consumption during the 10-day outage using a multiple bounded discrete choice method with a follow-up check (see Figure 6 below). For any respondent whose WTP is very high and marks the entire "yes" column, we ask a follow-up open-ended question: "what is the number that best represents the maximum amount you would be definitely be willing to pay (per day)?".


A)

Would you be willing to pay this amount extra per day to get the backup service during the outage?	Yes	Not Sure	No
Less than $10.00 per day	☑	☐	☐
$10.00-$19.99 per day	☑	☐	☐
$20.00-$29.99 per day	☑	☐	☐
$30.00-$39.99 per day	☑	☐	☐
$40.00-$49.99 per day	☑	☐	☐
$50.00-$59.99 per day	☐	☑	☐
$60.00-$69.99 per day	☐	☑	☐
$70.00-$79.99 per day	☐	☑	☐
$80.00-$89.99 per day	☐	☐	☑
$90.00-$99.99 per day	☐	☐	☑
More than $100.00 per day	☐	☐	☑

B)

You said that you would definitely be willing to pay **less than $50.00** per day but you might be willing to pay **up to $80.00** per day. That means you are willing to pay **up to $500.00** for sure but **no more than $800.00** during the 10 day outage.

Is this correct?

Yes | Let me try again

Would you be willing to pay this amount extra per day to get the backup service during the outage?	Yes	Not Sure	No
Less than $10.00 per day	☑	☐	☐
$10.00-$19.99 per day	☑	☐	☐
$20.00-$29.99 per day	☑	☐	☐
$30.00-$39.99 per day	☑	☐	☐
$40.00-$49.99 per day	☑	☐	☐
$50.00-$59.99 per day	☐	☑	☐
$60.00-$69.99 per day	☐	☑	☐
$70.00-$79.99 per day	☐	☑	☐
$80.00-$89.99 per day	☐	☐	☑
$90.00-$99.99 per day	☐	☐	☑
More than $100.00 per day	☐	☐	☑

Figure 6. Example response format used in eliciting respondent's WTP. A) In this example, the respondent indicates that (s)he would surely pay at least $50 per day and might be willing to pay as much as $80 per day for the low-amperage backup service during the 10-day blackout. B) After the respondent indicates his or her WTP using the table, a blue follow-up box comes up above the table to make sure that the respondent really understands the concept of total service payment (in this case, the respondent need to pay up to $500 for sure but no more than $800 since the outage duration is 10 days).

Following this initial WTP assessment, we provide information describing what services will and will not be available in respondents' homes and communities during the blackout. After that, we ask respondents to engage in an "electric appliance stacking game" which is similar to the one we used in our face-to-face interviews. In this way, respondents can construct their personal load under limited availability (< 20 Amps for the entire house) as a function of time of day (see Figure 7 below and Baik, Davis and Morgan (2018) for details).

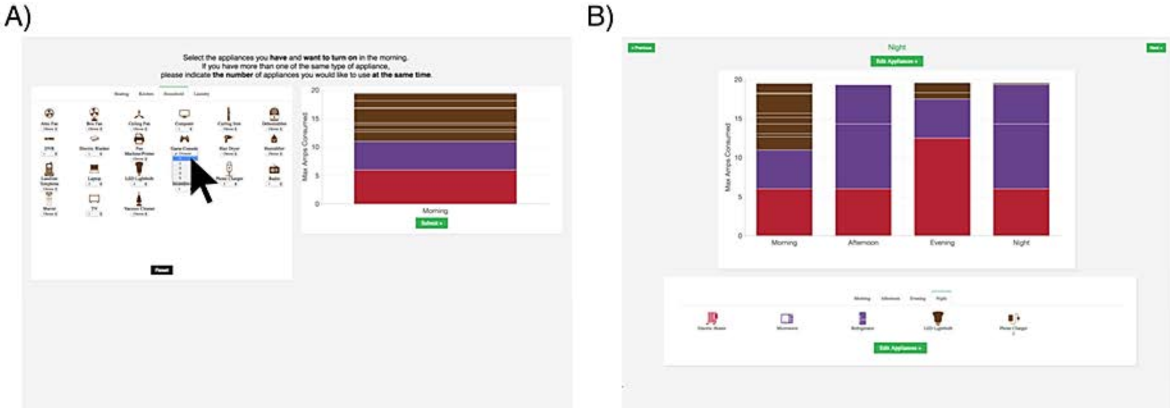


Figure 7. The online version of electric appliance stacking game. A) Each respondent is asked to select electric appliances (s)he has and wants to use during each time period. Each electric appliance belongs to one of the four subcategories (heating, kitchen, household, and laundry). After an appliance is selected the system stores its power consumption data. The height of each bar in the graph on the right side is proportional to the resulting current in Amps. The respondent can select any combination of electric appliances as long as the total current required is under the 20 Amps limit. B) After constructing their electricity consumption profile, the respondent has an opportunity to review the selected appliances and revise his or her selections if needed.

Because these first scenarios studied involve a 10-day blackout with temperatures below freezing, we next explain and ask respondents to estimate their economic losses including frozen water pipes, lost perishable food, lost income, and any other economic losses. Figure 8 shows the images we use to help respondents understand the risks of frozen water pipes, and how they can store and consume food safely during the outage. These exercises are followed by a second private WTP question for the backup service.

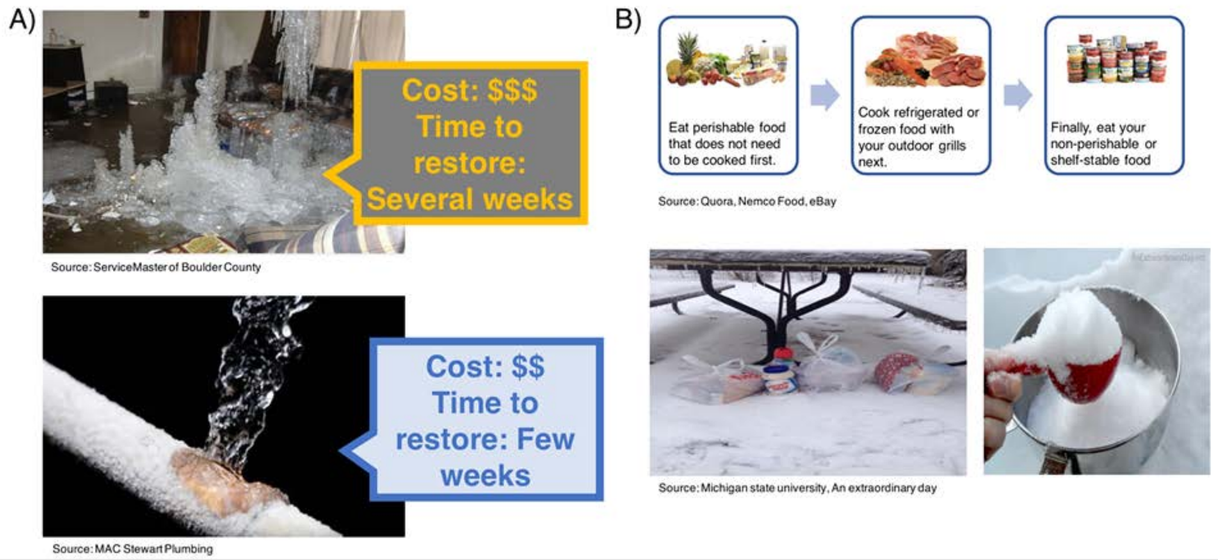


Figure 8. Example images used in the video explaining the monetary losses that respondents may suffer during the hypothetical blackout. A) We explain that respondents' water pipe will start to freeze and burst if they cannot get some heat or drain their pipes, and getting repairs done once the power comes back will take many weeks and costs a lot (top); we also tell them that they can sufficiently reduce their monetary losses and repair time if they can manage and drain most of the system (bottom). B) We introduce several strategies to consume respondents' perishable and non-perishable food until they receive emergency supplies from government (top) and to store their perishable food safely utilizing the cold weather (bottom).

Finally, we pose two questions that ask about the social value of backup service. Understanding private WTP is important in assessing the viability of backup service, but an approach that provides a service only to those who are prepared to pay for it raises issues of social equity. Also, we tell respondents to assume that many key private and public social services will not be prepared to cope with a WLD-outage (Apt et al., 2004). In other words, only a few critical private and social services that have their own backup generators and enough fuel or emergency backup supply contracts can be minimally operated (such as a few gas stations which have emergency backup generators, 911 and related dispatch centers and hospital emergency rooms), but most other services will not work immediately or may stop working after a few days. Having very few critical private and social services during an extended blackout would not only impose costs on individuals but also impose large collective social costs, especially for vulnerable segments of the population who may not be prepared for such outages (for instance, the flooding and ice storm of January 1998 struck Southern Québec, Ontario and the Northeastern United States, blacked out 2.3 million customers, and caused damages of $4.4 billion and 56 death, mostly because of carbon monoxide poisoning; NOAA, 2017). To that end, we ask respondents' WTP to support their neighbors directly (by supporting their vulnerable neighbors) and indirectly (by sustaining critical social services in addition to what they want to pay for their own private demands), and wrapped up the study.

The full online survey can be accessed at http://power.andrew.cmu.edu:5021/, select "Individual participants with participation code" and then enter "TestSurvey2018".

4.3 Web-development Technical Details

Rather than use one of several existing standard (textual) survey platforms (e.g., Qualtrics, Survey Monkey, or Google Forms), we developed our own web-based survey platform. We did this is to support responsive and interactive functions (such as informative popup messages, online electric appliance stacking game, and responsive WTP questions using multiple bounded discrete choice method and follow-up open -ended questions). The survey was implemented as a web application mainly built with HTML, CSS, and JavaScript for the frontend (i.e., respondent interface), Node.JS backend framework for the server (i.e., the backend processor), and a NoSQL database (integrated with Amazon AWS environment) to store the information about respondents and their survey responses.

The survey is divided into several pages to reduce the loading time, and the load on the web browser. In order to provide a consistent look and feel throughout the survey, all pages use the same basic design template defined in CSS files provided by a professional designer. Some pages provide informative pop-up messages or additional questions based on the respondent responses. These features are programmed in JavaScript. Some parts of the design and features use Bootstrap.

There are several features implemented in the platform to maintain integrity of the survey responses: 1) input validation, 2) timestamps, and 3) flow control.

- **Input Validation**: The server validates submitted responses from a respondent using a predefined set of validation rules for each page and question. Whenever a respondent wishes to move on to the next page by clicking the next button, the browser transmits the response to the server in a HTML POST request. The server will enforce a set of validation rules for each request. If a response passes all the validation checks, the responses will be saved in the database and the respondent will be allowed to move on to the next page. Otherwise, error message(s) will be returned to the respondent's browser to instruct the respondent to fix the error(s). Most of validation rules are specified in Validate.JS framework format, but some of them are manually programmed in the server code.
- **Timestamps**: The server stores a timestamp when a respondent starts the survey and completes the survey. This allows the administrator to verify whether the respondent has taken a reasonable amount of time to answer the questions, and to reject responses that are completed too rapidly or too slowly.
- **Flow Control**: To maintain consistent experience with the survey across all respondents, the server also validates whether a respondent accesses and answers questions in the proper order. This will prevent respondents from skipping a page or returning to a page to modify their answers.

The survey platform allows several methods for a respondent to start the survey. Different methods exist for each of the different ways the respondents are recruited and compensated for participating in the survey. A respondent recruited from Amazon Mechanical Turk (MTurk) needs to provide their

MTurk worker id. A respondent recruited through an organization needs to select their organization name and provide the organization-specific code. The administrator can add or remove organizations as needed. A respondent recruited from mail-out surveys or through social media would provide the validation codes provided in the recruiting advertisements. The information used by each respondent is stored in the database to provide compensation after completion of the survey.

Once a respondent provides the log-in information, the respondent is presented with the informed consent form with the agreement questions (stage 1 of Figure 9) and the questions to determine their eligibility (stage 2 of Figure 9). If the responses are not satisfactory, the respondent will be marked ineligible to participate the study, and the browser will redirect the respondent to the final page. If a respondent is eligible, then the server will internally conduct two coin flips to determine which of the two outage scenarios to use and the order of social WTP questions, and store the result of flips in the database (see Figure 10 below). When the respondent reaches the stage of the survey that is customized to an outage scenario, or social WTP questions, the server will use the result in the database to render appropriate page to the respondent's browser.

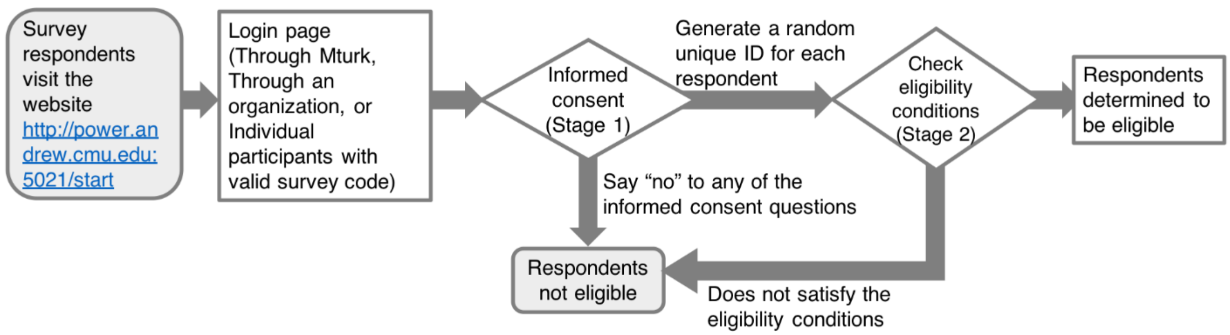


Figure 9. Sequence to create the survey and check the eligibility conditions.

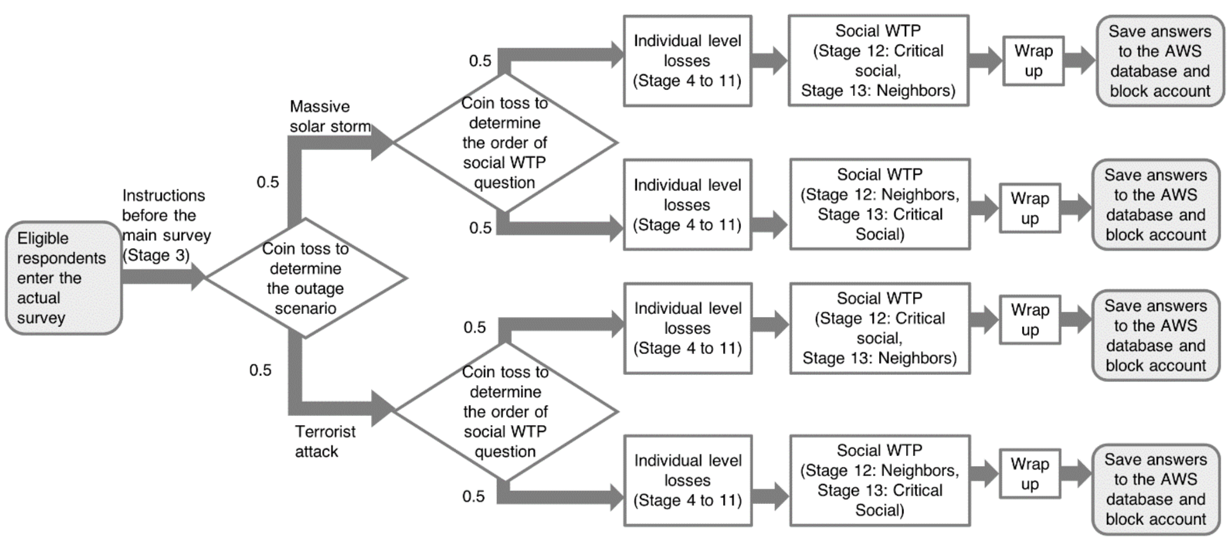


Figure 10. Sequence of interactions for the eligible survey respondents as the survey proceeds.

There are two crucial components of our survey that are not provided by the conventional survey platforms: the specialized response modality for WTP questions and the electric appliance stacking game. The screen capture of the response modality interface for WTP questions is shown in Figure 6. It involves a collection of three columns of checkboxes in a table. It has been enhanced to make it easier for respondents to express their WTP. Whenever the respondent checks/unchecks a checkbox, a JavaScript code automatically checks/unchecks other boxes in the table to maintain invariants. For example, if the respondent is willing to pay up to $50, then the respondent must also be willing to pay any amount less than $50. Thus, when the respondent checks $40-50 checkbox, the code will also automatically check $0-10, $10-20, $20-30, $30-40.

As described in Section 3, the electric appliance stacking game is a digitized version of the game in Baik, Davis and Morgan (2018). The screen capture of the game is shown in Figure 7. Both screens (Figures 7-A and 7-B) contain a list of names along with graphical depictions of household appliances. The properties of an appliance (icon, name, electricity consumption) and the list of appliances used in the game can be customized by the administrator. A chart library called Chart.JS has been used to generate the bar charts. Most of the interaction occurs in first screen (Figure 7-A). Whenever the respondent selects a new appliance or changes the number of appliances to use, the code recalculates the consumption and rolls back to the previous state if the consumption exceeds the pre-specified limit (which is 20 Amps in this study), otherwise the height of the bar in the chart will be adjusted to reflect the updated selections and the respondent's electric consumptions. When a user submits their selection by clicking the next button in the first stage without including some of the critical appliances (e.g., heater, water heater, or refrigerator), the game will show a confirmation message to remind the user that (s)he is missing what may be considered a critical appliance. Also, if a respondent does not select any appliance from Heating, Kitchen or Household category, the game also will show another confirmation message as a reminder. A second screen will display all information collected from respondents to date: a bar showing electric consumption per time period, and a list and number of appliances selected for each time period. The exercise is then repeated for each of the four time periods

5. Survey Plan and Research Questions

Using the web-based elicitation framework, we are in the process of eliciting residents' value of reliable electric services against WLD outages for residents in the Northeastern United States for the specific 10-day outage scenario. To participate in the study, respondents must be: 1) 25 years old or older, 2) have lived in Northeast region (one of Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey and Pennsylvania) for at least two years, and 3) be aware of, or responsible for their homes' electricity bills. The criteria for eligibility were tested in the pilot tests (for both face-to-face surveys and online surveys) and the face-to-face surveys, and then slightly modified before the actual implementation.

We are using several strategies to recruit survey respondents. MTurk is the largest and most often used subject-recruiting tool because of its low-cost time-efficiency, but MTurk users are assumed to be different than the general population. Previous studies show that MTurk users are often young, female, more liberal, more educated, and earn less than other internet-based convenience samples or national probability samples (Berinsky, Huber and Lenz, 2012). Thus, it would be difficult to have an appropriate representative sample if we only recruit respondents using MTurk. Instead, to obtain a more representative sample of Northeastern residents and electricity customers, we have not only advertised the study through MTurk but also have used address-based sampling and postal mail to request to respond over the Internet (Messer and Dillman, 2011). To select households, we first used https://openaddresses.io/ to randomly draw addresses (proportional to the population of each state) and then verified the validity of the addresses as residential. To increase the response rate, we sent $2 prepaid cash incentive with the cover letter first and then sent follow-up postcards after one week (Messer and Dillman, 2011).

Using the elicited preferences from respondents, we will test several research hypotheses such as whether the nature of the initiating outage event matters, even though the outage consequences are essentially identical. To date, we have recruited 202 respondents from MTurk. Preliminary results suggest that, as in the face-to-face study, providing more information helped the respondents think thorough the costs and inconveniences that they are likely to experience during the 10-day outage (for sure one-time WTP per day for the 20 Amps backup service: $32 to $49 on average, not sure one-time WTP per day: $50 to $69 on average; all $p<0.05$ from paired t-test after log-transformation), and significantly decreased the respondents' preference uncertainty (from $20 to $16 on average; $p<0.05$ from paired t-test after log-transformation). It also is beginning to look like the nature of the two initiating events may not have a large effect on the responses. More in-depth analyses will be conducted after finishing recruiting more respondents through mail advertisements.

Understanding the preferences of Northeast residents who have not experienced WLD-outages before is important, but it is also important to include people in our sample who have experienced extreme weather events along with WLD-outages so as to assess the extent to which respondents' previous experiences influence their preferences and WTP for electric services. Obviously, one of the best representative events is the extended outages that occurred as a result of Hurricane Sandy. To that end, we are in the process of contacting research groups that have conducted Hurricane Sandy survey studies (including World Trade Center Health Registry, with whom we have a proposal pending for access to their participation pool, and the New York City Department of Health and Mental Hygiene) in order to recruit a sample of Northeast residents who experienced the outages caused by Hurricane Sandy. The responses from respondents who experienced extreme weather events and WLD-outages will help us to understand what influence their real-life experiences with extreme weather events has had on the value they assess for limited reliable electric services and their economic and social preferences for a low-amperage backup service.

6. Discussion

6.1 Risks to the Power System, and Making the Power System More Reliable and Resilient

The incremental investment needed to provide a low-amperage backup service during outages may be too costly for many service territories, but some regions that face a significant risk of long outages may be interested in implementing a low-amperage backup service to reduce their vulnerability. As the Table 1 below shows, large outages were or could be caused by many kinds of events including natural disasters, operation errors, and pernicious physical- or cyber-attacks (National Academy of Science, Engineering and Medicine, 2017).

Table 1. The events that have caused or could cause large outages to the power system (Adapted from National Academy of Science, Engineering and Medicine, 2017, page 2).

	Events that have caused large outages over the last 30 years	
	Human induced	Natural disasters
Causes/Events	Physical attack	Drought and associated water shortage
	Cyber attack	Earthquake
	Operator or operation errors	Flood and storm surge
		Hurricane
		Ice storm
		Regional storms and tornadoes
		Space weather and other electromagnetic events
		Tsunami
		Volcanic events
		Wildfires

After reviewing the historical electric disturbance events (Office of Electricity Delivery and Energy Reliability, 2017) and the emerging threats to the major electric power system, we identified five representative risks which could result in widespread losses of electric power for extended periods of time:

- *A Series of Physical and/or Cyber Attacks on the Bulk Power System*.
- *Solar Storm Disruption of the Bulk Power System*.
- *Seismic events (especially Southern California)*.
- *Tropical Cyclones in the Southeastern Coastal Region (e.g., Florida, the Carolinas, and the Gulf Coast)*.
- *Ice Storms in the Northeast US and Southeast Canada region (e.g., upstate New York)*.

In the study, we have focused on the two emerging threats – terrorist attacks and solar storms for the following two reasons. First, there have been several efforts to estimate the economic and social impacts and mitigate the impacts of earthquakes, tropical cyclones and ice storms (Oklahoma Corporation Commission, 2008; Brown, 2009; Shaw Consultants International, Inc. 2010), but fewer studies have devised strategies to mitigate the risks posed by the terrorist attacks and large solar mass ejections to the bulk power system, and none have explored individual customer WTP for such events. Second, because terrorist attacks and solar storms could cause a major disruption to the bulk power system *without* damaging distribution circuits, providing a low-amperage backup service with modest system upgrades is more straightforward for these cases. For that reason, we considered a large regional blackout resulting from either organized terrorist attacks or a massive solar storm. Both scenarios are framed in terms of a very cold 10-day period in the northeast region when temperatures are below freezing so that there is for example a serious risk of economic and life losses.

6.2 Using the Web-based Survey Framework to Explore People's Preferences Under a Variety of Scenarios

While we have designed two specific hypothetical outage scenarios and are using them to elicit respondents' WTP to receive 20 Amps limited backup service during those outages, the survey framework can be generalized to support a wide variety of scenarios including outages of different durations, in different seasons, different locations, different levels of backup service coverage, and under a variety of emergency conditions. Once this system has been demonstrated, it is our hope that other researchers, as well as electricity-related decision-makers, will be able to use it design their own scenarios to elicit the value of reliable electric services in the context of their own interests and needs. For instance, this might include studies focused on specific customer segments, such as those that are particularly vulnerable. For instance, if a decision-maker is interested in the value of reliable electric services of a specific customer segments, decision-makers would be able to design few outage scenarios that threats the customer segments, customize the information and exercises that might be useful for the customer segments' value articulations, conduct studies, and use the results to develop strategies for enhancing the targeted customers' resilience.

One of the other benefits of the survey framework is that researchers can use the elicited preferences to generate customer damage functions. According to de Nooij, Koopmans and Bijvoet (2007) and Sullivan, Mercurio and Schllenberg (2009), residential customers' value of reliable electricity is determined by the three factors:

- Customer-related factors: perceived level of reliability and level of preparedness, one's electricity consumptions, level of inconveniences from prolonged outages, and one's demographic characteristics (income, household composition, house type, work from home, etc.);
- Interruption-related factors: The time when an outage occurs (weekday or weekend, weather, and time), the length of an outage, advanced notification of an outage (planned or unplanned), and the reason for an outage; and,
- Environmental factors: the region's level of risks from various natural disasters and system failures, and external/climate conditions during an outage.

In this first illustrative example, we fixed all the interruption-related factors and some of the environmental factors by using two detailed scenarios (i.e., we fixed the outage duration to 10 days, amount of coverage to limited (20 Amps to all the residential electric customer and full service to selected critical social services) and elicited the economic and social value of sustaining critical demands). However, the survey framework can be applied to many other scenarios, and the results from a wide variety of scenarios can be used to obtain residential customers' damage function. For instance, if decision-makers and relevant stakeholders are interested in understanding when the economic and social costs of WLD-outages substantially increase and justify some incremental investment, they would be able to conduct a series of studies with different outage durations while fixing all the other factors, such as amount of coverage, customer-related factors, and other interruption-related factors. Similarly, decision-makers who are interested in understanding the marginal value of reliable electric services would be able to conduct studies with different backup service coverages and see how much the value of backup power per kWh decreases as the amount of electricity provided increases.

In collaboration with other utilities and researchers in other regions, it would be possible to generate a customer damage function for residential customers in general. Using the function, decision-makers such as distribution utilities, distributed generation companies and suppliers, backup service providers, and smart-grid companies would be able to explore when upgrades in advanced distribution systems might be justified on economic grounds. Also, the framework could be used to elicit insights about the value of sustaining not only critical private demands but also social services (researchers can determine a specific set of social services that they think are important and want to sustain during the entire outage just like we did, but they can also assign some amount of power to social services and cycle on and off critical social services during the outage like Narayanan and Morgan (2012) suggest). Thus, by using respondents' social WTP to sustain such services, decision-makers and relevant stakeholders may also be able to roughly construct social damage functions and gain insight about how much and how long (if at all) should electricity be provided to social services.

Our current study is focused on eliciting the value of reliable electric services for residential customers, but the results could be combined with the interruption costs of industrial and commercial customers. By aggregating the value of reliable electric services from all the electricity customer groups, decision-makers should be able to make more informed investment decisions that incorporates all the electricity customers in a region and minimizes the entire economic and social impacts in the region.

6.3 Structuring Decision Problems: Benefits and Costs from Implementing a Low-amperage Backup Service

The considerable amount of consumer surplus that we are finding suggests that a region might be able to reduce interruption costs by providing a low-amperage backup service and sustaining critical private and social services; however, implementing such ability requires substantial investment especially in the beginning of the project (Silverstein, 2013; Baik, Davis and Morgan, 2018). Note that we only considered the direct benefits from implementing the low-amperage backup service (i.e., service payments at the time of each outage) and did not include other benefits such as reduced interruption costs of both major and minor outages and monetary benefits from increased efficiency and reliability during normal circumstances.

6.3.1 Required Technical Features to Provide a Low-amperage Backup Service

A region cannot completely avoid extreme events and natural disasters, but when there is a failure in bulk power system, distribution system or micro-grid operators might be able to take some proactive actions and mitigate the consequences. Here we are not simply interested in lessening the likelihood or number of WLD-outages but rather interested in limiting the scope and impact of those outages when they do occur, managing and coping with the events during the outages, restoring power rapidly after, and learning to better deal with other events in the future (National Academies of Science, Engineering and Medicine, 2017). That means we should put more effort into enhancing power system resiliency so that we can better deal with WLD-outages. There are several strategies to make the distribution power system more reliable and resilient.

With conventionally fed radial distribution feeders, customers in a distribution feeder may not be able to receive their electric services if anything happens in the bulk power system. With modest upgrade to advanced distribution systems, a region could operate a distribution feeder or a few distribution feeders as an isolated island and provide at least low-amperage backup service even if there is no power available from the central grid. As mentioned earlier, in the scenarios we are now studying we assume that the events leave the entire distribution system for the region intact; thus, we have focused on enhancing system operation and control, specifically in introducing modern smart technologies. However, if regions are expected to suffer extreme events that also damage critical distribution system components, they also need to consider implementing other strategies such as hardening critical but vulnerable infrastructure and establishing redundancies.

6.3.2 Costs and Benefits Associated with the Low-amperage Backup Service[7]

For the purpose of illustration, we considered implementing a low-amperage backup service for a distribution feeder that serves 2,500 customers. Following the assumptions described by Narayanan and Morgan (2012) and Baik, Morgan and Davis (2018), the total cost of implementing the ability to provide the low-amperage backup service can be calculated as follows:

[7] Portions of the text in this section are adapted and extended from Baik, Morgan, and Davis (2018). In Baik, Morgan and Davis (2018), we considered the residential customers' fixed payments to sustain their private critical demands and made plausible extrapolations from the 24-hour WTP results to explore the issues of supporting neighbors and other local social and private services. Here, we proposed using the elicited respondents' WTP to support vulnerable neighbors and critical social services instead of using respondents' private critical demands.

$$
\begin{aligned}
&Total\ incremental\ investment\ cost \\
&\quad = System\ upgrade\ cost + \ Annual\ O\&M\ cost + \\
&\quad\quad Smart\ meter\ upgrade\ cost\ for\ residential\ customers + \\
&\quad\quad Smart\ meter\ upgrade\ cost\ for\ critical\ social\ servies + \\
&\quad\quad Total\ fuel\ cost\ for\ residential\ customers + \\
&\quad\quad Total\ fuel\ cost\ for\ critical\ social\ services
\end{aligned}
$$

$$
= \$100{,}000 + \sum_{i=1}^{20} \frac{5{,}000}{1.03^i} + 2{,}500 \times 50 + 20 \times 40 + \sum_{i=1}^{n} \frac{9.8 \times 2{,}500 \times Year_i}{1.03^{Year_i}} +
$$

$$
\sum_{i=1}^{n} \frac{\$0.17/kWh \times 20A \times 120V \times \frac{1}{1000} Wh/kWh \times 24 hours \times (outage\ duration) \times 2{,}500 \times Year_i}{1.03^{Year_i}} +
$$

$$
\sum_{i=1}^{n} \frac{\$0.17/kWh \times (kWh\ required\ to\ sustain\ critical\ social\ services\ per\ day) \times (outage\ duration) \times Year_i}{1.03^{Year_i}}
$$

where n=number of outages during the lifetime, and $Year_i$*= Year when the* i^{th} *outage occurs*.

The value of sustaining high priority demands during WLD-outages can be estimated by the respondents' measured WTP to assure a low-amperage backup service. We assumed that all the residential customers make fixed payments for their own homes and community separately at the time of each outage. In case of low-income households who are already supported by low income home energy assistance programs, we assumed that their service payments are also covered by the programs. Then the total benefits from implementing the backup service can be calculated as follows:

$$
\begin{aligned}
&Total\ benefit = Benefits\ from\ private\ backup\ service + \\
&\quad\quad Benefits\ from\ social\ backup\ service
\end{aligned}
$$

$$
= \sum_{i=1}^{n} \frac{2{,}500 \times Service\ payment\ per\ day\ for\ private\ demands \times (outage\ duration_i)}{1.03^{Year_i}} +
$$

$$
\sum_{i=1}^{n} \frac{2{,}500 \times Service\ payment\ per\ day\ for\ vulnerable\ neighbors \times (outage\ duration_i)}{1.03^{Year_i}} +
$$

$$
\sum_{i=1}^{n} \frac{2{,}500 \times Service\ payment\ per\ day\ for\ critical\ social\ services \times (outage\ duration_i)}{1.03^{Year_i}}
$$

where n=number of outages during the lifetime, and $Year_i$*= Year when the* i^{th} *outage occurs*.

While we used the respondents' WTP to secure their private demands and homes to estimate the monetary benefits and their WTP to help their vulnerable neighbors and community to estimate the monetary social benefits, securing social critical demands also generates non-monetary private and social benefits including reduced injuries and deaths, especially from vulnerable segment of population who are often not prepared for extreme events nor able to afford high costs of the backup service. Those non-monetary benefits may be able to be roughly estimated from archived data of historical outages (such as, fatalities and injuries with few plausible assumptions from previous blackouts that occurred under similar conditions; Corwin and Miles, 1978).
Using the estimated costs and benefits, researchers can perform a series of order of magnitude calculations and examine whether such investments might be justified under various assumptions about outage frequency and duration. Decision-makers and relevant stakeholders could use the results

to inform general investment decisions about the distribution system upgrades. For instance, if the results suggest that residents have strong preferences for reliability (i.e., reduced economic and social interruption costs exceed the total investment costs), they would likely want to put more effort in to making the power system more robust; if not, they would need to determine what policies, subsidies or incentives are needed to make the investment attractive.

6.3.3 Recovering the Incremental Investment Cost While Reducing the Burdens on Utilities and Electric Customers

Recovering the costs through services charges may be too much of a burden to place on customers at the time such events occur or may never recover costs because they are very rare events. Instead, system operators or communities might be able to consider some strategies so that they can adequately recover the investment and operating cost and reduce the uncertainty surrounding investment. For instance, utilities might introduce a "backup service insurance program" which guarantees a low-amperage backup service whenever there is an outage and charge them every month a small amount of money to enroll in the program. Second, implementing the ability to provide the backup service requires substantial incremental investment, and it is often hard to justify the investment if there is no subsidy at all and individuals have to carry the full burden. Also, such backup service generates substantial non-monetary social and community benefits, and utilities provide the service only to those prepared to pay for it will raise issues of social equity. Thus, in future work we will use our social WTP results to understand how much people are interested in providing low-amperage backup service for their communities and whether supporting distribution system upgrades with tax (either by general tax revenue of subsidies from federal or state governments) is acceptable. If the result suggests that some portion of the investment can be supported by society's scarce funds, we will discuss how to share the financial burden with relevant stakeholders –government, community and utilities– to support vulnerable segment of population and sustain critical social and private services instead of asking electric customers to bear the full burden.

6.4 Behavioral Research Needs in Eliciting and Using Peoples' Preferences

From a policy-maker's perspective, it is essential to know the trade-offs people are willing to make among different options, such as people's WTP to adopt smart grid technologies and receive some forms of backup services during WLD-outages. While studies eliciting public values and preferences typically assume that respondents are rational and that they can make reliable and consistent judgments, their preferences are often not well articulated, especially for unfamiliar goods or services. Our previous face-to-face study suggested that the respondents had rough preferences in the beginning of the study, but they needed the information and exercises to better refine and articulate their values and reduce the range of uncertainty in their WTP. However, even by the end of the study, there still existed preference uncertainty, and the uncertainty about WTP for a low-amperage backup service remained slightly higher than that for full backup service. This suggests that respondents' preferences and values would be rendered uncertain and incomplete, and indicates that researchers need to put more effort into understanding the sources of uncertainty, reducing some of the uncertainty towards systematic attempts to help people articulate their preferences and values, and incorporating inherent and unavoidable uncertainty.

Also, during our face-to-face surveys, we encountered a few respondents whose demographic information and electricity consumption profiles were similar but who had very different reliability preferences. That means there exists large heterogeneity across people in their WTP not only due to different electricity use profiles, demographics, and needs but also due to other behavioral factors such as their impressions and experiences (including their own previous experiences and the experiences of others) of the given outage and media exposures to the relevant events. While we were not able to fully address the heterogeneity issue because of the lack of data, we would also like to collect sufficient amount of data in the upcoming online surveys and incorporate the wide range of preferences into policy decision-making.

7. Conclusion

Low-probability high-consequence interruptions in electric services of large spatial scale and long duration can give rise to enormous economic and social costs, including loss of life.[8] While these costs can be reduced if a low-amperage supply of electricity could be provided during such outages, at the moment, there has been no way to assess the value of such systems. The method we propose can elicit one critical input – well-reasoned and systematic preferences – to determining whether and where such investments might be warranted an informed judgment. Thus, the work will assist researchers, and in the future after further refinement of the approach, service providers, utilities, regulators, and other relevant stakeholders to map out the necessary full range of informed judgments and improve the robustness of electric power system.

[8] According to the Energy Information Administration, more than 85% of outages to the bulk electric system are caused by severe weather (e.g., thunderstorms, hurricanes, and blizzards); the annual cost of power outages caused by these events is estimated to be $18 to $33 billion (Executive Office of the President, 2013).

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Appendix A. Survey Protocol Used in the Face-to-Face Survey

Attached is Group 1's survey protocol that we actually used in the Pittsburgh study. The only difference between Group 1 and Group 2 is the order of WTP questions for the two backup services (Group 1 always started with WTP for the full backup service question first and then moved onto WTP for the partial backup service whereas Group 2 always started with WTP for the partial backup service and then moved onto the full backup service).

Thank you for your help in this study of the value of reliable electrical services. As stated in the handout, all of your responses will be strictly anonymous. First, you will be asked some basic questions about your household.

Part A. Information about your household

1. **Do you live in an apartment, attached house, or detached house?**

☐ Apartment ☐ Attached house (e.g., duplex or triplex) ☐ House

What neighborhood do you live in? (e.g., Shadyside, Oakmont, Sharpsburg...)

____

2. **How long have you lived in your current house or apartment?** _______ years

How long have you lived in Pittsburgh? _______ years

3. **How many people live in your household, including yourself?** _______ people

How many people are there in your household in each of the following age groups:

Preschool children	_________
K-12 children	_________
Adults under 30 years	_________
30-65 years	_________
Over 65 years	_________

4. **Do you work from home the majority of the time?** (Is your home a place both for business and living?)

☐ Yes ☐ No

If yes, please explain:

____

____

5. **Are there any life-critical devices in your house that require electricity** (e.g., life sustaining medical equipment that runs on electric power)**?**

☐ Yes ☐ No

If yes, do those devices have backup power? How long can they operate without electricity? Please explain:

____

____

Part B. Blackout during a hot summer weekend

1) **Hypothetical blackout scenario**

In this section, I would like you to imagine the following situation: A large regional blackout occurs on a <u>hot summer weekend</u> at a time when you and your household members plan to spend the weekend at home.

Imagine that it is the middle of August. At sunrise, you wake up and realize that the power is out. Assume that you can find a battery operated radio. It tells you that the power outage is not local, but instead extends across a large region (the gray area on the map below).

The radio says that several tornadoes struck big power lines in Indiana, knocking them down. This caused a blackout that spread to the entire Mid-Atlantic and Northeastern parts of the US (see map above). It also tells you that because the tornadoes did not knock down any power lines in the Pittsburgh region, the power company will be able to restore power within a day (in other words, there will be **<u>no power until sunrise tomorrow morning</u>)**.

Before we continue, I would like to ask you a question to make sure you understand the scenario:

1. When will the power come back on?

____

Unfortunately, you and your household members are stuck in Pittsburgh with no electricity in your home. It was hot last night, and today is expected to be one of the hottest days of the year. Please take a moment to describe what you think your day would be like without power, and any strategies you might adopt to cope with the blackout.

____
____
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Now, let's go back to our scenario. In addition to paying for the actual electricity you use, your monthly electricity bill includes charges for performing maintenance on the electricity system (e.g., distribution lines, transformers, etc.) and some limited protection of the system against blackouts. However, the bill does not include charges to provide electric services in the event of an unpredictable blackout. In this case, the National Weather Service (NWS) could predict the tornadoes; however, utilities could not prevent the blackout because it was too wide-spread, and they did not have enough time to prepare for the disruption.

Suppose that during the blackout there is a private local service that specializes in disasters and emergencies that can quickly hook up a generator to your house and provide **all** the electric power you would have normally used. Assume your cell phone has enough power to call to get that service and obtain a one-time payment for one day of immediate service provided by the company. You will receive a bill for the payment by mail.

In this case, I would like to know **how much you would be willing to pay** for this one-time service on a hot summer weekend day during the outage. For each of the following questions, please indicate whether you would be willing to pay that amount of money in exchange for the full day of generator service. For example, the first one: would you be willing to pay less than $5 for the full day of generator service? If yes, please check the "Yes" box. If you are not sure, please check the "Not sure" box. If no, please check the "No" box. Now, please repeat this for the remaining rows of the table.

	Would you be willing to pay this amount to get full service on a hot summer weekend day?		
	Yes	Not sure	No
Less than $5	☐	☐	☐
$5 to $9.99	☐	☐	☐
$10 to $14.99	☐	☐	☐
$15 to $19.99	☐	☐	☐
$20 to $24.99	☐	☐	☐
$25 to $29.99	☐	☐	☐
$30 to $34.99	☐	☐	☐
$35 to $39.99	☐	☐	☐
$40 to $44.99	☐	☐	☐
$45 to $49.99	☐	☐	☐
$50 to $54.99	☐	☐	☐
$55 to $59.99	☐	☐	☐
$60 to $64.99	☐	☐	☐
$65 to $69.99	☐	☐	☐
$70 to $74.99	☐	☐	☐

(For respondents whose willingness to pay is higher than $75 or lower than $5)
If you would be willing to pay more than $75, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

If you would only be willing to pay an amount that is less than $5, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

(For all respondents)
Please explain your response in a brief sentence or two:

____

____

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Now, let's suppose that there is a different service that uses smart meter technology to give you **some** electricity service during the blackout. This smart grid company can quickly connect your house to their smart power system and provide a **partial** amount of electricity for your entire house (about one-fifth of your normal power).

With this partial service, you would only be able to run **some** of the appliances you might want to use (e.g., you would have enough power to use your refrigerator, one freezer, one laptop, your one cell phone charger, and two lights, at the same time). Assume your cell phone has enough power to call the smart grid company and obtain a one-time payment for one day of immediate but limited power. You will receive a bill for the payment by mail.

In this case, I would like to know **how much you would be willing to pay** for this one-time service on a hot summer weekend day during the outage. For each of the following questions, please indicate whether you would be willing to pay that amount of money in exchange for the partial service.

	Would you be willing to pay this amount to get partial (about one-fifth of your normal power) service on a hot summer weekend day?		
	Yes	Not sure	No
Less than $5	☐	☐	☐
$5 to $9.99	☐	☐	☐
$10 to $14.99	☐	☐	☐
$15 to $19.99	☐	☐	☐
$20 to $24.99	☐	☐	☐
$25 to $29.99	☐	☐	☐
$30 to $34.99	☐	☐	☐
$35 to $39.99	☐	☐	☐
$40 to $44.99	☐	☐	☐
$45 to $49.99	☐	☐	☐
$50 to $54.99	☐	☐	☐
$55 to $59.99	☐	☐	☐
$60 to $64.99	☐	☐	☐
$65 to $69.99	☐	☐	☐
$70 to $74.99	☐	☐	☐

(For respondents whose willingness to pay is higher than $75 or lower than $5)
If you would be willing to pay more than $75, what is the largest amount you would be willing to pay to receive the partial service?

$____________

If you would only be willing to pay an amount less than $5, what is the largest amount you would be willing to pay to receive the partial service?

$____________

(For all respondents)
Please explain your response in a brief sentence or two:

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2) More information about your home and community during blackout

Next, you will be asked to think about the services that will be available during the blackout in your home and community, as well as the services that will not be available. The table below provides a list of some of the things that will and will not work in your home and community when the power is out for the entire region:

In your home		In community	
Will work	**Will not work**	**Will work**	**Will not work**
Old style telephones that have a rotary dial. Anything that runs on a battery, as long as the battery lasts (e.g., radios, flashlights, laptop computers, and cell phones). Natural gas and all normal water and sewer services.	New style telephones that include a plug to a power outlet. All electrical appliances that cannot also run on batteries, including air conditioners and blowers that circulate air. Cable and internet service.	Emergency service including 911 (via cell phone or rotary dial phone). Hospitals, police stations, and other places that have backup generators. TV and radio stations (most have backup generators). Natural gas and all normal water and sewer services. Bus service. GPS service.	Traffic signals. Street lights. Banks and ATMs. Most gas stations (pumps need electricity). Food stores (lights, refrigeration, and cash registers will not work). Most restaurants (very few have backup generators). Elevators in buildings without backup. Ventilator fans and lighting in traffic tunnels. Electric trolley service. Airport – major delays.

Before we continue, I would like to ask you a few questions to make sure you understand the scenario:

1. Will any of your neighbors or friends in the Pittsburgh area have power from the power company?

☐ Yes ☐ No

2. Will your laptop work if it was charged overnight? ☐ Yes ☐ No

3. Could you use the internet? ☐ Yes ☐ No

4. Could you use a cell phone to call the police in an emergency? ☐ Yes ☐ No

5. Could you spend the day in a local air-conditioned shopping mall? ☐ Yes ☐ No

Now we have listed the services that will be available in your home and community during a blackout. We would like to know if this information changes your willingness to pay for the full service. Would you like to change your willingness to pay?

☐ Yes ☐ No

3) Appliance card stack game and reasons why the outage would be inconvenient

Next, you will now consider the ways you consume electricity in a more detailed way. Assume that there is no blackout, and it is an average, hot summer weekend.

Let's start with the morning. The sun has just come up. If the power is on, what kind of appliances would you normally be using? Select the cards with the pictures of every appliance that you would use. If you would be using several lights, select a card for each one. Then place each card on the table above the other cards you have selected to make a column.

Now assume that it is in the middle of the day (afternoon). Again, it is hot, and you and your household members are at home. Once again, please select all the appliance cards and other electrical devices that might be operating if the power is on and stack them above each other to make a column.

Now assume that it is early evening (around dinner time). Remember it is summer so it is probably still bright outside. Once again, please select all the appliance cards and other electrical devices that might be operating if the power is on and stack them above each other to make a column.

Finally, assume that it is late evening, one hour before you go to sleep. Once again, please select all the appliance cards and other electrical devices that might be operating if the power is on and stack them above each other to make a column.

A day-long outage can be very inconvenient. These inconveniences come from many different sources. For example, you might not be able to keep your home at a comfortable temperature (because your air conditioner will not work); you may have difficulty finishing chores (such as the laundry or dishes); and you cannot enjoy some types of leisure or entertainment activities (such as watching the TV or using the internet).

Let’s go back to the appliance card stacks that you constructed. Please look over your electric appliances that you selected in each time period. You might feel inconvenienced if you are not able to use any of them. Please take a moment to describe the reasons why an outage might be inconvenient and rank them in order from most to least important.

[**Without any backup service**]

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Remember that we talked about a service that could use smart meter technology to give you some electricity during the blackout. However, that service can only provide you with the **partial** amount of electricity for your entire house (about one-fifth of your normal power). Please make a new stack that includes the appliances and other devices that you still want to run during each time period **within the limit**.

Once again, please look over your electric appliances that you selected in each time period. You might feel inconvenienced because you are not able to use other appliances due to the limit. Please take a moment to describe the reasons why an outage with partial backup service might be inconvenient and rank them in order from most to least important.

[**With partial backup service**]

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____
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Now we have identified how you use electricity during your day with and without partial backup service, and you have listed a number of reasons why the blackout might be inconvenient. We would like to know if this information changes your willingness to pay for the full service. Would you like to change your willingness to pay?

☐ Yes ☐ No

Now, I would like to know how much you value your electric services. Please indicate whether you would be willing to pay the indicated amount of money in exchange for the full day of generator service and partial backup service.

	Would you be willing to pay this amount to get full service on a hot summer weekend day?		
	Yes	Not sure	No
Less than $5	☐	☐	☐
$5 to $9.99	☐	☐	☐
$10 to $14.99	☐	☐	☐
$15 to $19.99	☐	☐	☐
$20 to $24.99	☐	☐	☐
$25 to $29.99	☐	☐	☐
$30 to $34.99	☐	☐	☐
$35 to $39.99	☐	☐	☐
$40 to $44.99	☐	☐	☐
$45 to $49.99	☐	☐	☐
$50 to $54.99	☐	☐	☐
$55 to $59.99	☐	☐	☐
$60 to $64.99	☐	☐	☐
$65 to $69.99	☐	☐	☐
$70 to $74.99	☐	☐	☐

(For respondents whose willingness to pay is higher than $75 or lower than $5)
If you would be willing to pay more than $75, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

If you would only be willing to pay an amount that is less than $5, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

(For all respondents)
Please explain your response in a brief sentence or two:

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____

____

	Would you be willing to pay this amount to get partial (about one-fifth of your normal power) service on a hot summer weekend day?		
	Yes	Not sure	No
Less than $5	☐	☐	☐
$5 to $9.99	☐	☐	☐
$10 to $14.99	☐	☐	☐
$15 to $19.99	☐	☐	☐
$20 to $24.99	☐	☐	☐
$25 to $29.99	☐	☐	☐
$30 to $34.99	☐	☐	☐
$35 to $39.99	☐	☐	☐
$40 to $44.99	☐	☐	☐
$45 to $49.99	☐	☐	☐
$50 to $54.99	☐	☐	☐
$55 to $59.99	☐	☐	☐
$60 to $64.99	☐	☐	☐
$65 to $69.99	☐	☐	☐
$70 to $74.99	☐	☐	☐

(For respondents whose willingness to pay is higher than $75 or lower than $5)

If you would be willing to pay more than $75, what is the largest amount you would be willing to pay to receive the partial service?

$____________

If you would only be willing to pay an amount less than $5, what is the largest amount you would be willing to pay to receive the partial service?

$____________

(For all respondents)

Please explain your response in a brief sentence or two:

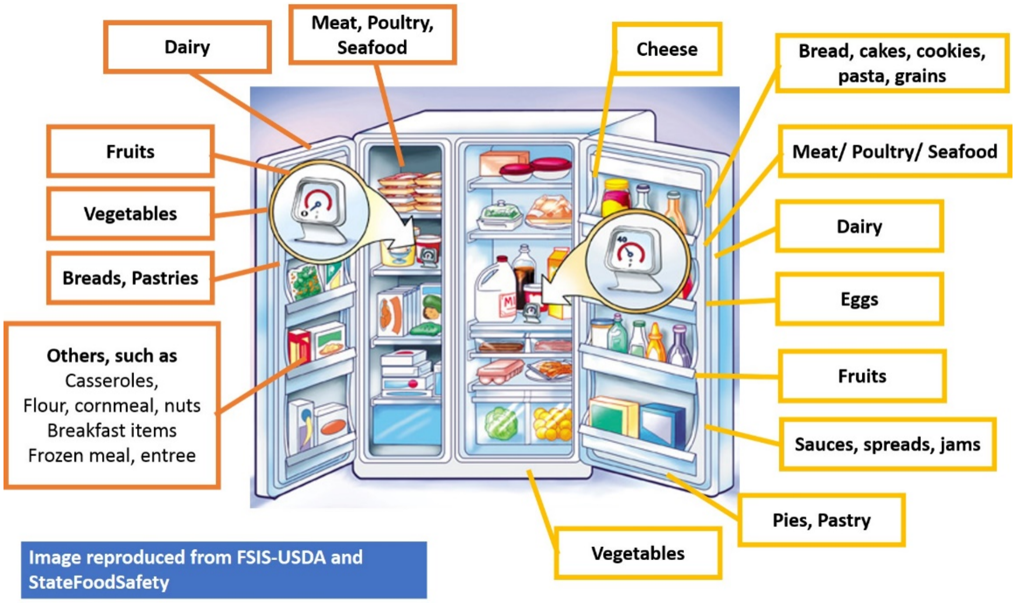
____

____

____

4) Value of perishable food

Next, let's focus on one specific inconvenience: spoiled food. Below we have provided you a picture of the contents of a typical refrigerator/freezer to help you think about the food you have:



The US Department of Agriculture (USDA) says that "perishable food stored in a refrigerator longer than 4 hours without power" should be discarded. Four hours may be too conservative, but if the power is out for a day you will definitely lose some of the perishable food in your refrigerator. Please describe how you feel about the food safety information from USDA and how you would actually respond to the recommendation (e.g., are you going to throw out all the perishable food?).

____

____

____

____

Please use the table below to estimate the value of the perishable food you have, and would need to replace if the power went out for a period of 24 hours.

	Your rough estimate of the value of perishable food that is in your refrigerator:	Your rough estimate of the value of perishable food that will go bad and need to be replaced:
Meat, Poultry, Seafood Raw or leftover cooked, Thawing meat or poultry, Salads: Meat, tuna, shrimp, Chicken, or egg salad, Gravy, stuffing, broth, Lunchmeats, hot dogs, bacon, sausage, dried beef, Pizza – with any topping, Canned hams labeled 'Keep refrigerated', Opened canned meats and fish, Casseroles, soups, stews	$	$
Dairy Milk, cream, sour cream, buttermilk, evaporated milk, yogurt, eggnog, soy milk, Open baby formula	$	$
Eggs Fresh eggs, hard-cooked in shell, Custards and puddings, quiche	$	$
Fruits Opened canned fruits and juices	$	$
Bread, Cakes, Cookies, Pasta, etc. Refrigerator biscuits, rolls, cookie dough, Cooked pasta, rice, potatoes, Pasta salads with mayonnaise or vinaigrette, Fresh pasta, Cheesecake	$	$
Some Pies and Pastry	$	$
Some Vegetables (except raw vegetables)	$	$
Some (soft) Cheese	$	$
Rough sum:	$	$

Just to compare, in 1999 a study conducted in New York found that the average value of perishable food in refrigerators and freezers across the city of New York was about $72, which is just over $100 when adjusted by inflation. Can you suggest why the number you just estimated is higher/lower? Are you willing to change your number (if so, why? and if not, why not?)?

____
____

Losing all the perishable food in your refrigerator may not be the only economic loss you would experience if the power goes out for a day on a hot summer weekend, especially if you work from home or own a home-business. Please explain and estimate any other economic losses you and others in your household might experience in the one-day power outage.

____
____

Now we have thought about the value of perishable food inside your refrigerator and other economic losses. We would like to know if this information changes your willingness to pay for the full service. Would you like to change your willingness to pay?

☐ Yes ☐ No

5) Wrapping it up

We have thought about what it would be like to spend a hot summer weekend day without electricity. Here, I would like you to tell me how much the provided information affected your value of reliable electric services, if at all.

First, please rate the exercises in order of importance regarding how much they affected your value.

	Not at all important	Slightly important	Moderately important	Very important
Information about the services available in your home and community	☐	☐	☐	☐
Appliance card stack game	☐	☐	☐	☐
Reasons why the outage would be inconvenient	☐	☐	☐	☐
Value of perishable food	☐	☐	☐	☐

Finally, now that you have had time to think about all this information, I would like you to once again fill in the table for how much you would be willing to pay to have full service and partial service.

	Would you be willing to pay this amount to get full service on a hot summer weekend day?		
	Yes	Not sure	No
Less than $5	☐	☐	☐
$5 to $9.99	☐	☐	☐
$10 to $14.99	☐	☐	☐
$15 to $19.99	☐	☐	☐
$20 to $24.99	☐	☐	☐
$25 to $29.99	☐	☐	☐
$30 to $34.99	☐	☐	☐
$35 to $39.99	☐	☐	☐
$40 to $44.99	☐	☐	☐
$45 to $49.99	☐	☐	☐
$50 to $54.99	☐	☐	☐
$55 to $59.99	☐	☐	☐
$60 to $64.99	☐	☐	☐
$65 to $69.99	☐	☐	☐
$70 to $74.99	☐	☐	☐

(For respondents whose willingness to pay is higher than $75 or lower than $5)
If you would be willing to pay more than $75, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

If you would only be willing to pay an amount that is less than $5, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

(For all respondents)
Please explain your response in a brief sentence or two:

____

____

____

	Would you be willing to pay this amount to get partial (about one-fifth of your normal power) service on a hot summer weekend day?		
	Yes	Not sure	No
Less than $5	☐	☐	☐
$5 to $9.99	☐	☐	☐
$10 to $14.99	☐	☐	☐
$15 to $19.99	☐	☐	☐
$20 to $24.99	☐	☐	☐
$25 to $29.99	☐	☐	☐
$30 to $34.99	☐	☐	☐
$35 to $39.99	☐	☐	☐
$40 to $44.99	☐	☐	☐
$45 to $49.99	☐	☐	☐
$50 to $54.99	☐	☐	☐
$55 to $59.99	☐	☐	☐
$60 to $64.99	☐	☐	☐
$65 to $69.99	☐	☐	☐
$70 to $74.99	☐	☐	☐

(For respondents whose willingness to pay is higher than $75 or lower than $5)
If you would be willing to pay more than $75, what is the largest amount you would be willing to pay to receive the partial service?

$____________

If you would only be willing to pay an amount less than $5, what is the largest amount you would be willing to pay to receive the partial service?

$____________

(For all respondents)
Please explain your response in a brief sentence or two:

____
____
____

Finally, let's consider an extraordinary situation. Suppose it is a special weekend, such as a birthday or anniversary. Several members of your family or friends have flown in from out of town to celebrate a family event. Under this scenario, how much would you be willing to pay for the full service?

	Would you be willing to pay this amount to get full service on a special weekend day during hot summer?		
	Yes	Not sure	No
Less than $5	☐	☐	☐
$5 to $9.99	☐	☐	☐
$10 to $14.99	☐	☐	☐
$15 to $19.99	☐	☐	☐
$20 to $24.99	☐	☐	☐
$25 to $29.99	☐	☐	☐
$30 to $34.99	☐	☐	☐
$35 to $39.99	☐	☐	☐
$40 to $44.99	☐	☐	☐
$45 to $49.99	☐	☐	☐
$50 to $54.99	☐	☐	☐
$55 to $59.99	☐	☐	☐
$60 to $64.99	☐	☐	☐
$65 to $69.99	☐	☐	☐
$70 to $74.99	☐	☐	☐

(For respondents whose willingness to pay is higher than $75 or lower than $5)

If you would be willing to pay more than $75, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

If you would only be willing to pay less than $5, what is the largest amount you would be willing to pay to receive the full day of generator service?

$____________

(For all respondents)

Please explain your response in a brief sentence or two:

____

____

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Part C. Information about yourself and your experiences from outages

How would you categorize yourself in terms of race or ethnicity?

☐ Caucasian ☐ Hispanic ☐ Black ☐ Asian ☐ Other

What was your total household income last year?

☐ Under $10,000 ☐ $10,000 to $30,000

☐ $30,001 to $50,000 ☐ $50,001 to $100,000 ☐ Above $100,000

Who pays for your electricity?

☐ You ☐ Another household member

☐ Your landlord (utility is included in the rent)

If you are paying for your electricity bill, roughly how much do you pay for your monthly electricity bill, on average?

$________/month

If you do not pay your electricity bill, can you roughly estimate how much you think your electricity bill would be?

☐ Yes, it is $_________/month. ☐ No

Can you estimate how much electricity does your household use per day?

_____________(kWh) or ____________(Amps)

Please describe your experience with power outages in your lifetime:

☐ I have never experienced an outage.

☐ I have experienced one outage.

☐ I have experienced more than one outage.

If you have ever experienced an outage, how long was the longest outage you have ever experienced?

☐ Less than a few minutes

☐ Less than an hour

☐ Several hours. Please explain:____

☐ Less than one half-day. Please explain:____

☐ Less than one day. Please explain:____

☐ Less than several days. Please explain:____

☐ Less than one week. Please explain:____

☐ Longer than one week. Please explain:____

Please tell me about whether you have the following items available to you in the case of a blackout:

☐ Flashlights in easy-to-find places
☐ Wind up or crank operated radio
☐ Wind up or crank cell phone charger
☐ Camping lantern
☐ Camping cook stove
☐ Solar energy storage
☐ Portable generator. Please explain: ____
☐ Stand-by generator. Please explain: ____
☐ Other non-generator. Please explain: ____

How inconvenient would it be if an outage lasted …?

	Not at all	Slightly	Moderately	Very	Extremely
Less than 1 hour	☐	☐	☐	☐	☐
1 hour to 4 hours	☐	☐	☐	☐	☐
4 hours to 8 hours	☐	☐	☐	☐	☐
8 hours to 1 day	☐	☐	☐	☐	☐
1 day to 3 days	☐	☐	☐	☐	☐
3 days to 1 week	☐	☐	☐	☐	☐
Longer than 1 week	☐	☐	☐	☐	☐

What is your best guess at the percent chance that your home will have at least one blackout that lasts longer than one hour in the:

	% in number (0 to 100)
Next year?	
Next 5 years?	
Next 20 years?	
Next 50 years?	

Thanks very much for your help with this study.

If you have questions or concerns,
feel free to contact:
Sunhee Baik, sunheeb@andrew.cmu.edu

Discussion of "Estimating Residential Customers' Costs of Large Long-duration Blackouts"

Discussant: Bernie Neenan
Affiliation: Energy Resource Economics

Summary

The Carnegie Mellon University (CMU) research team is to be commended for venturing where few have dared to tread: estimating what residential customers would pay to avoid an extended, in duration and geographic scale, electric service outage. They have chosen to employ contingent valuation (CV) to elicit willingness to pay values from electricity consumers, both for full service and partial service, to avoid some (or all) of the consequences of a widespread (entire northeast) long duration (10-day) outage, a total blackout due to a solar storm or a terrorist attack. It is an extension of how power reliability has been measured, employing CV, but an important departure from those conventions in how an outage is portrayed.

Numerous studies have used CV (discrete choice) to elicit willingness to pay values (WTP) for specified outages of short duration (under a day).[9] The CMU study is among the first to address efforts to measure WTP for widespread, long-duration, low probability (WLD) power outages employing CV. It acknowledges that conventional methods for valuing reliability are inadequate for resilience monetization.[10] It focuses on the extraordinary circumstances associated with a catastrophic power and other services outage, which requires considerable effort to create a decision situation that consumers can comprehend and assign a value to its avoidance. The subject research employs a multiple bonded WTP (MBWTP) approach that augments WTP responses with information on the degree of certainty respondents associate with the elicited WTP value, acknowledging some of the shortcomings of CV and developing forensics to detect when elicited WTP values may be biased.

This approach has its challenges, primarily that elicited WTPs have limited extensibility to other extended outage situations in other locations. WTP estimates are for a power outage where all attributes (primarily scope, duration and extent) are specified, producing a mean WTP value applicable is only to those circumstances. To understand how consumers value outages of different attributes (for example, in the summer, in a southern state, for longer period than 10 days, but not so widespread), a secondary empirical construct is needed that ties outage attributes to WTP (of VOLL), and the survey must be expanded to elicit WTP for those circumstances.

[9] Sullivan, M., Collins, M. Schellenberg. J., Larsen, P. 2017 forthcoming. Estimating Power System Interruption Costs; A Guidebook for Electric Utilities. LBL/DOE.
[10] See: Venkatachalam. 2004. The Contingent Valuation Method A review. Environmental Impact Assessment Review 24 (2004) 89-124.

The CMU research team proposes (but has not developed) damage function that links attribute levels to WTP, a common practice for reliability valuation.[11] That is an empirical association, not one developed form a comprehensive characterization of preference formation that other methods employ; for example, estimating a preference function (discrete choice experiment) that assigns weights to the attributes of outages, and macroeconomic impact modeling. Moreover, they must address how to gather WTP value for multiple, diverse outage situations within the limits of viable survey administration practices.

The CMU research is in the developmental stage; a survey instrument has been devised and initial tests conducted. The reported results (WTP estimates) are useful for evaluating the efficacy of the survey and its administration, but they should not be considered as representative of any population or applicable to other than specific circumstances stipulated. Additional research is needed to refine and finalize the CV survey instrument so its administration comports with accepted survey practices and produces data to support a more comprehensive characterization of extreme event outage costs and develop a more robust and widely applicable policy assessment platform that links attribute levels to WTP.

This line of research should be continued as it may prove to be an effective way to get estimates of how consumers value partial service availability during an extended power outage, but in conjunction with alternative methods so they can be compared in terms of cost, saliency, and extensibility. Discrete choice experiments (DCE) have gained acceptance (replacing CV) in many environmental use studies that address consumer valuation of hypothetic decision situations and establish relative values for outage attributes.[12] Macroeconomic impact approaches (regional I/O and computable general equilibrium) are alternatives in the sense that they provide a different perspective on the scale and scope of outage costs.[13]

DCE employs a comprehensive theory of how choices are made to elicit data that reveals how attribute levels effect preferences (and hence WTP). Macroeconomic models provide a comprehensive picture of how WLDs affect consumers and businesses, including adjustments by those not directly physically effected but harmed by resulting disruptions of the regional economy). They do so at the expense of associating losses to utility customer classes or population segments, which may be essential for policy determination and are critical in rate making. These are candidates for measuring the value of resilience that should be considered in developing the CMU approach so that comparisons can be drawn as their research progresses.

The CMU research team would benefit from greater stakeholder involvement in research activities during the developmental stage to ensure that the methods advanced are practical and credible and therefore widely utilized by the industry, and to provide realistic test beds to support the R&D process. This should include utility planners and pricing specialists, private firms developing backup power supply resources, and electric sector regulators and local planners, and of course consumers and businesses.

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[11] Sullivan op cit. use data form many reliability studies to develop such damage function.

[12] Recent applications of DCE have addressed residential preferences for alternative rate structures: Neenan, B., Bingham, M., Kinnell, J. Hickman, S. May 2016. Consumer Preferences for Electric Service Alternatives. Electricity Journal Vol. 29 Issue 5, pp. 62-71; and, the application of DEC to characterize residential customer preferences for PV investments (for project information contact: Nadav Enbar, nenbar@epri.com).

[13] These methods are described and compared and contrasted in the proceedings of a LBL/DOE workshop (forthcoming).

CMU Research Approach

The subject paper reports on an ongoing project by CMU researchers to develop a survey instrument to elicit data how consumers value of electric service resilience.[14] They contend that conventions for valuing reliability are not sufficient to measure the costs associated with WLD outages. Specifically, they recognize and seek to remediate the following shortcomings of conventional residential value of lost load (VOLL) studies:

- Failure to convey to survey respondents the nature, and hence the consequences, of the service outage for which costs are being elicited
- Lack of explicit recognition of the potential for cognitive bias by respondents
- Outages considered are of a day or less, generally 12 hours or less
- Only full loss of power service outage is included in the valuation elicitation
- Most all public services (water, natural gas, sewer, bans and emergency services) are assumed to be unavailable
- Use of CV methods that produce biased WTP estimates

The authors argue that for WLD outages, it is critical to develop measures of the value of partial outages because their previous research indicates that the marginal value of critical loads is substantially higher than that of the typical total electric load.[15] This a plausible contention because of the essential nature of the provision of key safety and life support services from electric devices relative to the marginal value of convenience. The CMU research seeks to develop a comprehensive and widely applicable web-based survey instrument that can be employed to inform utilities and regulators of the social benefits of the provision of partial service to customers during WLD outages.

A few observations about the maintained hypotheses and research premises are in order. First, some of the criticisms attributed to established reliability measurement methods are not fully warranted. Situational saliency has been recognized as a critical element of contingent valuation studies. The importance of establishing a proper (realistic and plausibly assessable) setting for the assignment of outage costs is a recognized element of most utility-sponsored studies. A recent report renews emphasis on the need to convey hypothetical outage situations in a way that places respondents in the appropriate decision situation.[16] Earlier outage cost research acknowledged the potential for cognitive bias and incorporated ways to identify and control their impact on the estimation of service value.[17]

Second, the CMU research approach is predicated on the assumption that CV/WTP is the best way to monetize the demand for alternative services such as emergency backup service. CV was developed as a means for measuring the welfare gain/loss associated with a very specific private or public good with specific attributes. For example, WTP to avoid having a power plant built in a park (use avoidance) or the

[14] They are focused on residences but the methods may have application to businesses.
[15] Balk, S., Davis, A., Morgan, G. Assessing the Cost of Large-Scale Power Outages to Residential Customers. Risk Analysis, Vol 00, No 0, 2017 DOI”10.111/risa. 12842 (copy provided by authors).
[16] Originally published as: Sullivan, M. J. & Keane, D. M., 1995. Outage Cost Estimation Guidebook, Palo Alto, CA: Electric Power Research Institute Update, which was revised in: Sullivan, M., Collins, M. Schellenberg. J., Larsen, P. 2017 forthcoming. Estimating Power System Interruption Costs; A Guidebook for Electric Utilities. LBL/DOE.
[17] Analysis Group. 1990. Residentials Outage Cost Survey: Final Report. Niagara Mohawk Power Corporation.

establishment of a park (use). Measuring what residences would pay to avoid WLD outages, so that utility and others' investment decisions to avoid (or ameliorate) them are optimal, requires knowing the importance of the individual service attributes (notice, duration, extent, and perhaps others) to those affected.

Third, there are many ways to provide backup power that would differ in the extent to which loads can be served and for how long and to how many. Costs to provide extended scope or scale backup service increase more than proportionally to the scale and temporal scope of that service. Outage attributes may exert different weights in preference formation and hence affect WTP. The WTP value elicited for a particular outage situation do not provide any indication of how that valuation would change if one or more of the attribute levels were changed; the marginal contribution of each. Eventually, a means for evaluating tradeoffs among outage attributes will be essential to design acceptable services as well as developing reliable segmentation characteristics (who is most likely to subscribe to which service package).

Finally, is the situation portrayed feasible, providing customers (selectively) power from the grid if they pay a daily fee (which is what the WTP intends to establish) to the utility (which is attributed to a Smart Grid investments). It's more likely that to avoid an outage in these situations, customers must either invest in power generation on their premises or belong to a local microgrid consortium that makes such investments (either of which could be sponsored by the utility or another entity). Self-supply in either case involves either a substantial up-front investment or a related commitment to ongoing payments. This may be a very different prospect than consumers just paying if a WLD ensues. All consumers are unlikely indifferent to an up-front payment and an installment payment obligation over time with the same net present value, and it adds to the decision risks that may influence WTP valuations. Moreover, self-supply investments may produce a stream of benefits outside WLD which should be made explicit as that may affect the WTP values elicited. These considerations should be resolved in the research so that utilities and others are confident that resilience valuations derived in this way produce predictable results.

What will customers pay to avoid extended and widespread outages?

There is much to be enthusiastic about the subject research as it properly convolves the duration and extent of outages in defining resilience. And, it seeks to develop a survey instrument that can be widely employed, under rigorous protocols and as occasion rises, to develop data to support a means estimating mean WTP for power under circumstances when normally residential electricity consumers would suffer substantial inconvenience and real losses. The CMU researchers are well-versed in the application of CV and have built into the survey ways to detect ad correct for biases at the development stage, the benefits of which are realized at the damaged function modeling stage.

It is widely accepted that conventional reliability studies are not up to the task of establishing the cost of an outage that extends several days; few studies have considered outages of even a half day (Sullivan et al. 2017). Clearly, the mean WTP values derived directly from reliability VOLL studies cannot be extended credibly beyond very localized outages of 12-16 hours. CMU research defined an outage as being widespread and lasting 10 days, which requires a revised approach to the assessment of WTP to avoid them. The underlying preference functions may be highly non-linear so linear extrapolation may be misleading. A secondary relationship must be postulated to derive such marginal valuations. The convention in reliability studies is to employ a damage function as an empirical characterization, not a preference relationship derived from an overarching theory of choice.[18]

The scope of the outage may influence WTP. Few reliability studies specified the scope of the outage as a characteristic; who else is affected? The geographic scope of the outage may affect the respondents' WTP if it assumes there are alternatives to get services elsewhere. If not specifically stipulated, a respondent may offer a lower WTP value because it thinks that the outage is not extensive, and supplier and power can be obtained nearby. [19] The CMU study properly (for CV elicitation) leaves no doubt that the respondent will have no power for 10 days unless it subscribes to the partial power assurance program. This represents the situation specificity needed to elicit creditable and actionable mean WTP resilience values. It may not be the best way to develop a comprehensive characterization of outage valuation over different circumstances (Sanstad 2016, EPRI 2017).

Recommendations

This promising line of research may benefit from the considerations raised below.

Expand the outage characterizations to include several attributes

The survey and service value modeling methods should be expanded to allow for estimating the value associated with:

- Longer and shorter outage durations
- The season when the outage occurs (summer may result in different valuation)
- Outages over larger and more focused geography areas
- Several levels of partial service provision (not just 20 amps)
- The context should include several root causes (for example, geographic phenomena such as flooding versus hurricanes versus ice storms) to see if WTP is depends on what caused the outage
- The effect on WTP of having localized microgrids or safe havens that provide centrally located, essential services such as food, water, communication (phones, internet), temporary shelter, transportation, medical help, and community interaction

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[18] Discrete choice experiments extract individual attribute values in a manner that preserves an overarching theory of how preferences are formulated. Macroeconomic models also derive outage value consistent with the notion of consumer valuation of situations. These are described in the LBL/DOE workshop and in: Measuring the Value of Electric System Resiliency: A Review of Outage Cost Surveys and Natural Disaster Impact Study Methods: EPRI, Palo Alto, CA: 2017. 3002009670, and Sanstad, A. February 2016. Regional Economic Modeling of Electric Supply Disruptions: A Review and Recommendations for Research. Lawrence Berkeley National Laboratory.

[19] A close examination of the many surveys collected and analyzed by LBL would verify or modify this statement. To the extent respondents are not clear as to what alternatives are available, outside of their premises, or could get essential or discretionary services the WTP valuations are biased, but the direction and extent are unknown. A curtailment service provider recruited customers in a NYC high-rise offering a low incentive to participate (compared to what others offered to get participation) by making available coupons that could be used at neighboring restaurants, coffee shops, movie theaters, etc. that had HVAC services). They offered substitute locales or activities to assuage the power loss. This approach is predicated on the outage being undertaken by customers voluntarily, and not the result of a general power outage, and comports with adaptive behaviors that are included in macroeconomic models but not in CV-based valuation methods.

Survey length and administration

The survey is long and complex. The authors reported respondents requiring 40-60 minutes to complete from the initial administration experience (about 200 respondents using MTurk). As a R&D instrument, it may be prudent to set aside response bias (failure to start or compete once started) that arises due to the survey's length to be able to conduct tests of the efficacy and effectiveness of specific elements.[20] There are important tradeoffs to consider, including researchers' desire to impose rigor on WTP estimates (through embedded forensics) and the need to consider a variety of outage situations. To be widely used, respondents should be able to complete the CV instrument in under 25 minutes. Moreover, it should be administrable in many modes and can accommodate local conditions while allow for pooling data collected across many for analyses.

Card stacking (end-use preference elicitation)

The card stacking exercise (respondents selecting which loads to operate in a given time period) was facilitated by the electronic survey instrument that imposed the 20-amp limit and reminded the respondent when in any period key services were not selected (hot water, heating, refrigeration). Respondents are not asked to select end uses in the order of perceived need and preference, so there is no reason to assume they do so. Operationally, when a selected device exceeds the period's 20-amp limit, it is removed from the stack, and a service with a lower (but compliant) amperage can be added.[21] As a result, the final set of appliances and services selected for each time period (the exercise is done for 6-hour blocks of the day) represents collective priorities (for each time period), but the last one chosen is not necessarily the marginal one.

The stacking exercise ignores that many end-uses do not have to operate the full six hours to provide suitable services. The HVAC could run periodically over the period and the oven, phone charging and other appliance services can provide the required conveniences running only a few minutes spread out over the 6-hour period. Doing so may leave slots for enjoying conveniences like TV, computer activities, gaming. In other words, residences may be able to devise rationing schemes based on providing energy services while adhering to the 20-amp limit.[22] To the extent to which such strategies are viable and discernible to respondents, the WTP valuations are biased upwards, in some cases perhaps substantially. [23] A wide range of WTP values across customers of seemingly homogeneous circumstances might be explained by there being some who understand the value of rationing that eludes others.

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[20] Dillman recommends a survey require no more than 20-25 minutes: Dillman, D., Smyth, J. Christian. L. 2009. Internet, Mail, and Mixed-Mode Surveys: The Tailored Design Method, Third Edition. John Wiley and Sons., NJ.

[21] Enterprising homeowners have recounted how they use a 1-2 kW generator to serve may needs by plugging and unplugging appliance. Consumers in Italy and Spain where residential serve is demand limited (at 3 or 5 kW) likely are well-versed in how to realize a high load factor. Home energy management devices are being developed specifically to manage loads under demand limits.

[22] Technologies are under development that would facilitate such practical rationing, for example embedding the control into the main circuit panel that can execute preset instructions that are revised as the situation warrants.

[23] Macroeconomic models built for resilience valuation explicitly recognize that adaptive behaviors can reduce the overall cost of an outage and should be accounted for in determining the extent to which preventive measure investments are undertaken (Rose, A., G. Oladosu, and S. Liao (2007). Business Interruption Impacts of a Terrorist Attack on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout. Risk Analysis, 27(3): 513-531.

Another shortcoming is that the WTP elicited after the stacking is conditioned on a 20-amp limit. If the level was raised to 30 amps (and to even higher levels), how much would the WTP increase and at what rate? Utilities and policy makers want to understand the marginal value of resilience in making system hardening investment decisions under a variety of weather and security conditions to determine what to spend on deterrence. Self-supply equipment providers will want to understand the marginal WTP for several levels of supply of varying availability.

More work needs to be done to demonstrate how eliciting WTP several times contributes to estimating WTP, especially using a damage function. As configured, the survey elicits WTP values for partial service three times: first after an initial discussion of such a service, then after the card stacking exercise and asking the respondent for direct cost estimates, and finally when the respondent is asked to indicate WTP so that partial service is available to needy households. Which of these values is to be used to develop estimates of the mean WTP for partial service and how would that be determined, and what role do the others play, if any?

Mean WTP values (associated with very specific conditions) have limited use in infrastructure investment decisions. Models are required to accommodate exploring alternative design considerations, a variety of outage situations, and different customer populations. The requirements of such models must be established at the survey design stage so the data provided comport with modeling needs. The research should address the need to provide a way to value tradeoffs among outage situations. How is a damage function constructed so that it conveys the implicit preference formation process the WTP is based on), and so that elicited preferences that are not internally contradictory, practically consistent, and hence not subject to the CV shortcomings CMU acknowledges.[24] Developing a linkage between multiple WTP valuations and a comprehensive characterization of how outage attributes influence the costs associated with an outage (the marginal attribute weights) is a logical next step.[25]

Respondents are asked to indicate what they would pay so (needy) others have power (even if they do not). Doing so is fraught with potential for strategic bias or empathy, especially after exposure to the doomsday description of the outage. This may result in very low or high WTP bids because the respondents think their response will affect what actually comes about. Unless the answer contributes directly to the estimation of WTP, this line of inquiry might be dropped to shorten the survey.

Asking respondents for estimates of direct costs from premises damages and food spoilage also adds time to the survey completion. Moreover, it’s not clear how the data provided contribute to the primary goal of estimating WTP for partial service. Premises damages are described explicitly and in a way that makes them seem inevitable (pipes will freeze at great cost and inconvenience). But, if the respondent anticipates that possibility and in the stacking assigns heating to every period as a priority, then these damages are less unlikely. Offering the result of the NY study on food losses ($65) as an example of the

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[24] CV was developed from consumer utility theory as a measure by the area under a demand curve (conceptually posited as welfare); how it changes as the result of a change in the level of consumption of a good or service that results from a policy? (Just, R., Heuth, D., Schmitz, A. 1982. Applied Welfare Economics and Public Policy., Prentice-Hall. Englewood Cliffs, NJ.)

[25] While economists derive WTP as a measure of welfare from a unifying theory utility maximization, other disciplines employ WTP as a way to associate value to changes in consumption without any overarching conceptualization of preference formation. The result is an empirical measure of value to which no unifying preference formation axioms are applied in estimating marginal WTP and preference anomalies can arise that are not detectable or correctable.

cost of perishable food losses may bias the WTP estimate, as does (in the opposite direction) the extensive instructions on how such losses can be minimized. These are considerations that can be raised up front so that respondents take them into account (internalized) in developing WTP. As constructed here, there seems to be no way to isolate the individual effect of these separate stimuli that have opposing effects on WTP.

Collaboration with the power supply community is essential

A well-designed resilience valuation initiative can use data collected from a variety of ways, for example: through routine utility surveys or customer interactions, asking for survey completions from specific locales where there are acknowledged reliability or resiliency concerns and from areas that have recently experienced an extended outage. Surveys may also be useful when fielded in collaboration with commercial firms seeking to provide backup power or develop microgrids. To accommodate these alternative sources of data, survey instrument and administration development must go beyond the interactive, online modality and develop methods that support in-person interviews and printed instruments mailed or handed out to be completed and returned.

Research suggests that high response rates to surveys to elicit electricity customer wants and needs can be achieved using direct mail that employs utility sponsorship and branding, along with adherence to Dillman's prescribed research practices.[26] The convenience and relatively low cost of electronic survey administration comes at the price of inherent bias due to underrepresentation of the effected population. Leveraging the relationship utilities and others providing power services have with consumers may result in better target customer representation at lower cost.

Expanding the community of interest and involvement to include community and government planners and technology developers may be challenging, but if done properly and patiently yields high rewards. It's never too early to get all stakeholders involved. They will provide insights that reveal limitations that can be overcome in the development stage that if not addressed result in not very useful data, or data that is used but is erroneous. A survey process crafted to be acceptable to utilities and others (because they see the value of the results) increases the possibility for collaborative administration over several service territories facilitating testing for cultural, geographic, and other sources of diversity of preferences.[27]

The collaborative mandate includes working with those developing similar resilience valuation approaches (DCE), and those taking a different approach such macroeconomic modeling (computable general equilibrium and I/O) to quantify the value of power services under extremely adverse conditions. LBL and DOE can support (and have been supporting) such collaborations, as well as entities like Edison Electric Institute, EPRI, NARUC and individual utilities. The goal is to create an environment

[26] Response rates of 60% and higher were achieved for a discrete choice experiment that has many similarities to WTP elicitation: Measuring Customer Preferences for Alternative Electricity Service Plans: An Application of a Discrete Choice Experiment. EPRI 3002005757.

[27] Tests revealed that the highest response rates come from utility sampling and branding; drawing names randomly from the utility's customer records and having the utility provide supporting the initial contact, leveraging the high level of familiarity they enjoy (Neenan, B., Bingham, M., Kinnell, J. Hickman, S. May 2016. Consumer Preferences for Electric Service Alternatives. Electricity Journal Vol. 29 Issue 5, pp. 62-71).

where all researchers collaborate toward a common end following common guidelines and with ample insight to the final uses of the results.

III. Economic Consequence Analysis of Electric Power Infrastructure Disruptions: An Analytical General Equilibrium Approach

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1. Introduction

Electricity service providers take steps to increase the reliability of their systems through mitigation measures that reduce the frequency and magnitude of potential outages. Such measures include strengthening individual pieces of equipment and protecting system connectivity against natural disasters, technological accidents and terrorist attacks (NRC, 2017). At the same time, direct and indirect electricity customers pursue a range of measures to reduce production and consumption losses once the disruption begins, which Rose (2007, 2017a) and others (e.g., Kajitani and Tatano, 2009; NRC, 2017) have characterized as "resilience". Some of these measures are inherent, in the sense that they exploit flexibility built into firms' production processes (e.g., the ability to substitute alternative power sources or the ability to shift operations to branch plants out of the affected zone) or households' consumption processes (e.g., the ability to reallocate activities over the course of the day to cope with periods of limited or no electricity supply). Some actions require expenditures in advance of the disruption, such as the purchase of storage batteries and back-up generators to be used once an outage commences. Still other actions involve improvisation, or adaptive, resilience after the outage begins, such as conserving electricity at greater levels than previously thought possible, altering production processes, finding new suppliers of other critical inputs whose production has been disrupted by the outage, and recapturing lost production once electricity is restored. A further strategy, more applicable to the electricity provider is dynamic economic resilience, which refers to the acceleration of the pace of restoration of electricity service. The distinction between reliability, as promoted by mitigation, and resilience is poignantly stated in a recent NRC report: "Resilience is not the same as reliability. While minimizing the likelihood of large-area, long-duration outages is important, a resilient system is one that acknowledges that such outages can occur, prepares to deal with them, minimizes their impact when they occur, is able to restore service quickly, and draws lessons from the experience to improve performance in the future" (NRC, 2017, p. 10).[1]

In this paper we address three questions. First, we investigate the economy-wide impacts of a large-scale disruption to electric power infrastructure. Second, we ask how mitigation and resilience might differ, in terms of both the representation of these elements within an economic model, and what their ultimate effects are likely to be on the magnitude impacts. Finally, we ask how the answers to the foregoing questions depend on key characteristics of the strategies, and of the affected economy. Previous research by the authors has demonstrated the methods for, and elucidated the broader economic consequences of, incorporating various risk reduction measures into multi-sector computational general equilibrium (CGE) models of economies affected by disasters (Rose et al., 2007; Sue Wing et al., 2016; Rose, 2017b). Energy-focused CGE models are the workhorse of assessments of the broader economic consequences of shocks or disruptions to energy supplies. However, Sanstad (2016) identifies several shortcomings of previous applications of CGE modeling, including the need for advances in the theory, clarification of important concepts (e.g., energy conservation versus energy efficiency), and greater justifications for the parameter values of these models. It is now common for such models to combine top-down representations of economic activity with bottom-up detail in electricity generation technologies (see, e.g., Sue Wing, 2008). The resulting disaggregated representations of electric power supply need to be constructed using numerical calibration approaches that reconcile incommensurate data from economic accounts with engineering specifications of the discrete technology options whose interactions will drive the model's emergent behavior. While the calibration process is relatively straightforward for aggregates of electric generators with different technologies and/or fuels, it is extremely challenging to resolve the use of inputs associated with elements of the transmission and distribution grid because of their network character and distribution across fine spatial scales.

This difficulty constitutes an important roadblock when investigation of the effects of electric power supply disruptions from natural hazards and potential terrorist threats necessitates representations of elements of the electric power system that are highly spatially disaggregated. In particular, for any given downstream sector, power generated by multiple, geographically dispersed generators upstream is conveyed by multiple infrastructural assets to multiple electricity consuming entities located in

[1] Dozens of definitions of resilience have been offered that emphasize multiple dimensions of the phenomenon. One important distinction is between definitions that consider resilience to be any action that reduces risk (e.g., Bruneau et al., 2003; USEOP, 2013), including those taken before, during and after an unforeseen event such as a power outage, and those that use the term narrowly to include only actions taken after the event has commenced—acknowledging, however, that resilience is a process. The latter definition does not ignore pre-event actions in building resilience capacity (e.g., the advance purchase of portable electricity generators) but notes that their implementation does not take place until after the outage has begun. This is in contrast to mitigation, which is pre-outage investment intended to make a system more resistant, robust or reliable (in standard engineering terminology) at the outset of the outage. Our definition simply chooses to focus on the basic etymological root of resilience, "to rebound", and thus emphasizes system or business continuity in the static sense and recovery in the dynamic one (see also Greenberg et al., 2007; Xie et al., 2018). Our emphasis here is on actions after the outage begins, which partially shifts inquiry away from a narrow focus on electricity suppliers toward consideration of the behavior of their downstream customers (see Section 2).

different service territories. This fundamental network structure of supply-demand linkages—and the allocation of electric power flows to its various arcs, exists at geographic scales much finer than those at which economic models simulate markets (e.g., individual counties). In addition, multi-sectoral economic models are ill-equipped to capture the physical characteristics of power flows (e.g., Kirchhoff's laws). Such details are simulated with much greater fidelity by dedicated electricity sector techno-economic simulations such as optimal power flow, economic dispatch or capacity expansion simulations. Moreover, these types of models already exist and are routinely used by electricity system operators and balancing authorities, and it is relatively straightforward to use them to quantify: (a) the magnitude of disruption shocks—i.e., the extent of unserved load to various classes of customers, and (b) potential supply-side resilience measures—i.e., ability for various deliberate investments in slack capacity or costly interventions to manage the power system differently might be able reduce curtailments.

Nevertheless, we note that explicit consideration of the foregoing details is rarely necessary for assessing the downstream economy-wide impacts of the supply disruptions that these models would simulate as emergent outcomes. The exception is instances where strong feedbacks exist between downstream responses to electricity supply curtailment and fundamental technological drivers of the disruption. Yet, such feedbacks do not necessitate the "hard" linkage (to say nothing of full integration) of multiple simulation models based on fundamentally different paradigms. Rather, such models can be "soft" coupled using emulation in conjunction with scenarios. In particular, one can envision the following three-step assessment process:

(i) An optimal power flow model is used to simulate several scenarios of disruption while incorporating mitigation activities of varying cost and effectiveness.

(ii) The simulation results are used to construct a reduced-form emulator of the envelope of resilience options, their opportunity costs, and their benefits in terms of moderating the disruption. (For recent efforts to construct reduced form emulators of economic models, see Chen et al., 2018; Rose et al., 2017.)

(iii) The resulting vector of electricity supply curtailments, along with the response surface of mitigation and resilience tactics and their bottom-up opportunity costs, are used in conjunction with a multi-sector economic model to simulate the broader economic effects of power disruptions.

The rest of the paper is organized as follows. Section 2 summarizes prior research on the economic consequences of electricity outages, identifying key gaps in the existing literature. Motivated by these opportunities, Section 3 provides a detailed description of our methodological approach, introducing the analytical model which we solve, yielding our main results, and a numerical application of that model: a two-week disruption in Bay-Area electricity infrastructure that reduces the latter's annual capacity by 4%. Analytical and numerical modeling results are presented in Section 4. Section 5 concludes with a brief discussion of caveats to the analysis and fruitful opportunities for future research.

2. Insights from Prior Research

Nearly all of the early literature on the economic consequences of electricity outages characterized impacts in terms of residential, commercial and industrial willingness to pay (WTP) to avoid disruptions of various durations, and reduce the probability and magnitude of these events before they took place. As such, the major strategy was mitigation, which included such tactics as strengthening equipment, improving connectivity, development of parallel systems, and having back-up equipment in place. All of these tactics were essentially intended to enhance robustness/resistance of the electrical system from the initial shock.

Much of the early economics literature focused on partial equilibrium (PE) analyses of electricity providers or their customers. With the exception of studies of actual events, economy-wide losses were typically not analyzed until the 1990s. They were, and continue to this day, to be measured primarily with the common denominator of dollars in terms of gross output (sales revenue) or GDP. These economy-wide or general equilibrium (GE) effects are of several types (Rose et al., 2007), involving losses incurred by different actors, through different transmission pathways, as summarized by Table 1.

Sanstad (2016) and others have reviewed various modeling approaches to estimating the economy-wide (typically at the regional level) impacts of electricity outages. The general leaning of these assessments is that CGE models are the preferred approach. Input-output (I-O) models are limited by their inherent fixed-coefficients character, inability to capture substitution behavior content, and lack of consideration of prices and the effects of factor market adjustments on consumers' incomes. CGE models are able to maintain the best features of I-O models—sectoral detail and ability to trace interdependencies—while overcoming these limitations. Macroeconometric models are especially adept at forecasting, but often lack the detail needed in this area of inquiry and are less able than CGE models to accommodate the kinds of engineering and electricity market details necessary to credibly simulate the economic consequences of electricity disruptions.

Table 1. Partial and General Equilibrium Impacts of Electricity Service Disruptions

Actor	Impact Pathway	Type
Direct customers of the electricity service provider	Commercial and industrial customers: reduced production due to facility downtime, damage to equipment or loss of perishable work in process or finished goods inventory, residential customers: reduced well-being. Direct customers are the demand side of the electricity market in a partial equilibrium sense, yet much of the partial equilibrium literature focuses only on the supply side.	PE, GE
Downstream customers of disrupted firms	Reduced production and profit due to production foregone because of inability to source crucial inputs produced by directly impacted firms.	GE
Upstream suppliers of disrupted firms	Reduced production and profit due to cancellation of orders for inputs because of production delays/idling of capacity by directly impacted firms.	GE
Households	Reduced income because of decreased labor hiring, wage remuneration and dividends of firms directly affected by the electricity outage, as well as their downstream customers and upstream input suppliers.	GE
All firms	Decreased consumer spending associated with declines in household income.	GE
All firms	Decreased investment as a consequence of lower revenue/profit of firms directly affected by the electricity outage, as well as their downstream customers and upstream input suppliers	PE, GE
All firms and households	Reduced production and consumption activity due to general increases in prices because of scarcity.	GE

The most recent modeling advances in this realm relate to various types of resilience defined in the previous section (Rose, 2007, 2009; Kajitani and Tatano, 2008). These papers shift the focus to the customer side, where substitution possibilities create many more opportunities for resilience that are by comparison much less costly. For example, the productivity-enhancing benefits of many energy conservation measures outweigh their costs, back-up generators are relatively inexpensive, as are outsourcing production to other facilities with excess capacity that have electricity service, and recapturing lost production at a later date via temporary overtime operation and extra shifts. While some of these measures require investments in physical planning or planning prior to the onset of an outage, many can simply be implemented if and when a disruption occurs. Moreover, downstream customers are also able to employ these measures, as well as temporarily draw down inventories, engage in input substitution, and replace domestically produced inputs that become scarce with similar commodities imported from outside the affected area. Rose and Liao (2005), Rose et al. (2007), Sue

Wing et al. (2016), and Rose (2018) have shown how many of such resilience measures can be included in CGE models.[2]

Several studies have measured the economic consequences of major electricity outages as summarized in NRC (2017): the New England-East Canada Blackout of 1998 ($4 billion), the Northeast Blackout of 2003 ($4 to $10 billion), and SuperStorm Sandy in 2013 ($14 to $26 billion). We note that most of these studies did not explicitly model or estimate most types of resilience on either the supplier or customer sides. Studies that have explicitly modeled various types of resilience include: the 1994 Northridge Earthquake (Rose and Lim, 2002), the 2002 Southern California rolling blackouts (Rose et al., 2005), and a hypothetical two-week shutdown of the Los Angeles (City) Department of Water and Power electricity system due to a terrorist attack (Rose et al., 2007). These studies all found that resilience substantially moderates losses, though the latter is likely to be overstated because the effects of potential rather than actual implementation of resilience tactics are quantified.

Few studies have examined the impacts of long-term electricity outages. This phenomenon would best be addressed by a dynamic CGE modeling approach. It would also place greater emphasis on dynamic economic resilience, which Rose (2009, 2017) defines as investment in repair and reconstruction so as to recover at an accelerated pace and decrease the duration of the outage in order to reduce losses. Of course, repair and reconstruction efforts are also important for shorter outages, and a good deal of literature has been developed to optimize restoration patterns, both to restore electricity and to achieve various societal goals with respect to customer priorities (see, e.g., Çağnan et al., 2006). Finally, we note that Rose (2009) has examined how resilience changes over time, with some tactics (e.g., Draconian conservation, inventories/storage) eroding and others (e.g., input substitution and technological improvisation) increasing.

3. Methods

Our approach explicitly recognizes that the economic effects of power disruptions depend critically on the geographically localized upstream topology of the affected electricity generation, transmission and distribution network, as well as the downstream structural and resilience characteristics of the economy that this network serves. This circumstance complicates broad assessment of blackouts in two ways: It limits our ability to develop general insights, threatening to make any conclusions context-specific, and it increases the fixed cost of undertaking numerical analyses by necessitating substantial investments in data development, model building, and calibration to capture the specific local and/or regional characteristics of electric power systems and the electricity-using economy. Our strategy here is to circumvent these obstacles entirely by setting up and solving an analytical model that abstracts

[2] For example, conservation can be included by changing the productivity parameter of a production function, while inherent input substitution and import substitution are an automatic aspect to this modeling approach, and adaptive input substitution and import substitution can be modeled by altering the input substitution elasticities and Armington elasticities, respectively. Several other resilience tactics, such as distributed generation and storage batteries, can be modeled by simply reducing the electricity supply disruption in the first place or by applying the production recapture factor to the initial results.

from realistic detail to capture the essence of the broader economic impacts in a manner that is simple, compelling, and easily adapted to a wide range of circumstances that can potentially arise in specific geographic locales.

3.1 An Analytical General Equilibrium Model

Our brutal abstraction is to reduce the supply side of the economy to two broad sectoral groupings, electric power and the rest of the economy, indexed by $j = \{E, N\}$, respectively. Output of the electric power sector is indicated by q_E, and its price by p_E. Electricity production requires the input of generation, transmission and distribution infrastructure capital. Denoted k, this input is assumed to be a sector-specific fixed factor with rate of return r. Electricity production also depends on the input of a composite factor, z_E, which is mobile among sectors, is in perfectly inelastic aggregate supply and has a ruling price w. Output of the rest-of-economy sector is indicated by q_N, and has a price p_N. Rest-of-economy production relies on intermediate inputs of electricity, x, and inputs of the composite factor, z_N. Production is assumed to be of the constant elasticity of substitution (CES) variety, in electric power and the rest of the economy parameterized by technical coefficients α and β and elasticities of substitution σ_E and σ_N, respectively. Infrastructure capital in the power sector and electricity in the rest of economy are assumed to be necessary inputs, implying that $\sigma_E, \sigma_N \in (0,1]$. Electricity supply satisfies N's intermediate demand as well as household demands final consumption of electricity, c. Households also consume the entire rest-of-economy output. Households derive utility, u, from consumption of c and q_N and are endowed with CES preferences, parameterized by the technical coefficient ϕ and elasticity of substitution σ_U. Both inputs are assumed to be necessary, implying that $\sigma_U \in (0,1]$. The variables, parameters and equations of the model are summarized in Table 2.

Following Fullerton and Metcalf (2002) and Lanzi and Sue Wing (2013), the model of the economy is posed as a system of log-linear equations in which a "hat" over a variable represents its logarithmic differential (e.g., $\hat{x} = d \log x / x$), which can be interpreted as a fractional change from an initial equilibrium level. On the supply side of the economy, producer behavior is captured by three sets of equations: sectoral production functions (1)-(2), associated free-entry conditions guaranteeing zero economic profit with perfectly competitive supply (3)-(4), and the definition of producers' input substitution possibilities (5)-(6). The demand side of the economy is represented by two equations, households' utility function (7) and the definition of their elasticity of substitution (8). The supply and the demand side of the economy are linked by the markets for electricity and rest-of-economy output. Producers are linked to each other via input competition for the fixed endowment of the composite factor. Households and downstream firms are linked through their competition for the electricity sector's output. These constraints are captured by the supply-demand balance conditions (9) and (10), respectively.

Table 2. The Analytical General Equilibrium Model

A. Variables

	Electric sector Output	Rest of economy output	Electricity infrastructure	Electricity demand	Composite factor	Utility	Mitigation
Quantity	$\hat{q}_E$	$\hat{q}_N$	$\hat{k}^*$	$\hat{c}, \hat{x}$	$\hat{z}_E, \hat{z}_N$	$\hat{u}$	$\hat{b}$
Price	$\hat{p}_E$	$\hat{p}_N$	$\hat{r}$		$\hat{w}$		

B. parameters

α	Electricity sector infrastructure output elasticity	σ_E	Electricity sector elasticity of substitution
β	Rest-of-economy sector electricity output elasticity	σ_N	Rest-of-economy elasticity of substitution
λ	Electricity sector share of aggregate factor supply	σ_C	Consumption elasticity of substitution
γ	Household share of aggregate electricity supply	ξ	Power sector backup share of infrastructure
ϕ	Household electricity share of total expenditure	δ	Power sector backup share of factor input
		η	Factor-to-backup transformation elasticity

C. Model equations

Outage model with inherent resilience only		
Electric power sector production function	$\hat{q}_E = \alpha\hat{k}^* + (1-\alpha)\hat{z}_E$	(1)
Rest-of-economy sector production function	$\hat{q}_N = \beta\hat{x} + (1-\beta)\hat{z}_N$	(2)
Electric power sector zero profit condition	$\hat{p}_E + \hat{q}_E = \alpha(\hat{r} + \hat{k}^*) + (1-\alpha)(\hat{w} + \hat{z}_E)$	(3)
Rest-of-economy sector zero profit condition	$\hat{p}_N + \hat{q}_N = \beta(\hat{p}_E + \hat{x}) + (1-\beta)(\hat{w} + \hat{z}_N)$	(4)
Elasticity of substitution in electricity production	$\hat{k}^* - \hat{z}_E = -\sigma_E(\hat{r} - \hat{w})$	(5)
Elasticity of substitution in rest-of-economy production	$x - \hat{z}_N = -\sigma_N(\hat{p}_E - \hat{w})$	(6)
Household utility function	$\hat{u} = \phi\hat{c} + (1-\phi)\hat{q}_N$	(7)
Elasticity of substitution in final consumption	$\hat{c} - \hat{q}_N = -\sigma_C(\hat{p}_E - \hat{p}_N)$	(8)
Electricity supply-demand balance	$\hat{q}_E = \gamma\hat{c} + (1-\gamma)\hat{x}$	(9)
Composite factor supply-demand balance	$\lambda\hat{z}_E + (1-\lambda)\hat{z}_N = 0$	(10)
Alternative model with inherent and adaptive resilience		
Electric power sector production function	$\hat{q}_E = \alpha(\hat{k} + \xi\hat{b}) + (1-\alpha)\left(\hat{z}_E - \frac{\delta}{\eta}\hat{b}\right)$	(1’)
Elasticity of substitution in electricity production	$\left(\hat{k} + \xi\hat{b}\right) - \left(\hat{z}_E - \frac{\delta}{\eta}\hat{b}\right) = -\sigma_E(\hat{r} - \hat{w})$	(5’)

We assume that the economy is initially in equilibrium. The model’s system of algebraic equations account for the economy-wide consequences of electricity supply interruptions through the channel of a secular adverse shock to infrastructure capital, with the expected percentage capacity loss given by $\hat{k}^* = \mathbb{E}[\hat{k}] < 0$. The solution to the algebraic system gives the expected economic consequences of a blackout. The system is made up of the ten equations (1)-(10) in eleven unknowns $\{\hat{q}_E, \hat{c}, \hat{x}, \hat{p}_E, \hat{q}_N, \hat{p}_N, \hat{z}_E, \hat{z}_N, \hat{w}, \hat{r}, \hat{u}\}$. To close the model we treat the composite factor as the numeraire commodity using the normalization $\hat{w} = 0$, which we include as an additional equation. This approximation is valid where the value of electric power production ($p_E q_E$) is much smaller than that of the rest of the economy ($p_N q_N$), which at the scale of United States regions is almost always true. In this situation factor markets and prices will only be modestly impacted even in the event of a severe shock to electricity infrastructure. This result is a system with as many equations as unknowns, in which closed-form algebraic solutions for the latter can easily be obtained as functions of the shock, $\hat{k}^*$.

Notwithstanding the model's abstract character, it has many advantages. Its solution is simple, in the sense that although the unknown variables are generally complicated algebraic combinations of the underlying parameters, the fundamental linearity of eqs. (1)-(10) guarantee that the resulting expressions are linear functions of the initiating shock. The simple insight is that the combinations of parameters whose values might differ according to the specific domain of any individual study can be thought of as elasticities whose magnitudes (and, potentially, signs) will vary with the particular characteristics of the shock and the impacted economy. The model's simplicity and genericity enable it to be flexibly parameterized to capture a broad range of economies at a variety of geographic scales. This in turn facilitates the expeditious creation of zeroth-order estimates of business interruption losses from disruptions of different magnitudes. It does so by enabling the economic consequence analysis to be decoupled from detailed electric power system modeling, which expedites assessment by enabling the two investigations to proceed in parallel and have their results subsequently combined.

The model's algebraic framework also enables us to explore the implications of inherent resilience and mitigation. On the supply side, inherent resilience is determined by the opportunities to substitute the composite factor for damaged infrastructure capacity in E and for scarce electricity in N, determined by the values of σ_E and σ_N. Symmetrically, on the demand side inherent resilience arises out of consumers' ability to substitute other goods and services for electricity as the latter's supply is curtailed, which is captured by the value of σ_U. Turning to mitigation, power producers will attempt to offset the negative economic impacts of blackouts via deliberate investments in backup generation, transmission and distribution capacity, indicated generically by b. While inherent resilience is assumed to be a costless property of the benchmark economy embodied in the elasticity of substitution parameters, mitigation via backup investments incurs an opportunity cost.

We assume that the backup technology can be produced by investing a portion, z_E^{Backup}, of the factor input to the electricity sector. The net quantity of the factor available to produce power,

$$z_E^{Net} = z_E - z_E^{Backup}$$

can be expressed in log differential form as

$$\frac{z_E^{Net}}{z_E}\left(\frac{dz_E^{Net}}{z_E^{Net}}\right) = \left(\frac{dz_E}{z_E}\right) - \frac{z_E^{Backup}}{z_E}\left(\frac{dz_E^{Backup}}{z_E^{Backup}}\right)$$

This investment yields backup capacity according to the elasticity of transformation, η:

$$db = \frac{\partial b}{\partial z_E^{Backup}} dz_E^{Backup} \Rightarrow \frac{dz_E^{Backup}}{z_E^{Backup}} = \underbrace{\left(\frac{\partial b}{\partial z_E^{Backup}} \Big/ \frac{b}{z_E^{Backup}}\right)}_{\eta}{}^{-1} \frac{db}{b} \Rightarrow \hat{z}_E^{Backup} = \frac{1}{\eta}\hat{b}$$

We exploit the simplifying assumption that the magnitude of backup investment is small compared to the overall quantity of factor input ($z_E^{Backup}/z_E = \delta \ll 1$). The result is the approximation

$$\hat{z}_E^{Net} \approx \hat{z}_E - \delta \hat{z}_E^{Backup} \approx \hat{z}_E - \frac{\delta}{\eta}\hat{b} \tag{11}$$

which we substitute into the second terms on the right-hand side of eq. (1) and the left-hand side of eq. (5). The backup technology provides the benefit of extra infrastructure capacity

$$k^{Net} = k + b$$

which in log differential form is given by

$$\frac{k^{Net}}{k}\left(\frac{dk^{Net}}{k^{Net}}\right) = \frac{dk}{k} + \frac{b}{k}\left(\frac{dk}{k}\right)$$

Assuming that the benchmark quantity of the backup technology constitutes a small fraction of conventional capacity ($b/k = \xi \ll 1$), we obtain the approximation

$$\hat{k}^{Net} \approx \hat{k} + \xi\hat{b} \tag{12}$$

which we substitute into the first term on the right-hand side of (1) and the left-hand side of (5).

As shown in Table 2, augmenting the model to incorporate inherent resilience yields the new system of equations (1'),(2)-(4),(5') and (6)-(10). The number of equations is the same as before, but the addition of the variable, $\hat{b}$, makes the system under-determined. We therefore use the model to explore how undertaking different levels of backup investment can moderate or exacerbate the adverse consequences of an infrastructure shock, elucidate the economic consequences of various combinations of $\hat{b}$ and $\hat{k}$. A particular advantage of our simple analytical framework is that it enables us to solve for the level of backup capital that can minimize disruption of operational infrastructure ($\hat{k}^{Net} \to 0$), the electricity supply ($\hat{q}_E \to 0$) or welfare losses ($\hat{u} \to 0$) for a given expected curtailment of infrastructure capacity. As we go on to illustrate, these criteria have different economic consequences.

3.2 Numerical Application: A Two-Week Power Outage in California's Bay Area

As is common in theoretical studies, the model's algebraic solutions can be challenging to interpret, especially in cases where the responses of key variables cannot be unambiguously signed, with the result that their direction of change depends on the parameters. To obtain additional insights, we numerically calibrate and simulate the model in an experiment that showcases its capabilities for assessing the economic consequences of a shock to infrastructure. Our application is the impact of a 14-day disruption of electricity infrastructure in five counties of California's Bay Area (Alameda, Contra

Costa, San Francisco, San Mateo). Using the simple assumption of constant daily average electricity load, this interruption can be interpreted as a 4% reduction in the region's annual electricity supply capacity ($\hat{k}^* = -0.04$).[3] This shock is quite extreme. To put it in context, in the US Geological Survey's HayWired earthquake scenario, ground shaking, liquefaction, and subsequent fires and landslides trigger immediate loss of power for 95% of customers in Alameda, with restoration of service to 83% of customers within 7 days. Over a 6-month post-earthquake recovery period, similar patterns of disruption and restoration translate into integrated power supply curtailments of 3.9% in Alameda, 2.7% in Santa Clara, 2.5% in Contra Costa, 1.8% in San Mateo, and 1.3% in San Francisco (Sue Wing et al, 2018).

Values for the economic parameters in Table 1 were calculated by aggregating social accounting matrices for the five counties for the year 2012, constructed by IMPLAN. These are summarized in Table 3. Electric power production is highly capital intensive, with inputs of capital accounting for 42% of the sector's output. We assume that the total value of various kinds of infrastructure account for one quarter of this amount, which suggests that the infrastructure cost share and output elasticity is just over 10%. As the Bay Area is the hub of California's digital economy, downstream production activity served by the power sector is not only large by comparison—accounting for 99.6% of the demand for the region's endowment of primary factors, it is also responsible for the bulk of the demand for electricity, accounting for 81% of supply in contrast to the residential sector's 19%. Even so, households' electricity spending is only 1.4% of their total expenditure, with the remainder allocated to consumption of the output of industries in the rest-of-economy aggregate. Relative to other inputs to downstream production, intermediate electricity plays an even smaller role, with a sectoral cost share of only 0.6%.

Table 3. Parameters of the Numerical Model

α	λ	β	γ	ϕ	ξ	η	δ
0.104512	0.004106	0.004995	0.19208	0.014424	0.15	0.5-1.25	0.02

Our model's highly aggregate and stylized character means that the parameters that determine the opportunity cost and penetration of the backup technology will necessarily have a less rigorous empirical basis. We assume that the backup technology's share of infrastructure capacity in the baseline equilibrium is 15%, the same as the operating reserve margin required by the California Independent System Operator (CAISO). The elasticity of transformation between primary factors and reserve generation, transmission and distribution capacity, as well as the benchmark share of the power sector's factor hiring allocated to provide these services, are both more speculative. For the elasticity parameter we assume that, on one hand, power producers would be unwilling to sink resources into the backup technology if such investment were not sufficiently productive (i.e., of sufficient capacity to moderate the cost of adverse shocks), and, on the other hand, that if such investments were highly productive firms would pursue them to such an extent as to render regulation

[3] The scenario characterizes the physical impacts and economic consequences of a rupture of the Hayward Fault—see Detweiler and Wein (2017).

unnecessary. This in turn suggests that η is neither highly inelastic nor highly elastic. Accordingly, we consider values in the range $\eta \in [0.5,1.25]$ to be plausible. We calibrate the share based on the values of the remaining parameters. The assumption that the benchmark prices of infrastructure and the composite factor do not differ appreciably leads to the approximations $k/q_E \approx \alpha$ and $z_E/q_E \approx 1-\alpha$. We further assume that the productivity elasticity of backup investment is near unitary ($\eta \approx 1$), which allows us to express the latter as $z_E^{Backup} \approx b$. Combining our approximations with the definition of the share leads to

$$\delta = \frac{z_E^{Backup}/q_E}{z_E/q_E} \approx \frac{\alpha}{1-\alpha}\frac{z_E^{Backup}}{k} \approx \frac{\alpha}{1-\alpha}\frac{b}{k} = \frac{\alpha}{1-\alpha}\xi$$

which yields a plausible value of 0.0167. We round this result to 2%, which represents an upper bound, given our unavoidably approximate calibration procedure.

We treat the elasticities of substitution as exogenous parameters whose values are simply assumed. At the regional scale of our investigation, infrastructure capital is a necessary input to electricity supplied from the grid, and power is a necessary input to both firms and households, which suggests that the values of all elasticities are at most unity. The extreme technological difficulty of using other productive inputs as large-scale substitutes for infrastructure capacity in power generation, transmission and distribution suggests that the inputs to the electricity sector are relative complements ($\sigma_E \ll 1$). Accordingly, for our model simulations we consider low and high values for that sector's elasticity of substitution, $\sigma_E = \{0.01,0.25\}$. By contrast, firms and households both possess myriad opportunities to substitute other inputs for electricity supply in response to supply curtailments and/or price increases. We therefore consider substitution elasticities in the range $\sigma_N, \sigma_U \in [0.25,1]$.

4. Results

4.1 No Substitution

We begin by investigating the extreme case where economic actors do not engage in substitution. Although admittedly unrealistic, we note that this corresponds to the assumptions implicit in PE studies that treat prices, power sector output demands and/or inputs supplies as fixed. The infrastructure disruption has straightforward economic consequences. If power producers do not react to infrastructure curtailment by adjusting their factor usage, then the quantity of output declines according to the product of the infrastructure output elasticity and the shock. Downstream, if neither intermediate nor final consumers alter their demands for inputs of factors and the rest-of-economy good (respectively), as the electricity supply declines, their electricity demands will decline by the same percentage amount as the fall in supply. Accordingly, we have

$$\hat{q}_E = \hat{x} = \hat{c} = \alpha\hat{k}^* < 0 \tag{13}$$

while downstream output in the rest of the economy is reduced by the amount

$$\hat{q}_N = \alpha\beta\hat{k}^* < 0 \tag{14}$$

triggering a welfare decline of

$$\hat{u} = \alpha(\phi + (1-\phi)\beta)\hat{k}^* < 0 \tag{15}$$

A key feature of our loglinear setup is that the magnitude of the initiating shock always exceeds the changes in sectoral output and welfare in percentage terms. This result stems from the fact that the benchmark value of electricity infrastructure is smaller than the output of the power sector and downstream production and consumption.[4] Consequently, when expressed on the same annual percentage basis as the shock, the impacts of a two-week infrastructure disruption are modest: a slight decline in electricity supply and demand (0.4%), negligible reduction in rest-of-economy output (0.002%), and a small welfare loss (0.13%). Eqs. (13)-(15) trace these small effect sizes to electricity's small share of households' expenditure, and, particularly, downstream firms' costs.

4.2 Inherent Resilience Via Input Substitution

In the more realistic situation where producers and consumers do engage in substitution, the results differ substantially. We begin by defining the quantity

$$\mathcal{D}_0 = \big(1-\alpha(1-\lambda)\big)\sigma_E + \alpha(1-\lambda)\big(1-\gamma(1-\beta)\big)\sigma_N + \alpha(1-\lambda)\gamma(1-\beta)\sigma_U > 0$$

which plays the role of the denominator of the algebraic expressions of variable changes and is unambiguously positive. The impact on power supply is unambiguously negative, as before,

$$\hat{q}_E = \alpha\big\{\lambda\sigma_E + (1-\lambda)\big(1-\gamma(1-\beta)\big)\sigma_N + (1-\lambda)\gamma(1-\beta)\sigma_U\big\}\mathcal{D}_0^{-1}\hat{k} < 0 \tag{16}$$

but here it is smaller in magnitude.[5] A second unambiguous impact is an increase in the electricity price,

$$\hat{p}_E = -\alpha\mathcal{D}_0^{-1}\hat{k} > 0 \tag{17}$$

The impact on intermediate electricity use depends on the values of the parameters

[4] Assuming no price response, the upstream capital input coefficient determines the percentage change in power supply. The downstream intermediate and final electricity input coefficients determine the change in the rest-of-economy output and the direct (via the residential electricity demand channel) and indirect (via the downstream goods demand channel) effects on household utility.

[5] The numerator and denominator have identical second and third terms. The magnitude of the impact on the power sector is less negative because the magnitude of the first term in the denominator, $\big(1-\alpha(1-\lambda)\big)\sigma_E$, exceeds that of the first term in the numerator, $\alpha\lambda\sigma_E$.

$$\hat{x} = \alpha\left\{\lambda\sigma_E + \left(1 - \lambda\left(1 - \gamma(1-\beta)\right)\right)\sigma_N - \gamma\lambda(1-\beta)\sigma_U\right\}\mathcal{D}_0^{-1}\hat{k} \tag{18}$$

The outcome depends on the competition for power between intermediate and final demands, which is determined by the relative magnitudes of the elasticities of substitution. For curtailment of demand by downstream firms, the restriction on the parameters is

$$\sigma_U < \frac{1}{\gamma(1-\beta)}\sigma_E + \frac{1 - \lambda\left(1 - \gamma(1-\beta)\right)}{\gamma\lambda(1-\beta)}\sigma_N$$

suggesting that households' elasticity of substitution between residential electric power and rest-of-economy output must not be "too large". If electric power and downstream producers' outputs are both necessary goods, the inequality above will be satisfied if the elasticities of substitution among inputs to the producing sectors are sufficiently large that their weighted sum on the right-hand side above exceeds unity.[6]

The sign of impacts on downstream economic output, residential electricity use and welfare are all ambiguous as well:

$$\hat{c} = \alpha\left\{\lambda\sigma_E + \left(\beta - \lambda\left(1 - \gamma(1-\beta)\right)\right)\sigma_N + (1-\gamma\lambda)(1-\beta)\sigma_U\right\}\mathcal{D}_0^{-1}\hat{k} \tag{19}$$

$$\hat{q}_N = \alpha\{\lambda\sigma_E + (\beta - \lambda(1 - \gamma(1-\beta)))\sigma_N - \gamma\lambda(1-\beta)\sigma_U\}\mathcal{D}_0^{-1}\hat{k} \tag{20}$$

$$\hat{u} = \alpha\left\{\lambda\sigma_E + \left(\beta - \lambda\left(1 - \gamma(1-\beta)\right)\right)\sigma_N + (\phi-\gamma\lambda)(1-\beta)\sigma_U\right\}\mathcal{D}_0^{-1}\hat{k} \tag{21}$$

For these impacts to be negative, the main restriction on the parameter values that they share is that the output elasticity of electricity in downstream production exceeds the share of the factor endowment accounted for the power sector:

$$\beta > \lambda\frac{1-\gamma}{1-\gamma\lambda}$$

Additional restrictions are, for welfare (21), the sufficient condition, $\phi > \gamma\lambda$, and, for rest-of-economy output (20), the sufficient condition

$$\sigma_U < \frac{1}{\gamma(1-\beta)}\sigma_E + \frac{\beta - \lambda\left(1 - \gamma(1-\beta)\right)}{\gamma\lambda(1-\beta)}\sigma_N$$

The essence of substitution's moderating effect is that producers (consumers) are able to use relatively

[6] Note that the weights on σ_E and σ_N are strictly positive.

larger quantities of factor (rest-of-economy) inputs in an attempt to compensate for declines in the quantities of inputs of infrastructure or electricity. By eqs. (5), (6) and (8), the extent to which actors adjust along these margins depends on the values of the elasticities of substitution, in conjunction with general equilibrium feedback effects on prices that induce relative price changes. For the power sector, the potential for adjustment is indicated by setting $\hat{q}_E = 0$ in (1) and simplifying to obtain

$$\begin{aligned} -\frac{dz_E}{dk} &= -\left(\frac{z_E/q_E}{k/q_E}\right)\left(\frac{dz_E}{z_E}\Big/\frac{dk}{k}\right) \approx \frac{\alpha-1}{\alpha}\frac{\hat{z}_E}{\hat{k}^*} \\ &= (1-\alpha)(1-\lambda)\left\{\sigma_E - \big(1-\gamma(1-\beta)\big)\sigma_N - \gamma(1-\beta)\sigma_U\right\}\mathcal{D}_0^{-1} \end{aligned} \tag{22}$$

which is positive so long as the factor-infrastructure elasticity of substitution is sufficiently large, i.e.,

$$\sigma_E > \big(1-\gamma(1-\beta)\big)\sigma_N + \mathrm{n}\gamma(1-\beta)\sigma_U$$

Applying similar mathematical arguments to eqs. (2) and (7) yield the potential adjustment by downstream producers and consumers as

$$-\frac{dz_N}{dx} \approx \frac{\beta-1}{\beta}\frac{\hat{z}_N}{\hat{x}} = \frac{\beta-1}{\beta}\left\{\frac{\lambda\sigma_E - \lambda\big(1-\gamma(1-\beta)\big)\sigma_N - \gamma\lambda(1-\beta)\sigma_U}{\lambda\sigma_E + \Big(1-\lambda\big(1-\gamma(1-\beta)\big)\Big)\sigma_N - \gamma\lambda(1-\beta)\sigma_U}\right\} \tag{23}$$

$$-\frac{dq_N}{dc} \approx \frac{\phi-1}{\phi}\frac{\hat{q}_N}{\hat{c}} = \frac{\phi-1}{\phi}\left\{\frac{\lambda\sigma_E + \Big(\beta-\lambda\big(1-\gamma(1-\beta)\big)\Big)\sigma_N - \gamma\lambda(1-\beta)\sigma_U}{\lambda\sigma_E + \Big(\beta-\lambda\big(1-\gamma(1-\beta)\big)\Big)\sigma_N + (1-\lambda\gamma)(1-\beta)\sigma_U}\right\} \tag{24}$$

Respectively, these expressions' signs are positive for $\sigma_N > 0$ and $\sigma_U > 0$, and are negative only in the limiting situations where electricity is strictly complementary to use of the factor in the case of producers, or rest-of-economy output in the case of consumers. The important implication is that estimates of the economic consequences of outages should account for the tendency of the rest of the economy to exploit any opportunity to replace relatively scarce and expensive power with other inputs that are relatively abundant, and cheaper.

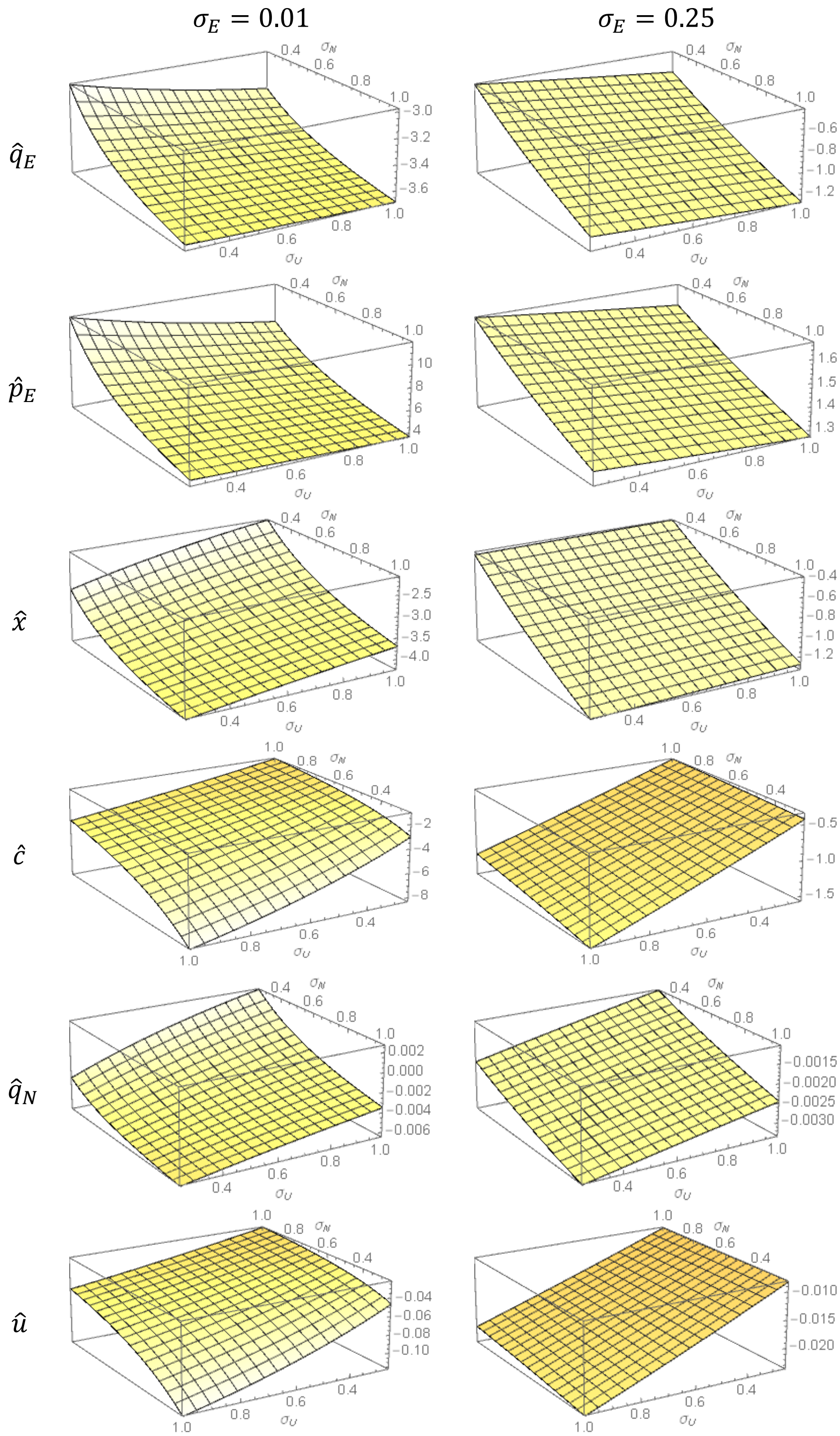

Figure 1. Impacts of a Two-Week Electricity Infrastructure Disruption on the Bay Area Economy: Inherent Resilience (% change in the value of each variable from its baseline level)

Figure 1 illustrates the net effects of these forces in our Bay Area disruption scenario. The response surfaces make clear that while the impacts on variables' percentage changes may be linear in the initiating shock, they are nonlinear in the parameters. There are unambiguously negative impacts on electricity supply (between -3.6% and -0.6%), intermediate and final electricity demands (-4% to -0.4% and -8% to -0.5%), and welfare (-0.1% to -0.01%). Electric power becomes unambiguously more expensive (1.3% to greater than 10%), while the output of the rest of the economy contracts or expands slightly depending on the combination of substitution elasticity values (between -0.06% and 0.002%). With the exception of the electricity price, increases in the scope for producer and consumer substitution shrink the absolute percentage magnitude of economic consequences. Under many parameter combinations, this results in impacts that are of smaller magnitude than the initiating shock. Not surprisingly, this is overwhelmingly true for electric power producers' ability to substitute factors for infrastructure: the larger the value of σ_E the more the impacts shrink toward zero, and become linear in the parameters. For the supply of, price of, and intermediate demand for, power, as well as rest-of-economy output, the second strongest determinant of the response to a disruption is the rest of the economy's elasticity of substitution, whereas for residential electricity consumption and utility, this role is played by the household elasticity of substitution. The results for $\hat{u}$ indicate that the economy-wide benefit of substitution is to moderate the welfare cost of the shock in Section 4.1 by one to two orders of magnitude.

4.3 Mitigation

The counterfactual equilibrium of the model with backup investment is algebraically too complex to yield clear analytical insights. Notwithstanding, it allows us to solve for changes in the quantity of backup capacity that satisfy the three criteria discussed in sub-section 3.1. The first is the investment that minimizes the loss of infrastructure capacity, which by (12) simply follows the fixed rule

$$\hat{b}^{K0} = \hat{b}\big|_{\hat{k}^{Net}=0} = -\xi^{-1}\hat{k}^*$$

The second is the investment that minimizes power supply disruption, which we find by setting $\hat{q}_E = 0$ and solving for $\hat{b}$ as a function of the parameters:[7]

$$\hat{b}^{E0} = \hat{b}\big|_{\hat{q}_E=0} = -\alpha\eta\{\lambda\sigma_E + (1-\lambda)\big(\gamma(1-\beta)\sigma_U + \big(1-\gamma(1-\beta)\big)\sigma_N\big)\}\mathcal{D}_1^{-1}\hat{k}^*$$

Similarly, the third is investment that minimizes welfare loss, which we find by setting $\hat{u} = 0$ and solving for $\hat{b}$:

$$\hat{b}^{U0} = \hat{b}\big|_{\hat{u}=0} = \alpha\eta\{\lambda\sigma_E - \lambda\big(\gamma(1-\beta)\sigma_U + \big(1-\gamma(1-\beta)\big)\sigma_N\big) + \beta\sigma_N + (1-\beta)\phi\sigma_U\}\mathcal{D}_2^{-1}\hat{k}^*$$

[7] In the polar case of no substitution, power producers do not adjust their gross factor input, and reduce their net factor input by an amount that exactly offsets their allocation of resource to backup investment. The effect of mitigation is therefore to simply replace $\hat{k}^*$ with $\hat{k}^* + \xi\hat{b}$ in eqs. (13)-(15), in the event of which the optimal backup is simply $\hat{b} = \hat{b}^{K0}$.

Here, the denominators $\mathcal{D}_1$ and $\mathcal{D}_2$ are complicated functions of the parameters.

To understand the implications of these expressions we numerically parameterize them based on Table 3. Focusing on the role played by our technology parameters, we evaluate $\hat{b}^{E0}$ and $\hat{b}^{U0}$ at representative values of the elasticities of substitution ($\sigma_N = 0.5, \sigma_U = 0.75$) while varying the factor elasticity of backup transformation and the baseline share of backup capacity. The results, shown in Figure 2, highlight the nonlinear response of backup investment to these parameters. Under either criterion, the optimal level of investment is for all practical purposes invariant over a wide range of combinations of η and ξ. The analytical solutions that underlie the figure indicate that in this region, the elasticities of the response of backup capacity to the shock range from -6.6 to -7.2, which closely parallel the value of the infrastructure disruption minimizing elasticity, above ($1/\xi = 6.7$). These responses correspond to increases in backup capacity of around 27%.

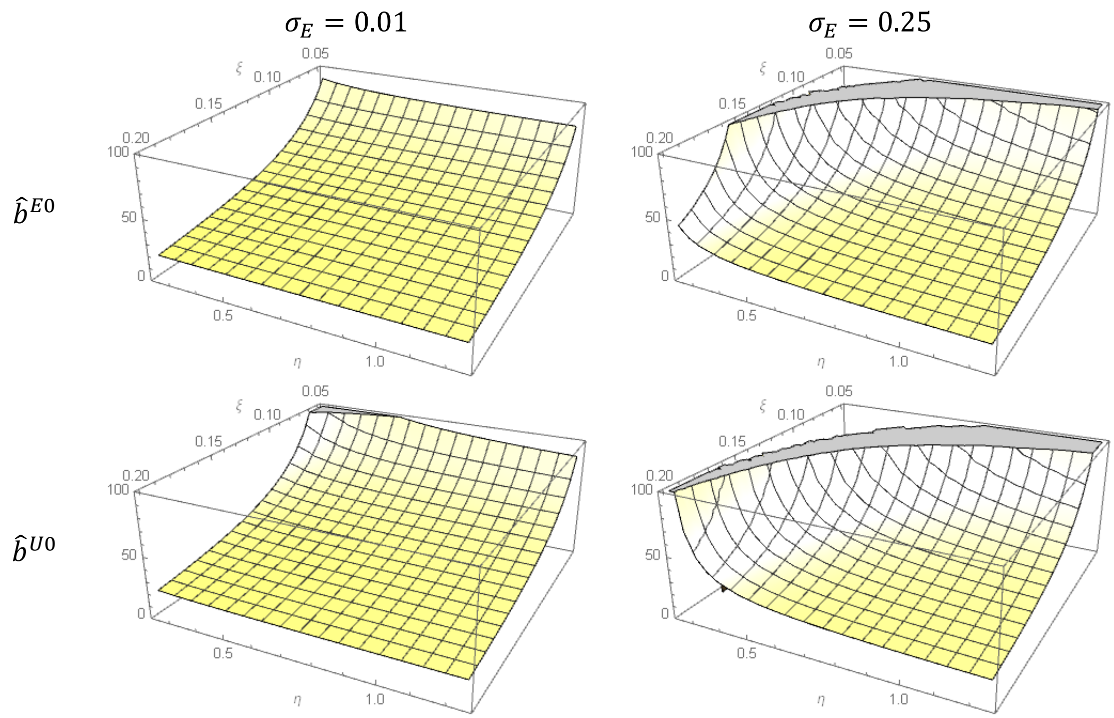

Figure 2. Energy Supply Disruption Minimizing and Optimal Backup Technology Penetration (% change in backup capacity from its baseline level)

As either the productivity of factors diverted to backup capacity additions or the baseline share of backup capacity decline, the investment response becomes exponentially larger, with values of η below 0.4 and ξ below 0.1 inducing increases in backup infrastructure of more than double their baseline level. This behavior is more sensitive to the pre-existing level of backup technology, which is not surprising considering that the model solutions are interpreted as percentage changes, and ξ indicates the base off of which that change is calculated. For even smaller values of the two parameters, the increase in the elasticity of $\hat{b}^{E0}$ and $\hat{b}^{U0}$ to the shock is asymptotic, which suggests that there is no feasible way to satisfy their respective criteria given how much additional backup capacity needs to be added to the small installed base, and/or the quantity of resources that must be diverted to this effort, due to the low productivity of the investment transformation technology. Particularly noteworthy is the fact that such a problem arises when it is possible for power producers to directly substitute factor inputs for specialized infrastructure capital ($\sigma_E = 0.25$). Conversely, with strict input complementarity ($\sigma_E \to 0$), deliberate investment in backup capacity is the sole margin on which electric power producers are able to adjust to maintain baseline levels of supply. The range of values of η and ξ with modest levels of investment is correspondingly broadened.

We close by assessing the consequences of the shock under both uncertainty of the substitution parameters and mitigation investment in backup capacity. In the counterfactual equilibrium with mitigation, each of the variables takes the form $\mathcal{F}\hat{k} + \mathcal{G}\hat{b}$, where $\mathcal{F}$ and $\mathcal{G}$ are complicated algebraic functions of the parameters. We therefore focus on the numerical solutions to the model with backup investment set at the levels $\hat{b}^{K0}$, $\hat{b}^{E0}$ and $\hat{b}^{U0}$, above. Table 4 reports the median and range of values of the variables calculated under 32 different combinations of the substitution elasticities, while keeping the technology parameters fixed at representative values ($\eta = \{0.5, 0.75\}$, ξ and δ as in Table 1). Across scenarios there are only slight differences in the median level of investment, from 27% to 33% (27% to 41%) when backup investment is more (less) productive. Compared to the impacts in section 4.2, backup capacity has a substantial moderating influence on changes in both electricity prices, downstream quantities of electricity inputs and economic output, and consumers' welfare. In particular, despite the fact that the welfare losses in the absence of mitigation are small, the net effect of backup capacity expansion is to further reduce them by up to an order of magnitude. For a given baseline backup capacity, these benefits depend critically on the productivity of the factors of production that power producers divert toward its expansion. At the low productivity optimum, the warranted level of capacity can more than double under the worst-case combination of our substitution elasticities.

Finally, the results emphasize that although the magnitude of investments that minimize losses of infrastructure capacity and output might be similar in magnitude, they nonetheless incur welfare losses. The reason is that neither measure fully internalizes the opportunity cost of the factors that must be diverted from alternative productive uses in the process of making such investments. Even in the stylized environment of the present model, where factor prices are assumed to be constant, the reallocation of factors among industries will give rise to general equilibrium effects that induce broader changes in commodity prices, supplies and demands.

5. Discussion and Conclusions

We have developed a simple analytical general equilibrium model of the economy-wide impacts of electricity infrastructure disruptions. The model's counterfactual equilibria throw into sharp relief two key factors. The first is the role of substitution as an inherent resilience mechanism, which gives rise to changes in commodity prices and quantities, and concomitant reductions in welfare, that are much smaller in magnitude than the initiating shock. The second is the ability for deliberate investments in mitigation to further dampen the consequent price and quantity changes, and ultimate welfare losses.

Table 4. Effects of Backup Capacity Investment on the Consequences of Infrastructure Disruption (median % change in the quantity of each variable from its baseline level, minimum and maximum values in square braces)

$\hat{b}$	$\hat{q}_E$	$\hat{p}_E$	$\hat{x}$	$\hat{q}_N$	$\hat{c}$	$\hat{u}$
Inherent resilience via substitution only						
—	-2.1	2.7	-1.7	-0.0025	-1.4	-0.023
—	[-3.7,-0.42]	[1.3,12]	[-4.2,-0.39]	[-0.0065,0.0027]	[-8.3,-0.34]	[-0.12,-0.0081]
Backup investment that minimizes infrastructure disruption ($\hat{b} = \hat{b}^{K0}$)						
$\eta = 0.5$						
27	-0.083	0.24	-0.083	-0.0044	-0.096	-0.0059
—	[-0.37,-0.035]	[0.039,0.48]	[-0.39,-0.026]	[-0.0048,-0.0041]	[-0.45,-0.015]	[-0.011,-0.0046]
$\eta = 0.75$						
27	-0.034	0.098	-0.034	-0.0029	-0.039	-0.0035
—	[-0.15,-0.015]	[0.015,0.19]	[-0.16,-0.011]	[-0.0031,-0.0028]	[-0.19,-0.007]	[-0.0055,-0.003]
Backup investment that minimizes electricity supply disruption ($\hat{b} = \hat{b}^{E0}$)						
$\eta = 0.5$						
32	—	-0.0079	0	-0.0049	0	-0.0048
[27,38]	—	[-0.022,-0.0044]	[-0.002,0.0009]	[-0.0054,-0.0044]	[-0.0038,0.0083]	[-0.0054,-0.0043]
$\eta = 0.75$						
29	—	-0.0048	0	-0.003	0	-0.0029
[27,30]	—	[-0.012,-0.0029]	[-0.0011,0.0005]	[-0.0031,-0.0029]	[-0.0022,0.0047]	[-0.003-0.0028]
Backup investment that minimizes welfare loss ($\hat{b} = \hat{b}^{U0}$)						
$\eta = 0.5$						
41	0.37	-0.63	0.37	-0.0055	0.38	—
[28,110]	[0.12,2.2]	[-3.3,-0.31]	[.076,2.6]	[-0.012,-0.0039]	[0.27,0.81]	—
$\eta = 0.75$						
33	0.21	-0.34	0.21	-0.0031	0.21	—
[27,48]	[0.081,0.68]	[-1,-0.2]	[0.05,0.79]	[-0.0036,-0.0024]	[0.16,0.25]	—

Additional insights were developed via a numerical case study investigating the consequences of a two-week electricity infrastructure outage in California's Bay Area. Inherent resilience and mitigation drive a wedge between the initiating shock and the actual reduction in electricity supply. With inherent resilience due to substitution alone, power output declines between -3.7% and -0.42%, the electricity price increases by 3% to 12%, intermediate and residential electricity use fall by -4.2% to -0.39% and welfare declines by 0.02%. Mitigation via expanding backup infrastructure capacity can reduce these effects by as much as two orders of magnitude, and, in the limit, completely nullify the loss in welfare. In percentage terms the ultimate welfare impacts are small, ranging from -0.13% assuming no substitution whatsoever to -0.0081%.

The measure of welfare impact used here is a more theoretically consistent indicator of the economy-wide burden of disruptions than commonly-used partial equilibrium measures of cost. To put our results in context, we treat the change in utility as percentage equivalent variation, which we then multiply by the combined annual personal income of our affected counties ($537 Bn in 2016). With no substitution, this suggests a worst-case nominal economy-wide net cost of $1 Bn, which is reduced to $123-644 M by inherent resilience due to substitution, $19-30 M with additional infrastructure capacity-preserving backup investment, and $15-16 M with supply-preserving investment. By contrast, applying an average $2/hour long-duration residential outage cost (e.g., Sullivan et al, 2015: Table 5-7) to the 2.2 million households in our affected Bay Area counties (CA DOF, 2017) yields a cost of our disruption scenario of $1.5 Bn in the residential sector alone!

Disparities such as these point to the pressing need for research to reconcile costs derived from general equilibrium frameworks of the kind developed here with bottom-up, partial equilibrium estimates of WTP. We conjecture that one reason for this divergence is potential bias in residential customers' responses to stated preference surveys that reflects misperceptions of household substitution possibilities as the prices of both electricity and other goods change. In such circumstances, WTP is given by eq. (3), and is at the upper end of the range of estimates discussed above. It is less clear whether similar kinds of perceptual biases might influence estimates of commercial and industrial customers' WTP—given that these respondents are acutely aware of their own production costs. However, what our analytical framework drives home is that, because of the input-output structure of the economy, simply adding up WTP estimates from residential and commercial/industrial customers is likely to seriously overstate the true welfare costs of electricity disruptions.[8]

Further considering the supply side, it is more difficult to quantify what our results mean in terms of the direct cost to power producers entailed in expanding backup capacity by the percentage amounts in Table 3. This points to what is perhaps the most important limitation of this study: its stylized, highly simplified character that requires additional research to be rendered consistent with the physical reality of the power system. The latter is particularly relevant for our mitigation results, which rely on the artifice of a monolithic backup technology. Detailed engineering and/or power system simulation studies to elaborate the constituents of this black box, the manner in which their interactions determine backup performance, and their operational and investment demands for different inputs—

[8] Note that in our simple closed economy, $\hat{q}_N$ identifies both the effect on the output of downstream commercial and industrial electricity users as well as the consequences for households' consumption of that output. This structure suggests that in a more general open-economy setting, a portion of the forgone output that would implicitly be embodied in nonresidential customers' WTP will also end up as a component of the reduction in households' consumption, and hence residential WTP. The larger the overlap between forgone production and forgone residential nonelectric consumption, the larger the potential for double-counting.

particularly capital, can yield much needed empirical constraints on the values of the key uncertain parameters ξ, δ and η.

We take pains to acknowledge important elements that our economic model does not include. It ignores the income effects associated with changes in factor prices driven by shifts in the marginal productivities of both the power sector infrastructure fixed factor and the intersectorally mobile generic factor. In a regional economic system such price changes tend to be dampened by factor movements across the regions' boundaries, and we have eschewed explicit representation of these economic processes for the sake of keeping the analysis simple and tractable. Also omitted are inventories and imports from outside the region of goods and the composite factor, which together constitute an additional margin of adjustment with the potential to further moderate the shock's effects on prices, reallocation of goods and factors, and consequent welfare losses

A further concern is that the model is insufficiently detailed in terms of the number of electricity using sectors it represents, and, particularly, its omission of intermediate inputs to production, to be useful for policy analysis. Our stylized representation of consumer behavior is far too aggregated to accommodate representation of multiple income and/or demographic groups that are likely to differ systematically in their inherent flexibility and ability to engage in substitution, as well as their financial and technical capacity to adopt deliberate resilience measures. We speculate that the differences in the magnitude of welfare losses that might result from these inequitable circumstances could conceivably serve as an indicator of the potential for broader adverse noneconomic consequences (e.g., social unrest) about which regulators care.

In the disaster literature, the concept of mitigation generally incorporates hardening of infrastructure that enables assets to continue to deliver services at levels close to their design capacity while withstanding the effects natural or anthropogenic hazards (e.g., building stronger structures and equipment, or burying power lines underground). We have defined mitigation as costly investment in back-up (spare or redundant) capacity that facilitates smaller reductions in output from a given shock. Infrastructure hardening is qualitatively different. When such investments are made ex ante, they moderate the initial capacity loss, which is manifested as a reduction in the magnitude of the shock. (Note that this is distinct from inherent resilience, which enables economic actors to respond more elastically to a shock of a certain magnitude.) In this analytical setup the challenge is to compare in a consistent fashion the general equilibrium benefit of aggregate cost savings against the partial equilibrium investment expenditure when the latter's economy-wide opportunity costs are not explicitly taken into account.

The broader related issue is that the relative abilities of mitigation and resilience measures to moderate the economywide losses calculated here depend on these measures' costs and benefits. On the cost side, mitigation measures as we have modeled them always require expenditure, while many types of inherent resilience need not, being a byproduct of production flexibility associated with routine investment decisions not specially related to power outages. For example, an important element of supply-side inherent resilience is the availability of multiple facilities with sufficient slack capacity in the benchmark equilibrium to facilitate low-cost shifting of production to locations unaffected by an outage. Importantly, while there are no costs directly associated with input substitution as represented within the model, indirect costs still arise as a consequence of the general equilibrium feedbacks on relative prices of producers and consumers reallocating inputs that are imperfectly fungible. On the benefit side, mitigation expenditure simultaneously reduces losses to direct and indirect customers, whereas pre-existing inherent resilience measures must be undertaken by each customer individually. A key unknown is the potential for mitigation scale economies, namely, whether lumpy upstream backup capacity investments might actually be less than the individually smaller direct and indirect costs incurred by numerous downstream customers, and whether the benefits of such heterogeneous, uncoordinated expenditures exceed those of shorter duration of less geographically widespread power disruptions. Unfortunately, capturing these processes requires substantial extensions to our simple modeling framework, and so we defer them to future inquiry.

Finally, an important limitation of our analysis is that does not consider adaptive resilience. For example, conservation—i.e., price and non-price induced input-saving technical change by producers and consumers—is an important tactic that, all else equal, may temporarily preserve the levels of output and consumption. Other post-outage adaptive resilience measures, such as production recapture (temporarily scheduling additional shifts post-outage, taking advantage of normal slack capacity to make up for forgone output), can be low as well, depending on the benchmark economy's equilibrium level of slack capacity. However, the cost advantage of adaptive resilience is that it need not be implemented until the outage has taken place. In risk-benefit modeling, advance expenditures on inherent resilience or infrastructure hardening are balanced against mitigation benefits that must be multiplied by the probability of occurrence of a hazard. However, in the case of adaptive resilience, costs and benefits both arise only in the event of a disruption. The inherent resilience of firms' input substitution or spatial reallocation of production also need not be multiplied by this probability. The benchmark regional economy embodies the possibilities to do so, but actual substitutions does not need to take place unless an outage occurs.

How then might our analysis inform the development and application of CGE models to analyze electricity disruptions' broader economic consequences? It is important to realize that a more sophisticated economic simulation model will still be subject to many of the uncertainties that have proved difficult to constrain in the present framework, but at least are capable of being dealt with parametrically. This highlights the need to steer well clear of the trap of spurious precision: while elaborating the present model to include multiple sectors and household groups can certainly yield additional insights, that in itself is no guarantee that the resulting impacts will be accurate. This point is especially relevant given that the substitution possibilities on which the ultimate general equilibrium consequences depend need to be captured by elasticity parameters that are unlikely to be empirically validated at the fine sectoral, spatial and temporal disaggregation necessary to capture the impact of power disruptions. Indeed, if the length of the blackout being investigated is sufficiently brief, CGE models may not be the appropriate analytical tool, as the assumption of equilibrium implicitly assumes that adjustments take place over the so-called economic "short period", the approximately ~6-month horizon on which producers and consumers detect price signals and alter their behavior in ways that enable markets to clear. At the same time, our model is one of disequilibrium analysis in relation to a power outage shock. Moreover, substitution elasticities can be constrained to very low levels representing limited equilibrium adjustment possibilities in the short period. A related point is that the model's static character precludes its application to elucidate the role of general equilibrium interactions in the dynamics of recovery from power disruption events, and how they might influence the relative cost, effectiveness and desirability of different backup technology options.

All of the foregoing limitations can be expeditiously addressed through a program of research to develop dynamic multi-sectoral (and perhaps additionally, multi-regional) CGE simulations and couple them with techno-economic power system models. But in advance of such efforts coming to fruition, we feel the type of model developed here is sufficiently simple and flexible that it can be easily adapted to a broad range of situations at a variety of geographic scales to provide first-order insights on the economic consequences of long-term power disruptions.

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Discussion of "Economic Consequence Analysis of Electric Power Infrastructure Disruptions: An Analytical General Equilibrium Approach"

Discussant: Tim Allison
Affiliation: Argonne National Laboratory

The proposed methodology and economic modeling approach represents a valuable path forward in the analysis of the impacts of long-term electric power disruptions on regional economies. The paper highlights a fundamental problem with the analysis of power disruptions using "top-down" modeling approaches, namely, that the geographic-specific characteristics of any given transmission and distribution network, the economic characteristics of the most important electricity consuming sectors, and utility-specific mitigation and resilience all present significant data availability issues. Without these data, any proposed framework would not allow generalizable conclusions across localities or regions that might subsequently be subject to power supply disruptions.

The approach combines a simple representation of the economy as a two-sector, static, computable general equilibrium (CGE) model, with an electric power sector and a rest-of-the-economy sector. Input-output data is used to characterize the flow of goods, services capital and labor between intermediate and final demand sectors, with constant elasticity of substitution (CES) production functions. The model captures supply-side resilience through the substitution of damaged infrastructure by composite factor inputs, with mitigation captured through investments in backup generation, transmission and distribution capacity, while on the demand-side, resilience is measured as the ability of consumers to substitute other goods and services for electricity. As mitigation occurring through investment in back-up equipment is assumed to incur an opportunity cost, the model also measures the effect of different levels of investment in back-up technologies on economic cost (welfare).

The model is tested for a two-week loss in electric load in the Bay area, with a number of simplifying assumptions. Back-up technology's share of infrastructure capacity is assumed to be the same as the reserve margin, while the elasticity of substitution between reserve generation, transmission and distribution capacity, and the baseline share of power sector factor allocated to provide these services, are assumed to be moderately elastic. This assumes that electricity providers would not invest in backup technology if it did not moderate the cost of adverse shocks, and that if such investments were highly productive, firms would already be pursuing such opportunities. As power is a necessary input to both firms and households, the values of all elasticities are assumed to be moderately inelastic. It was found that the substitution resulting from changes in commodity prices and quantities, and the resulting reductions in welfare, were much smaller in than the initial shock, and that the investment in mitigation further dampened the consequent price and quantity changes and welfare losses.

As the authors point out, their approach has some shortcomings before it can yield more accurate results and recommendations for useful policy analysis. Some of these shortcomings relate to data, some to the modeling approach.

The availability of data to accurately characterize back-up technologies is an area that would need exploring. To produce a robust modeling approach, detailed utility power systems simulation studies would be required to measure the performance of feasible existing and prospective back-up technologies, and their implications for different inputs, particularly capital. To include the role of risk and time, differential adaption rates for existing capital infrastructure, and adoption rates for an array of new technologies, across utilities, would also need to be considered. The approach assumes that the elasticity of substitution between reserve generation, transmission and distribution capacity are moderately inelastic, and that the substitution elasticities among firms and households are assumed to be moderately elastic. As is the case with many regional impact analyses using a CGE approach, the ability of sectors and households to respond, and therefore the extent of their resilience, is dependent on the extent and timeliness of their response to changes in relative factor prices. Additional research to provide elasticity data for a range of sectoral and household substitution elasticities would make the model output more useful for policy analysis.

The modeling approach has a number of areas for where enhancements could be made. Firstly, the model divides the regional economy into two sectors, an electric power sector and a rest-of-the-economy sector, and therefore does not accurately represent the remaining electricity consuming sectors and is not capable of accurately measuring changes in intermediate inputs to production and substitution effects that occur with the loss of electricity supply. Secondly, the static character of the model means it is unable to capture the dynamics of recovery from power disruption events, and how they might influence the relative cost, effectiveness and desirability of different back-up technology options. Lastly, the approach does not include the welfare effects associated with the differential marginal productivity of capital associated with investment in power sector back-up technologies and investment in other sectors, or the mitigating effects on prices of the interregional flow of capital.

With the development of CGE modeling framework as a means of fully characterizing sector-specific and economy-wide substitution effects, and consequently the economic impacts and welfare effects that would occur with energy generation and distribution infrastructure disruptions and other supply-side shocks, the emphasis has shifted away from a simpler input-output approach to measuring impacts at the local and regional level. In their standard form, “off-the-shelf” commercial input-output modeling packages have been specified to any one, or combination of counties or states. While these models are not capable of measuring substitution effects, the careful specification of first-round substitution activity in the major sectors directly affected by supply disruptions using industry specific, regional data, generated separately, followed by estimation of subsequent round effects, have yielded policy makers with detailed information at a variety of geographic scales. Although differing substitution elasticities across sectors can be specified in CGE models, allowing them to provide more accurate estimates of economic impact and welfare effects than is the case with input-output models, model development issues and data requirements have meant that, to date, there are no commercially-available CGE modeling packages, meaning that in the near-term, this modeling approach is unlikely to be widely available to policy makers for routine, geographic-specific analyses of electricity disruptions.

IV. Using Stated Preferences to Estimate the Value of Avoiding Power Outages: A Commentary with Input from Six Continents

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1. Introduction

This paper presents suggestions and other commentary about practices for estimating the value of avoiding electric power outages, specifically practices based on stated preferences. "Stated preferences" refer, in this case, to practices that value outage[1] avoidance by asking electricity customers how much it is worth to them, rather than by other means such as inferring the value they place on outage avoidance from their investment in back-up power supplies. Stated preference-based practices predominate for estimating the value to residential customers of avoiding power outages, and are also sometimes used for estimating the value to businesses of avoiding power outages (e.g. Scarpa 2013, AEMO 2014). Outage valuation studies have usually been about outages lasting less than 24 hours, but this paper also includes a section about stated preference-based valuation of longer outages. The intended audiences for this paper are outage valuation researchers, practitioners of outage valuation, users and potential users of outage valuation results, students, and others who may be interested in the topic.

A substantial portion of the content of this paper consists of quotes and paraphrased comments from a survey of researchers with a specialization or interest in stated preference-based valuation. The author recruited those commenters by contacting a set of researchers who had published on the topic of stated preference-based valuation (not necessarily of power outages) and by sending an email to the Resecon email list of approximately 2000 individuals interested in resource and environmental economics research. The researchers who responded are Sabah Abdullah, Vic Adamowicz, Riccardo Boero, Jed Cohen, Cristóbal de la Maza, T. Robert Fetter, Amanda Harker Steele, Martin Heintzelman, Saul Lach, Aaron Praktiknjo, Mehrshad Radmehr, Johannes Reichl, Riccardo Scarpa, Friedrich Schneider, Robert Turner, and Ben Witherell. They reside, or have done the bulk of their power outage valuation work, on the continents of Africa, Asia, Australia, Europe, North America, and South America. They will be referred to below as "the commenters." Their quotes in the text below are lightly edited for ease of reading. The author has endeavored to properly attribute all of the content in this paper that came from the commenters.

[1] As used in this paper, "outage" means an interruption of the electricity supply to a customer.

Current and proposed practices in the United States serve as a case study, but the comments are relevant to utility outage valuation in much of the world.[2] The author asked the commenters for commentary about current and proposed residential power outage valuation practices in the United States, as described in *Estimating Power System Interruption Costs: A Guidebook for Electric Utilities* (Sullivan et al. 2017, henceforth the "draft Guidebook"). That document is a draft circulated for comment, shared with the commenters with the encouragement of its authors. It largely reflects power outage valuation practices that currently prevail in the United States, but it also incorporates some modifications recommended by its authors, who conduct a large portion of the power outage valuation studies for electric utilities in the US. The appendices to the present paper show short portions of the draft model questionnaire that is in the draft Guidebook, and also show the questions that the author of the present paper asked.

The authors of the draft Guidebook are Michael Sullivan, Myles Collins, Josh Schellenberg, and Peter Larsen. They have a great deal of experience designing and using outage valuation surveys, so there is much wisdom embodied in the draft Guidebook. However, the draft Guidebook's authors have tried to keep their methods similar enough to those described in a 1995 guidebook (Sullivan and Keane 1995) that the results of their old and new studies can be combined in meta-analysis for the Interruption Cost Estimate Calculator (ICE Calculator, 2018) to estimate the effects of variables such as region, duration, and start time of outage on its perceived costs[3]. Also, they are constrained by the preferences of the electric utility companies that pay for their studies, even if the costs of the studies are ultimately charged to ratepayers.

Since 1995, researchers in the field of non-market valuation have developed new methods and learned more about what methods are likely to perform best, from experimentation and analysis reported in a now vast literature. Most of the commenters are among those researchers. Their comments in this paper draw from that literature as well as from their non-market valuation research and practice on six continents. For valuation practitioners and researchers everywhere, advice and ideas, especially if tailored to the task at hand, can help in deciding what practices are worth trying. This paper offers such input, from a diverse set of sources.

2. Payment Vehicle and Scenario Posed in Valuation Question

[2] However, Fetter (2018) commented that there are parts of the world where "outages are typically daily, sometimes twice per day, and last for several hours" and where "in some cases, outages can last for weeks or even months." He notes that this paper's "focus on methods implies it is broadly applicable to many non-US contexts" but "that applicability has limits." In "household surveys about consequences and averting behavior" in such places, "the survey choices… would likely be quite different."

[3] As used in this paper, the "costs" of a power outage means the net monetized value of the effects of the power outage, including effects that are not monetized in everyday life, such as discomfort, safety risks, and lack of productivity. Furthermore, in this paper, "costs" generically refers to either equivalent variation or willingness to pay for a smaller expected or deterministic number or severity of outages, or compensating variation or willingness to accept for a larger expected or deterministic number or severity of outages, depending on the researcher's or practitioner's purpose and choice of methods

The present paper deals only with direct costs of power outages, which are defined here as the costs to those households and businesses whose residences or business properties, respectively, lose their electric power service from the grid as part of the outage or outages being valued. For residential customers, a large portion of the direct costs of an outage may come from discomfort, inability to engage in certain activities, and risks of injury, crime, and death. These experiences are not bought and sold, so there are no prices for them that can be used to value them. As a result, researchers typically use non-market valuation methods, developed largely by environmental economists, to estimate the costs of a particular potential outage or set of potential outages. These surveys, known as "stated preference" surveys, attempt to determine the most each respondent would be willing to pay to avoid the outage. In power outage valuation surveys, the good to be valued is a reduction in power outages, and is a public good because it affects everyone who would otherwise use the de-energized part of the grid. Researchers have found that the question or questions used to ask respondents how much the good is worth to them should ask about some scenario that the respondents will find credible (Arrow et al. 1993, Johnston et al. 2017).

This section will discuss four means of outage avoidance that can be given in that scenario. They are a utility investment in reliability, an on-site backup generation system, an off-site arrangement with entities other than the utility, or an unspecified means. A separate decision is whether to ask about one outage or multiple outages, and whether the outage avoidance should be deterministic or stochastic.

The decisions made based on power outage valuation results are usually about how much electric distribution utilities should invest in reliability. One option for the main valuation question in outage valuation questionnaires is a single dichotomous choice (yes-or-no) question about whether the respondent favors an investment that would reduce electric outages but also increase the respondent's electricity bill by a specified amount. Posing a single dichotomous choice question is a standard practice for eliciting the values of public goods (Arrow et al. 1993, Champ et al. 2003, Johnston et al. 2017) because under certain conditions it is incentive compatible, meaning that it is in the respondent's interest to answer honestly (Johnston et al 2017). Those conditions include that the question seems consequential to the respondents. In the case of power outage valuation, being "consequential" means that the survey has a non-zero probability of determining whether some costly action to improve reliability is taken (or some cost-saving action that worsens reliability is taken).

However, based on their experience and research, the authors of the draft Guidebook (Sullivan et al. 2017) do not want the reliability improvement expenditure that their surveys ask about to be "associated with the utility, because we do not want the respondent's feelings toward the utility to bias the response. They might think that they already pay enough and don't want to give another penny to the utility...or they may think that this study is just a way for the utility to figure out how much it can make off of selling backup power. Having a third party provide…backup service is a way to avoid this" (Collins 2018). For this reason, the main residential power outage valuation question in Sullivan et al.'s (2017) model questionnaire, question A4 below, uses a different scenario that does not involve paying the utility company for the reliability improvement:

A4. Suppose a company (other than [Utility]) could provide you with a battery backup service to handle all of your household's electricity needs during this outage. With this backup service, you would not experience the outage and would not have to make any adjustments.

Please indicate the one-time amount you would be willing to pay for this backup service to avoid this particular outage. *(Please circle or specify one amount.)*

$0 $1 $3 $5 $7 $10 $12 $15 $20 $25 $30 $40 $50 $75 $100

Other (please specify) $_________

Notably, this question does not ask about an expenditure to improve the reliability of the power supply *from the grid*, even though the results of such surveys are usually used to decide about expenditures to improve the reliability of the power supply from the grid. The author of the present paper asked the commenters for their comments on this survey question. The replies illuminate difficulties of finding a good alternative to asking about investment in greater reliability of the power supply from the grid, if the purpose is to use stated preferences to estimate the value that people place on avoiding interruptions of power from the grid. As Adamowicz (2018) wrote in his comments, "This is a challenge."

2.1 Asking About Battery System to Avoid a Single Outage

Witherell (2018) wrote, "This is confusing to me. You are asking for willingness to pay for a backup service, which seems like a long-term solution, but to avoid a single outage." Cohen (2018) wrote, "It is not really possible to pay a one-time fee for a specific outage in order to have a backup generation system installed." Similarly, Turner (2018) commented, "asking people the amount they are willing to pay for a backup service for a particular outage may not seem very realistic to respondents. I think respondents will find it difficult to think that way."[4]

The authors of the draft Guidebook ask about a single outage (as in question A4, above) because that allows them to "do the modeling and develop the customer damage functions for outages of different durations" (Collins 2018). It might be possible to do that while also effectively addressing the concern in the preceding paragraph by asking the respondent to suppose that she will have a specified set of outages in the following year without the outage avoidance expenditure, and a different set with the outage avoidance expenditure. Here is a crude example to illustrate: "Suppose that without the reliability program you will have two power outages next year. Suppose that the second one would happen on a summer evening at 8 pm, and that you would not know how long it would last, but that it would end up lasting four hours. Now suppose that the reliability program would not prevent the first outage, but would prevent the second outage. Please indicate the one-time amount you would be

[4] As of April 4, 2018, the Guidebook authors were planning to change the guidebook questions, such as A4 above, so that they will ask about a "backup power system" and keep the energy source generic, rather than specify that batteries would be used (Collins, 2018). In the present paper, most of the comments about the battery backup valuation question still apply if the energy source is generic.

willing to pay next year for this reliability program." A table showing the outcomes with and without the "reliability program" might help to convey the information more clearly. Relative to a simpler question, this question might cause more confusion, and more answers that reflect that confusion. The testing that should be done of all new questions could give some indications of what proportion of respondents would misunderstand this question and how much that would affect the responses.

Praktiknjo (2018) suggested that status quo bias may reduce stated values of avoiding one outage, because experiencing that outage would return the respondent to her status quo. He suggests asking for valuation of changes between frequencies in which neither is the status quo. One could do this by asking about willingness to pay[5] for a more effective reliability program versus a less effective one. Incidentally, choice experiments, discussed elsewhere in this paper, could serve well for valuing reliability differences between scenarios that are not the status quo.

Turner (2018) suggested, "I expect they would find it easier to say how much they'd pay for a service that provides backup service for a year, when the number of outages is uncertain (but you could provide an expectation to them, perhaps based on historical averages)." Witherell (2018) suggested that option as well as another: "Maybe change to 'avoid outages for a year.'" It would also be possible to ask about a percentage reduction in the number of outages, or about cutting the durations of future outages by some amounts, though a different means of avoiding the outages would be more credible than a battery backup in a question solely about reducing the number of outages.

In a point that may support the idea of asking about avoiding multiple outages instead of just one, Harker (2018) pointed out that ascertaining willingness to pay to avoid one power outage may not be sufficient to predict the willingness to pay to avoid several outages because an individual's willingness to pay may not be proportional to the number of outages avoided. For example, a respondent might adapt to a relatively high frequency of outages by having candles and flashlights on hand, reducing his willingness to pay to avoid each individual outage.[6]

De la Maza (2018) recommended asking a question in which the respondent is choosing not between two numbers of outages but between two probability distributions of outages:

> The valuation task is presented as an ex-post situation that will occur with certainty. In general, an outage corresponds to a risky prospect where individuals face a small probability of suffering a welfare loss. Although the latter presentation corresponds to a decision under risk and might be

[5] "Willingness to pay" means the maximum dollar amount (or other currency amount) that a particular person or group of people would be willing to pay for a particular good, service, or outcome. In the context of this paper, willingness to pay refers to the maximum dollar amount that a particular person or group of people would be willing to pay to avoid a particular outage or set of outages.

[6] A significant increase in average time per year without power is plausible, given that it happened in the United States several years ago, before the average time per year without power declined. The US "Department of Energy 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)" (Larsen 2016). In addition, outage valuation studies can inform utility decisions about when to replace costly distribution equipment that may become less reliable over time as a result of its age or as a result of increasing demand.

subject to several biases discussed elsewhere (Kahneman and Tversky 1979), it represents better the decision being valued. In decisions under certainty, risk is not involved and hence an ex-post valuation of an outage event might fail to include a risk premium costumers are willing to pay to avoid the risk ex-ante.

Ideally, the uncertainty would extend to how many outages, how long they would last, and the conditions under which they would occur such as temperature, day, and time (Boero, 2018).

Meeting the peak electricity consumption of a household can require a large amount of storage capacity, such as two or three Tesla Powerwall 2 systems (Tesla 2018, Electricities of North Carolina 2018). De la Maza (2018) wrote, "If participants recognize that providing such a service would require a massive storage capacity, the hypothetical scenario can seem implausible." It may be that only a very small proportion of respondents would recognize that.

2.1.1 Value of Specifying Geographic Scope of Outage

Cohen (2018), Reichl (2018), and Praktiknjo (2018) commented that the geographic scope of the outage is likely to matter to some households. Geographic scope affects how far the customers would have to go for various services and whether any services in the home other than electricity would be absent, such as television and Internet service, telephone service, and running water including that for flushing toilets. Cohen wrote that he, Reichl, K. Moeltner, and M. Schmidthaler (2018) found that "in European nations, local scope vs. national scope of outages makes a huge difference (about double) in the willingness to pay to avoid the outage." He continued, "We have a paper currently under review which we believe explains this by showing that respondents do not just worry about the electricity to their home, but also electricity provision to the infrastructure around their home (e.g. hospitals, internet, traffic lights, water supply, etc.)"

As a result, if the question does not specify the geographic scope, "the scope of the outage is something that the respondent would have to assume" (Cohen 2018). The respondents' assumptions about this that are unknown to the researcher would be a cause of unexplained heterogeneity in the results, and also might not match the outage characteristics that the researchers intended to value.

Geographic scope poses a particular challenge for studies that use a battery or other backup generation system at the residence to estimate willingness to pay to avoid outages that may affect the availability of services other than electricity. In order for the study to more closely mimic one that asks about avoiding a widespread outage, the respondents would have to be told, or to assume, that with the backup system, no services would be interrupted. That would imply that without the backup system, no significant services inside or outside the residence would be interrupted except ones in the residence that rely on electricity. If the researchers wish to estimate values for an outage with that characteristic, this is not a problem. Otherwise, it would be likely to cause at least a small difference between the scope of outage for which values are elicited and the scope of outage that the researchers wish to value. Compared to short outages, long power outages are more likely to involve significant interruptions of other services, including both other services in the home (e.g. telecommunications and water) and services outside of the home (e.g. traffic lights, gasoline, grocery sales, and jobs).

2.1.2 Battery Backup May Not Be Valued the Same as Increased Grid Reliability

Abdullah (2018) suggested that a battery backup might also be perceived differently than would avoiding a grid power outage for reasons other than geographic scope, and that that too might cause a difference in the value placed on each. De la Maza (2018) continued, “Further, other attributes of the hypothetical scenario can be embedded in the service. For example, participants could consider the potential environmental impacts of waste management of battery storage on their valuations.” Answers to the battery backup question might also be affected by people’s assumptions about how much of their time would be required to let the battery system be installed, or the space it would occupy, its aesthetic effects, or their enjoyment of having new technology in their home. Adamowicz (2018) wrote, “The battery back-up is easy to understand. But it also may generate its own set of biases and cues. Individuals may have perspectives on such back-ups that do not correspond with the conception of backups that is being considered here. Is there another technology that could be used?”

2.2 An Additional “Backup” Technology Option

A technology that prevented the outage altogether would, of course, more closely match a utility investment that prevented the outage. For the question to seem consequential and thereby incentivize the respondents to reply more carefully, the respondents need to believe that the use of the technology is a possibility and that it is made more probable if they answer affirmatively, but what they believe need not be true. One “technology” that could altogether prevent some outages is a fast shutdown arrangement with a large nearby power user such as a factory. The reason to ask about such an arrangement in the question instead of asking about a utility investment to prevent the outage would presumably be to avoid asking a question that involves additional payments to the utility in the question. To ask a question that minimized the perceived role of the utility in the reliability improvement, the question could emphasize that the payment would go entirely to the large nearby power user. If necessary, the question could specify that the arrangement with the large nearby power user is made not by the utility but by the state public utility commission, the county government, another state or local government entity, or the region’s transmission system operator (if it is separate from the utility). The resulting payment to that large power user could still be collected via a small surcharge in electric bills, or could be collected via some other means such as a small increase in property tax.

Both battery systems and an arrangement with a large local power user are outage reduction methods that are better suited for eliciting valuation of short-duration outages, since battery systems with energy storage sufficient for many hours of a household’s typical electricity consumption are quite expensive, and since an arrangement with a large local power user is more likely to prevent short outages than long ones.

2.3 A Question with No Explanation of How the Outage Would Be Avoided

Three of the commenters suggested considering a stripped-down question: de la Maza (2018) recommended “a more general framing, avoiding a description of the technology to provide the service.” Witherell (2018) suggested possibly asking simply the amount the respondent would be willing to pay “to avoid ‘this particular’ outage, without the ‘how’ it would be avoided.” As Abdullah (2018) put it, the question could simply be something along the lines of “How much would you be willing to pay to avoid this 4-hour outage?” These commenters are suggesting that this might be the best option even though it does not follow the common practice in non-market valuation of stating in the question how the service would be provided.

2.4 Asking About Utility Investments in Reliability of Supply from the Grid

As mentioned at the beginning of section 2, another option is to frame the valuation question as a question about investment in improved reliability of supply from the grid, which is in reality usually the kind of decision made with the results of electric outage valuation surveys. The authors of the draft Guidebook recommend avoiding this option out of concern that respondents give lower willingness-to-pay answers if they believe that their payments would go to their electric utilities, as explained near the beginning of Section 2.

A conventional principle in economics is that the consumer is the best judge of what is best for himself. Under that principle, if the prospect of the utility company receiving the payment reduces customers’ WTP for the reliability improvements, and that reduction of WTP is not based on a distortion such as a misunderstanding or inadequate consequentiality of the question, then that reduced willingness to pay is what should be used in the utility company’s or regulator’s decision about whether the improvements are worth making. However, the reader might or might not agree with this principle, and a meaningful proportion of the respondents’ answers might indeed be influenced by misunderstandings about how the funds would be used by the utility.

In summary, the means of outage avoidance that is postulated in the outage valuation questions can be an on-site backup generation system, an off-site arrangement with entities other than the utility, an unspecified means, and utility investment in reliability. Each has advantages and disadvantages. The designers of a stated preference-based outage valuation survey must also decide whether to ask about one outage or multiple outages, and whether the outage avoidance should be deterministic or stochastic.

3. Addressing Bias in Responses

3.1 Testing for Bias in Responses

Responses may be biased because of misunderstanding of the question, protest, strategic answering, or hypothetical bias. Hypothetical bias refers to the tendency of people to state a willingness to pay for something that is different than they would actually be willing to pay if faced with a real decision about whether to buy that thing. “Ask a hypothetical question and you will get a hypothetical response,” wrote Scott (1965). Hypothetical bias is generally an upward bias, but it does not seem to apply to all goods (Johnston et al. 2017), and its magnitude seems to differ substantially among different types of goods.

Using multiple methods to estimate the value of the same outage or set of outages can give some indication of whether at least one of the methods is biased. The methods could include different survey-based methods and could potentially also include revealed preference methods[7] and "blackout studies." Blackout studies are empirical studies of the costs of past outages. Stated preference-based and revealed preference-based methods generally produce an estimated frequency distribution of the values that customers place on outages, so it might be possible, for some group of customers, to compare not just the estimated means but also the estimated frequencies of values across some portion of the distribution, or across all of it. Zero and very high values may be of particular interest, since they have large effects on the mean, and also because they may reflect hypothetical bias, misunderstanding, protest, or strategic answering that affects the proportion of respondents who choose $0 as their answer.

Johnston et al. (2017) recommended checking whether the customers who respond to the survey are different from those who do not, in terms of information that the utility possesses, such as electricity consumption, geographic area, electricity use, and amount of time the account has been under the current name. The purposes of this are to check whether the survey results may be biased by having an over-representation of customers with certain known characteristics, and to be able to correct for that. However, those who answer may also be different in ways that are not observable. As Reichl noted, "Usually you have characteristics (those used for stratification) but the variables are likely not explaining response behavior enough to function as an instrument." For example, the customers who care more about outages, and who value avoiding them more highly, may be more likely to respond to the survey. Another of the possibilities is that customers who have more free time may both value outages less and be more likely to answer the survey. One way to check for this is to check whether the customers who answer the survey only after multiple communications from the survey administrator tend to value outage avoidance differently than the customers who answer the survey at the first opportunity, even after controlling for the known characteristics of the respondents (Johnston et al. 2017). If so, that would suggest that those who responded are not representative of the whole population of customers.

Field validity tests could check for bias in stated willingness to pay to avoid power outages. Lianfan et al. (2017), Rakotonarivo et al. (2016), and Vossler et al. (2003) are examples of field validity tests, dealing with goods other than power outages. The cost reductions for batteries have made it less expensive than before to conduct one or more field validity tests for that purpose with batteries. A field validity

[7] The value that customers place on avoiding power outages can, under some circumstances, be inferred from their mitigation investment decisions and grid outage probabilities. Doing so constitutes a "revealed preference" study. There seem to be only a few in the literature. Beenstock et al. (1997), Matsukawa and Fujii (1994), and Caves et al. (1992) are three of them. Revealed preference studies can be useful as a check on estimates based on other methods, though they may be of less use for understanding the value small customers place on outages because transaction costs may have prevented small customers from installing a backup generation source even if the reliability gain would be worth the price of the system.

test using batteries may be worthwhile even if batteries are judged to be not the best outage avoidance method to ask about in most outage valuation surveys. Researchers could check for hypothetical bias by asking some people hypothetically if they would pay X dollars for a specified battery energy storage system, and by also actually offering the same system to other people for X dollars, where X is a number chosen by the researchers that varies from household to household and has the same frequency distribution in both the hypothetical questions and the real offers, or at least overlapping distributions. This would be valuable information because it would give an indication of how much survey-based estimates of outage value overstate the actual value. The users of the estimates could adjust them accordingly. Another reason it would be valuable is that it would let researchers know that they should use, or continue to use, strategies for reducing hypothetical bias. Incidentally, this would work for businesses as well, even though the surveys to find out the value to them of an outage sometimes ask about their objective losses rather than their subjective valuation. Some state government might be willing to provide the subsidies, especially a state government that had already decided to offer subsidies for battery energy storage systems.

3.2 Reducing Hypothetical Bias

Loomis (2014) discussed strategies for reducing hypothetical bias, and what is known about the effectiveness of the various strategies, based on the research literature. Some strategies that have been effective in experimental tests include *ex ante* strategies such as exhorting the respondents to be honest and realistic, asking them to sign a truthfulness oath before answering the valuation question(s), having multiple respondents discuss the decision before they each make it, asking the respondents how much they think *others* would be willing to pay, and making the survey seem consequential to the respondents. De la Maza (2018) recommended including the second and third of these five strategies in the power outage valuation protocol in the draft Guidebook.

The strategies that have been effective at reducing hypothetical bias in experimental tests also include *ex post* strategies such as fitting a multi-variable regression function to the responses then discarding responses that are more than three standard deviations from the conditional mean. Witherell (2018) too suggested “using a standard deviation cut-off or similar statistical threshold,” saying that Appendix A’s recommendation to remove the highest 0.5% of responses “seems arbitrary and maybe too low.” In addition, Adamowicz (2018) recommended that questionnaires “include reminders that tell people they will have less to spend on other things (substitutes). This has been shown to improve validity.”

Some of the methods apply only to dichotomous choice questions, discussed briefly at the beginning of section 2, which in this context are typically yes-or-no questions about whether the respondent would be willing to pay a specified amount in exchange for a specified reliability improvement. One such method is to also ask the respondents who answer yes how certain they are that they would be willing to pay the specified amount, and then to change to “no” the answers of respondents who answer below some level of certainty. Some research has indicated that the average of the certainty answers is a good choice of cutoff for correcting for hypothetical bias, and some has indicated that 7 on a commonly used 0 to 10 certainty scale is a good cutoff. Loomis (2014) writes, “This approach is particularly relevant in valuing public goods that the respondent may have not thought about or…which they had never thought of in monetary values." Avoiding a power outage satisfies the second of Loomis's criteria, and avoiding a long-duration power outage satisfies both of his criteria. In a field validity test, discussed above, respondents to the hypothetical question can be asked to rate the certainty that they would buy at the price in question, and the result can be used to determine the cutoff that will cause the thus-adjusted result of a hypothetical question to match that of a real-money question.

3.3 Responses of Zero Dollars

In US electric utility surveys of customer valuation of power outages, roughly half of residential customers answer $0 when asked how much they would be willing to pay to avoid an unannounced power outage of initially unknown duration that ends up lasting one hour (Sullivan et al. 2015). When subsequently asked (e.g. in question A4a in the sample survey in Appendix B) whether their value of avoiding such an outage is really zero or whether they answered zero for some other reason, most respondents check the box indicating that it is really zero.[8] Here is question A4a:

A4a. **If you circled $0 in question A4**, is that because the service is really worth nothing to you or is there some other reason? (Check one)

- ☐ Worth nothing
- ☐ Other reason (please explain)

____

____

In A4a, the alternative to checking the box that says one's value of avoiding the outage is really zero is to check the box that says "Other Reason (please explain)," which is followed by two lines for writing one's explanation. It could be that some respondents who check the box next to "My value is really $0" do so not because it is true but because they prefer not to spend the time or effort necessary to write an explanation. This may be particularly true of those who gave an answer of zero out of protest, apathy, or misunderstanding. Abdullah (2018) suggested giving additional answer choices that do not require writing, such as "Opposed to service improvement," "Service improvements are not a priority to me," "Distribution utility should pay for this electric service or reliability improvement," "Need more information to answer," and "Other reason (Specify)." This would also reduce the need for subjective judgment on the part of those analyzing the responses.

De la Maza (2018) recommended eliminating question A4a because it "suggests to participants that a zero value is not an acceptable response," which "can induce subjects to accept a higher cost that they would not accept otherwise, to avoid being questioned on moral grounds by the researchers. A key

[8] If the respondent gives another reason that indicates protest, their valuation answer is removed from the dataset before calculation of the distribution of customers' willingness to pay to avoid outages.

recommendation in valuation experiments is to avoid forcing subjects (involuntarily) to provide a positive willingness response (Hanley et al. 2001)." Adamowicz (2018), on the other hand, wrote, "It is a very good idea to ask about the zero bids." It would be possible to satisfy the recommendations of both of these commenters by showing the questions about bids of $0 only after the valuation question or questions have all been answered.

Regarding the *reason* that approximately half of respondents value avoidance of a one-hour outage at $0, Praktiknjo (2018) wrote, "I believe this might have something to do with the elasticity of substitution and may indeed reflect the "true" discomfort of the households (as much as the other responses are true…)," and that hypothesis is explained in Praktiknjo (2014). Witherell concurred, writing, "I think for most people short duration outages really are $0 value."

In contrast, Cohen (2018), on behalf of himself, Reichl, and Schneider, wrote,

> We feel that this proportion is overstated, at least in our experience. I do not think we reported percent of respondents with zero WTP in our papers, though we do always calculate it during modelling. In Cohen, Moeltner, Reichl, and Schmidthaler (2016), we find that 85.9% and 70% of the draws of the WTP parameters are positive, in winter and summer respectively, using a Bayesian Gibbs Sampler. It is worth noting that these figures are from outages with a minimum of 1 hour, and a European sample. We find strong international heterogeneity, so the percentage of zero WTP could indeed be much higher in different sampled populations.

Adamowicz (2018) noted that modeling respondents' zero willingness to pay in a hurdle or Kristrom-type spike model can help in some situations.

A related matter is that some respondents may not consider the possibility that someone in the household will be doing something important that requires electricity, or wanting to begin something important that requires electricity, at the time of the outage. De Nooij et al. (2007) cited an older study to illustrate how the cost to customers of an outage can vary according to when it occurs:

> Day and Reese (1992) note that, while interviewing people in the USA about power interruptions in the previous year, many people recalled an interruption that had occurred five years earlier. This interruption happened shortly before the Thanksgiving dinner. Some of the victims became so angry that they drove to the electricity company and threw their half-cooked turkeys at the office building.

4. Questionnaire Content Prior to the Main Valuation Question(s)

Johnston et al. (2017) observed that "even subtle differences in questions asked prior to valuation tasks may affect respondents' subsequent choices, as shown by Cai et al. (2010)." In keeping with that observation, Reichl (2018) offered a possible explanation for the higher incidence of answers of $0 in the US surveys, and it is the first of several observations from the commenters that deal with questionnaire content before the main valuation question or questions. In the sample survey in

Appendix B, the main valuation question, which provides the main value estimates from the questionnaire, is question A4. It uses a payment card format, also called a bid card format, which simply means it shows dollar values from which one can choose. In some of the US surveys, there may have been at least one *open-ended* valuation question before the main valuation question. Two such questions, A2 and A3, are present in the sample survey in Appendix B, and are repeated here:

A2. How much do you think it would cost your household in extra expenses **and** in inconvenience or hassle to adjust to this outage? If necessary, please refer to the definitions on page 2.

$ ______ extra expenses **and** inconvenience costs

A3. Of the above amount, how much of it would be **just for the extra expenses**?

$ ______ extra expenses **only**

Question A2 asks, "How much do you think it would cost your household in extra expenses **and** in inconvenience or hassle to adjust to this outage?" There is a reason for that question before the main question, which is to help the respondent prepare to better estimate the value he gives in response to the main valuation question. However, an open-ended valuation question before the main question may also bias the answers to the main question away from what the respondent's maximum willingness to pay would be in a real backup system leasing situation. Reichl wrote, "An explanation of the high number of zero willingness-to-pay responses may be the open-ended format, where people may fear to seem stupid if their response lies massively out of the expected range. To be on the safe side they then opt for 0, as they are not aware that even a small number such as $1 is a qualified response." If they answer $0 to the first question, then after doing so they are less likely to indicate a larger value in response to any later question about the same outage. "To get a different answer in the response question as you propose would basically require that people confess having made a failure in their initial reply, which is quite against human nature."

This phenomenon can apply even if the answer to the first question is greater than $0. The presence of the prior question may cap and consequently lower the respondent's answer to the main valuation question. Some respondents may give an answer to a question like A2 that is lower than the answer she would otherwise give to a question like A4 and lower than her willingness to pay in a real backup battery leasing situation, and then repeat her A2 answer, or give a lower answer, in response to a question like A4. Cohen (2018) gave a reason why one's answer to A2 might be a less reliable indicator of one's willingness to pay in a real backup battery leasing situation than one's answer to A4 would be: "Asking respondents to value the costs of their 'inconvenience' is asking them to directly translate a non-market value into currency units. This is difficult for people to do as only economists think in terms of monetization of tradeoffs." Heintzelman (2018) expressed a similar doubt "about asking people to list their costs, and then asking them about their WTP. People might not be able to realistically estimate their costs and, in addition, I suspect that their WTP then gets anchored to these estimates." Scarpa (2018) commented that asking about expenses

> is flawed because it encourages mental accounting of expenses directly linked to the outage. The

> expense compensation concept is very far from the correct welfare measure of reference, which is the compensating variation. Because the unit of electricity is valued for its use in producing something else in the household production function, but it is often essential, the real compensating variation depends on the value of the output it contributes to producing.

De la Maza (2018) recommended a different way of helping the respondents think about the services they would lose in the event of a power outage, that does not ask them a valuation question before the main valuation question: “In a recent effort, Baik et al. (2018) introduced subjects to the valuation task with questions aiming to help participants to reflect on their consumption and hence their potential losses. A similar effort is recommendable for this type of surveys.” As part of this,

> losses that are season-dependent such as heating services or air-conditioning should be highlighted. Further, other types of losses not associated with energy consumption directly are possibly relevant and should be described in detail. Medical services might be impaired by an outage limiting access to hospitals or drug stores. In several locations with high crime rates, electricity service provides indirect protection against theft or other types of assaults.

5. Choice Experiment vs. Bid Card vs. Dichotomous Choice

The main valuation question in most of the US outage valuation studies to date asks the respondent how much she would be willing to pay to avoid an outage, as in question A4, which appears in section 2 and in the sample survey in Appendix B. This a “contingent valuation” question, and more specifically, its array of answer values that the respondent can choose is called a “bid card” or “payment card.” Other surveys, called *discrete choice experiments* or simply *choice experiments,* are a newer alternative. They do not ask for explicit dollar valuations but instead ask the respondents to choose from among different outage scenarios, often three, which differ in a few characteristics including how much the respondent would be charged or would save. The other characteristics could be duration of outage and frequency of outages, or some other combination of characteristics. The estimated frequency distribution of respondents’ valuation of outages with different characteristics can be inferred from the answers. Ozbafli (2012), Carson and Czajkowski (2014), and Hess and Daly (2014) discussed choice experiments. Pepermans (2011), Carlsson and Martinsson (2008), Beenstock et al. (1998), and Ozbafli and Jenkins (2016) offered different examples of choice experiments to value electricity supply outages. Scarpa (2013) and Ozbafli (2012) listed others. Johnston et al. (2017) is a particularly recent and authoritative paper that provides a useful discussion of the relative merits of choice experiments and contingent valuation questions, based on the literature through 2016. Instead of providing a redundant discussion, this paper will share some of the commenters’ views about these two options for valuation of reductions in power outages.

Adamowicz (2018) wrote,

> It’s possible that [switching to a choice experiment format] may be beneficial. It may mimic a market-like choice more clearly, and it may be easier for respondents to process. There is relatively little research on exactly this question, but we are currently doing some. Based on the limited literature and our own findings, tables [that show the attributes of each option in each choice in a

> choice experiment] may make it easier for respondents to answer such questions, as long as the attributes are fairly well known to them.

Arguably, power outages lend themselves well to being characterized as a set of attributes. The ones that in almost all studies change from question to question are the start time and how long it lasts. In a choice experiment, the other attribute that should change from question to question is the cost to the customer, such as the increase in its monthly electric bill. Three is an easy number of changeable attributes to have in choice experiment questions. Harker (2018) discussed a related, second possible advantage of choice experiments: "I think a choice experiment approach is likely to be the most appropriate method available to estimate the value of power outages because it allows the researcher to explicitly examine how the individual attributes (e.g. length of time, time of day, season, etc.) associated with different outage durations impact WTP." Contingent valuation (including bid card) questions allow this too, but might not do so as efficiently. Scarpa (2018) recommended using a choice experiment approach, as he and others have been using, though he commented that a contingent valuation question such as A4 in the sample survey in Appendix B is also viable. Abdullah (2018) commented that choice experiments avoid multiple sources of bias. Radmehr (2015) used a choice experiment technique for WTP and choice for micro-generation solar panels. "I believe it provides results that are not biased" (Radmehr, 2018). De la Maza wrote that choice experiments (also called "conjoint analysis surveys") are "a superior alternative to contingent valuation that allows for variation in attributes within subjects, and can be used to detect non-compensatory behavior." He continued,

> Although contingent valuation can successfully derive sound willingness to pay values from participants in some cases, it requires each respondent to state a maximum willingness to pay for a service not available in the market, a task that requires a high cognitive burden if no reference value is at hand (Fischoff 1991). A conjoint analysis survey can mimic more closely a more realistic market scenario where trade-offs among different attributes are required and prices are previously stated, revealing willingness to pay implicitly (de Dios Ortuzar and Willumsen 2011, Louviere 1988). In general, I recommend using a conjoint analysis survey to value electric power outages.

Adamowicz (2018), who wrote in the passage above that switching from a bid card format to a choice experiment format may be beneficial, wrote that "bid cards are often a source of concern. Changing the ranges can result in different outcomes because of value cues."

The bid card in the model survey in Appendix B has $100 as the highest response that can be circled. In the draft Guidebook, $100 is the highest response that can be circled even in the model survey that asks about a 24-hour outage. De la Maza (2018) wrote that this will discourage respondents from giving an answer above $100 (Tversky and Kahneman 1974). "Food spoilage alone could account for higher losses." To combat this problem, he recommended that "pre-testing [to determine whether] a range with a maximum value of $100 covers the range of potential responses adequately should be included in the protocol."

In addition, using the same bid card choices in all of the draft Guidebook's model surveys, which ask about outages as short as one minute and as long as 24 hours, encourages the valuation of 24-hour outages to be more similar to the valuation 1-minute outages than it would be if the values that can be circled were higher for the 24-hour outage and lower for the 1-minute outage.

However, Adamowicz (2018) commented that "interestingly there is some new work that Christian Vossler is doing that shows that bid cards work quite well in recovering values (in public goods anyway)."

"Both can work," wrote Witherell (2018).

> I think choice experiments are good for valuing non-market things that can be represented by a bundle of attributes, but they probably do not offer a big advantage for estimating the value of power outages. I think that choice experiments and contingent valuation have their pros and cons and therefore it is a good idea to focus-test your design, regardless of your initial selection of method. The payment card approach will likely become cumbersome and lead to fatigue bias with too many variable options. A choice experiment is very sensitive to survey design and its results can be more difficult to interpret.

Turner (2018) made a point about the suitability of choice experiments if several outage times or durations need to be considered (as is common in US outage valuation studies), and thought-intensive questions (A2 and A3 in the sample survey in Appendix B) need to be asked about each of those outages: "I think the current approach [in Appendix B question A4] is better than a choice experiment approach since it would be cumbersome to ask your first three questions [(A1-A3)] for each case if several cases were presented together in a choice experiment." This would be much less cumbersome if questions such as A2 and A3 were not present. In some studies, the study designers might choose to omit them as a result of the factors discussed in section 4.

The Australian Energy Market Operator (AEMO 2014), advised by Scarpa (2013), decided to use contingent valuation to estimate the value of an outage with certain characteristics, and choice modeling to estimate the effects of changing those characteristics, making the outage longer or shorter, at a different time, etc. AEMO used this combination for residential customers and small and medium-sized businesses.

An alternative to both the contingent valuation option (including bid cards) and the choice experiment option is the option of a dichotomous choice question, which is standard practice for valuing public goods and is discussed briefly at the beginning of section 2. Again, this option consists of asking each respondent a single dichotomous choice (yes-or-no) question: whether they would want the reliability of the grid to be improved by a specified amount if it would cost them a specified amount. This type of question may elicit more honest, careful answers because, unlike bid card and choice experiment questions, it is incentive-compatible under certain conditions. Being "incentive compatible" means that it is in the respondent's interest to answer truthfully. The conditions for the question to be incentive-compatible (Johnston 2017) include that the question be consequential. Like with choice experiments, the estimated frequency distribution of respondents' values for the reliability improvement can be inferred from the answers. It is likely that more respondents will be needed to achieve the same statistical power, but this could be worthwhile if the lack of incentive compatibility of bid card and choice experiment questions sufficiently biases the results of surveys that use them.

Whether the lack of incentive compatibility of bid card and choice experiment questions sufficiently biases them depends in part on whether a sufficiently large number of the respondents to a choice experiment or bid card question understand that it is not incentive compatible, and consequently answer strategically rather than honestly. To answer strategically in a way that truly has positive expected value to her, a respondent needs to have an expectation about whether the reliability improvements would be worth more to her than they would cost her. Then, if she expects that the improvements would be worth more than they would cost her, she needs to understand that it is in her interest to exaggerate her willingness to pay. If she instead expects that the improvements would be worth less than they would cost her, she needs to understand that it is in her interest to understate her willingness to pay.[9,10] It is also possible for respondents to reply strategically in a way that is not truly in their interest, for example because of misperceptions about what strategic answers would be best for them. That still biases the results away from what the results would be if no participants answered strategically.

6. Other Best Practices and Suggestions

Asking people who have recently experienced a power outage about their willingness to pay to avoid a similar outage in the future could improve the estimates of the values of outages, provided that it anger does not bias the answers. Carlsson et al. (2011) investigated the effect of a recent outage on

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[9] Vossler et al. (2012) reported that, in their study, which used a choice experiment to elicit valuation of forest conservation, strategic answering seemed to have a negligible effect on the study's overall results. When the questions were hypothetical, about 2% of participants reported that they answered strategically. When the questions involved real money, 10% to 25% of participants reported that they answered at least one question strategically. The bias introduced by strategic answers may tend to be larger or smaller in response to contingent valuation questions than in response to choice experiment questions. For example, respondents may understand better how to answer strategically when answering a contingent valuation question than when answering a choice experiment question.

[10] This footnote discusses the effect of rejection of extreme answers on the incentives for respondents to give strategic answers that are extreme (i.e. that greatly exaggerate or understate their true willingness to pay). Some readers are likely to find it not worth reading. Even the possibility of a respondent's answer being rejected as implausible should not necessarily limit her strategic exaggeration or understatement, unless she believes the numerical threshold for rejecting responses is likely enough to be unaffected by the values of the responses. A sufficiently savvy respondent might expect it to be affected by the values of the outliers, since outlier rejection rules in which it is not may be rare. For example, if the rejection rule were that answers are rejected if they are more than some number of standard deviations above the conditional or unconditional mean, then an answer rejected under that rule could still shift the final value estimate upward because it would still increase the standard deviation and hence could cause one or more high replies to be retained rather than rejected. Another example is that if the rejection rule were instead to reject the highest x% of responses, where x is some pre-determined percentage (such as 0.5% in the draft Guidebook), then a response above that threshold would cause another high response, that is not as high, to be accepted rather than rejected. What matters for limiting responses is what the strategic, sufficiently savvy respondents (if there are any) guess or otherwise *believe* about the probabilities of different categories of outlier rejection methods. Consequently, using an outlier rejection rule in which the responses do not affect the numerical threshold will not reduce strategic answering unless the participants know that such a method will be used. Telling them that such a method will be used could do more harm than good.

willingness to pay to avoid outages.

One of Johnston et al.'s (2017) many recommendations is that pre-testing with focus groups is a necessary part of survey design, to make the questionnaire understandable and credible to a wide range of respondents. Another is that detailed documentation of the study design process, implementation, analyses, and results is crucial for the later ability of others to replicate the study, interpret it correctly, and use its results in meta-analyses. Documentation is also important for allowing others to check that the preparation, implementation, and results analysis were done without unnecessary sources of bias. Witherell (2018) seconded this recommendation. The documentation should include a priori plans for how to deal with the issue of protest responses (de la Maza 2018). These recommendations apply not just to studies by academics but also to studies commissioned or conducted by utilities.

In addition, de la Maza (2018) recommended that "a debriefing section should also be included at the end of the survey to understand differences in the losses accounted for in the valuation." It should include "follow-up questions…to detect response motivations (including protest responses)." Adamowicz (2018) wrote that participant perceptions, including misperceptions, can introduce bias, and that understanding the perceptions can help in identifying at least the directions of the biases.

Questions that ask the responding individual how much he or she would be willing to pay may underestimate the value of avoiding outages if the analysis of the results assumes that the responses represent the whole household's value for avoiding the outage. If the analysis instead assumes that the whole household's value for avoiding the outage is, on average, the individual's response times the number of people in the household, then it may overestimate the value of avoiding outages. An alternative is to ask for an estimate of how much the household would be willing to pay. De la Maza made some related comments: "The receptor of the survey is not clear. If participants are self-selected within the household, individuals not responsible for paying the electricity bill might answer the survey. The survey should be implemented face-to-face if possible and directed to household heads."

Reichl (2018) wrote, "we recommend defining quotas for certain demographic variables and ensuring a balanced sample during the data collection process to reflect well the larger population (e.g. age groups, gender, urban vs. rural, etc.)."

Don Dillman developed a set of methods for obtaining much higher response rates to surveys (Dillman et al. 2014). In the case of mailed surveys, these include, for example, handwriting the addresses on the envelopes, and using regular stamps instead of mass-mailing stamps.

Witherell (2018) observed that using email "would introduce bias, if not all randomly selected households have email addresses." This could possibly introduce bias by causing those with email to be more likely than others to participate in the survey.

Abdullah (2018) recommended repeating the duration of the outage in the valuation questions. In

Appendix B, this applies to questions A2-A4. For example, "Please indicate the one-time amount you would be willing to pay for this backup service to avoid this *particular four-hour* outage," where the italicized words are the suggested addition. Praktiknjo (2018) recommended adding a comment section in the questionnaires. To reduce the cost of the survey by replacing the cash that is typically included in US survey envelopes, Witherell (2018) recommended, "Maybe a private retailer would be willing to partner, so instead of cash, maybe give an Amazon gift card, as an example."

Regulators should remain vigilant to the possibility that one or more surveys conducted or commissioned by utilities could be designed to produce biased results, to produce the result that will better serve the profit of the utility. The regulated rates of return that electric utilities are allowed to earn on their investments tend to be higher than the cost of capital, so it can be in utilities' interest for their methods of estimating the value of outage avoidance to produce high estimates, to encourage regulators to approve new reliability investments. This would be an example of what is known as the Averch-Johnston Effect (Sherman 1985). Alternatively, they may want their methods to produce low estimates, or low estimates for some customers such as residential ones, because they fear being held liable for the cost to customers of outages. Survey design, such as the answer choices given and the wording and order of questions, can significantly affect the outcomes. This issue could be addressed by having the public utility commission itself, or other agency, commission any ratepayer-funded valuation studies. Failing that, the issue could be addressed, potentially less effectively and at higher cost, by requiring documentation of data, decisions, and methods (as recommended by Johnston et al 2017 for other reasons as well); checking it for potential sources of bias; having some surveys designed by researchers who do not receive industry funding; and checking the results of industry-funded surveys against the results of the non-industry funded researchers.

7. Considerations for Long-Duration Outages

One principle that could differentiate long from short outages is when safety or sanitation is likely to start to be significantly affected, for reasons that may include extreme indoor temperatures, crime, thirst, food spoilage, and full toilets. These qualitative changes in circumstance matter most to households. For businesses, a power outage is likely to be costly from the start. But for most households, these qualitative changes that take time to develop can make an outage much more costly. As a result, the pattern that business losses from a power outage dwarf household losses, a common finding in estimates of the costs of short-term outages at least in the US, may be less pronounced in future studies of the costs of long-duration outages. In short, household costs may account for a larger proportion of the estimated values of long-duration outages.

When it is necessary to use a specific duration, in hours, to define the boundary between short- and long-duration outages, one could apply the principle above to choose that duration. The amount of time required for an outage to significantly affect aspects of safety and sanitation will vary greatly, but at least 24 hours and longer than 24 hours are two naturally appealing options.

The practices used for short-duration outages may be adapted to value long-duration ones too.[11] This would require less development and testing of different practices, though that advantage is smaller, or absent, if there is a set of practices for valuing long-duration outages that someone has already developed and tested, that would perform at least as well.

For valuation of short-duration outages in the US and other places with existing high-quality studies, there is an advantage in repeating the same practices in the new studies, for meta-analysis that will enable estimation of the value of outage reductions in other places and times in the same country or region. This does not yet apply to studies of long-duration outages, so the case for adopting a new set of practices is much stronger, if that new set is to be based on the current, accumulated lessons from research and experience.

The commenters made some suggestions that apply to valuation of short-duration outages, but that are particularly important for valuation of long-duration outages. Harker observed that “It also may be helpful to add a temperature dimension to the description of each outage scenario.” This could replace the season as a parameter in the questions. That could also improve the applicability of one region’s survey results to other regions, because the value estimates could be adjusted for the temperature differences.

Witherell (2018) suggested that, to be able to use the size of the outage to better predict the value of avoiding it, “you could include another variable for distance to nearest alternative power source.” Heintzelman (2018) wrote, “I think it would also be valuable to know how respondents might value community resources that may or may not be available during a significant outage – shelters, emergency services, local medical services, groceries, financial services, gasoline, etc.”

Witherell (2018) also pointed out that the months-long, post-hurricane power outage in Puerto Rico presents a very unfortunate but rare and potentially very informative case of a long-duration, widespread power outage, from which researchers could estimate the value of an actual long-duration, widespread power outage via a “blackout study.” The author is not aware of the existence of any thorough blackout study. The practices necessary for thorough blackout studies may need to be developed. In addition, there is value in being prepared to begin collecting data quickly during future long-duration outages.

8. Conclusion

In planning an outage valuation study for a given area, there is a tension between repeating the practices used in the past and using a different set of practices. On the one hand, research and experience probably indicate that new or different practices are better, at least if one is starting from scratch. On the other hand, repeating the set of practices used in past studies in culturally and economically similar places has the significant advantage that it facilitates meta-analyses that can, with

11 Sullivan and Schellenberg (2013) did this.

data from enough studies or large enough studies, estimate the effects on valuation that result from different circumstances such as different outage durations, locations, times of the week, times of the year, and years (i.e. time trend).[12] For utilities, utility regulators, and other decision-makers who use survey results from elsewhere ("benefit transfer") to estimate the value of reliability-improving investments in their territories, understanding the effects of such circumstances enables them to better estimate the value of the investments in their case. In the United States, there have been at least ten residential power outage valuation studies that have used similar methods, thanks in part to the influence of the last power outage valuation guidebook by Sullivan, published 23 years ago (Sullivan and Keane 1995). Some other countries and regions of the world might have a similar situation. In these places, there is an advantage in continuing with the previously used methods until another method is found to be sufficiently better to justify a break with past methods. The newer methods should periodically be evaluated against the older methods, and the newer results compared with the older results, to test whether such a break is justified. If it is, the meta-analysis based on the past methods may remain useful for a time, in conjunction with the results of the newer methods, until there are enough new results to fully replace it. In the case of the US, the older methods are largely reflected in the draft Guidebook, and have some concerning features, discussed above.

As of early 2018, Lawrence Berkeley National Laboratory has funding for a national outage valuation survey. This is an example of a large US outage valuation study funded by government rather than by utility companies. This survey's large size and comprehensiveness, and its freedom from electric utility control, may justify a switch to methods other than those described in the draft Guidebook, if there is a sufficiently tested set of suitable new methods or there is enough time and budget to develop, test, and refine the set to be used.

In some other parts of the world, there may be very few or no outage valuation studies to date, but an intention to conduct at least one in order to better inform decisions about potential investments in electric supply reliability. In those places, there may be much less benefit to making the new study highly comparable to the results of studies that use old methods, because those studies that use old methods are from elsewhere, and there is great international heterogeneity in outage avoidance values, as mentioned above. Those who will decide on the design of future studies have multiple models to choose from in the non-academic and academic literature. Sullivan et al. (forthcoming) will be one, and is similar to the method in Sullivan and Keane (1995). Some other models started with a blank slate more recently, and consequently have been able to more fully adopt practices believed to be best at a more recent time. AEMO (2014) and Baik et al. (2018) are examples of the latter. In both

[12] The outage costs per kWh from US studies that are similar to Sullivan and Keane (1995) and Sullivan et al. (2017) have been used to create an "Interruption Cost Estimate Calculator," available at http://www.icecalculator.com/. To calculate the estimated annual cost of outages for a particular set of customers, a user of the site can enter the share of load consumed by large C&I customers, small and medium C&I customers, and residential customers; the state or states in which the outage occurs; the number of outages per year; the average duration of outages; when the outages occur; and the share of customers with back-up generation. The calculator provides user-modifiable default values of some of these variables from past studies. The calculator then outputs the estimated cost of those outages.

situations, research and suggestions are likely to be important. This paper has presented suggestions drawn from research and experience on six continents.

9. Further Reading

The journal papers and books referenced above are potential further reading on particular topics, and the text gives some indication of their respective content. Among them are a few works that are broadly applicable to stated preference-based valuation of power outages and may be of interest to some readers. One is the final version of the Guidebook that is used in draft form as an information source in much of this paper. If it has the same name as the November 15, 2017 draft, it will be called *Estimating Power System Interruption Costs: A Guidebook for Electric Utilities* (Sullivan et al, forthcoming). Another is *The Economics of Non-Market Goods and Services: A Primer on Nonmarket Valuation* (Champ et al. 2003). A particularly recent one is "Contemporary guidance for stated preference studies," by 12 authors including Adamowicz (Johnston et al. 2017). In it, its authors summarize what they judge to be best practices for stated preference valuation studies, based on over thirty years of research by numerous researchers, and refer the reader to research papers that address the various practices in greater detail (Johnston et al. 2017). Their 60-page paper is intended to be "a set of guidelines for [stated preference] studies that is more comprehensive than that of the original National Oceanic and Atmospheric Administration (NOAA) Blue Ribbon Panel on contingent valuation [(Arrow et al. 1993)], is more germane to contemporary applications, and reflects the two decades of research since that time." Indeed, almost everything in it is germane to valuation of electric power outages. It contains additional recommendations that apply to outage valuation studies and are not repeated in this paper, as well as additional detail and citations regarding some of the topics in this paper. In addition, Davis (2018) contains a bibliography with one or more journal articles or books in each of the following labeled topic categories pertinent to non-market valuation: Conjoint analysis (choice experiments) generally, populations and samples, elicitation context, survey questions, interpretation, internal process, protest responses, responses more generally, coherence tests, response exclusion criteria, discrete choice statistical models, and aggregation.

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Appendix A. Draft Process for Residential Outage Valuation

This summary of the process described in Sullivan et al. (2017) is written by Daniel Shawhan. Any errors in the summarization are his.

The Draft Guidebook's Recommended Process for Estimating the Value of Residential Power Outages

…in the current draft, which is to be modified and published by Lawrence Berkeley National Lab

1. The reason that utilities want to know the value of electricity supply interruptions is usually so they can better judge what investments in improved reliability are worthwhile. Here is my summary of the process recommended in the draft Guidebook:
2. Build stratified random sample of households, stratified on annual electricity use (and, rarely, based on location e.g. if incomes vary greatly from one part of the utility's territory to another).
3. Communicate with each selected customer in the following steps:
    a. Mail a letter with $2 to $5 requesting the customer's participation and providing a URL and participant ID number to fill out the survey online.
    b. Send an email about five days after sending that letter, with the same information. (Only to those customers for which the utility has email addresses.)
    c. Send several email reminders in the days following the first one.
    d. About two weeks after sending the first letter, send another letter and a paper copy of the survey to those customers who have not filled out the survey online.
4. Use a survey like that shown on the next three pages. Ask the customer to value between five and eight interruption "cases." The next three pages show two sample cases. For a given customer, leave the start time, season, and day type (weekday or weekend) the same in all of the cases, but vary these between surveyed customers.
5. For customers that answer that they have $0 willingness to pay to avoid the interruption, ask question 4a (on the second page after this one).
6. Use the willingness to pay answers (question 4 on the second page after this one) to estimate average WTP.
7. Discard the highest 0.5% of valuations per kWh as outliers based on misunderstanding or other error. Use judgment to discard others that seem invalid (e.g. same answer to all questions).
8. Use a two-part regression model specification for the customer damage function. For the first part, specify a probit model to check whether some known characteristic made customers more or less likely to respond to the survey (in which case adjust for that). For the second part, specify a Generalized Linear Model.

Appendix B. Three Pages from the Sample Questionnaire

The italicized parts of the first and third pages of this appendix are summaries of parts of the draft residential outage valuation questionnaire in Sullivan et al. (2017) that are not reproduced here. Daniel Shawhan wrote those parts. Any errors in the summarization are his.

Three Pages from the Sample Survey in the Draft Guidebook

I have omitted some introductory text and some introductory questions such as how many outages the customer remembers in the last year.

IMPORTANT

As you answer the questions, please remember these two definitions:

Inconvenience or hassle costs

When a power outage occurs, a household may experience inconvenience or hassle costs while adjusting to the outage. Among others, these may include having to use candles if it is dark, having to dine out, not being able to watch television or not being able to use the internet.

Note: If you have solar photovoltaic (PV) panels installed, your household will still experience the power outage and your PV system will not feed electricity into the grid.

Extra expenses

These may include food spoilage, dining out or lost wages for lost work time due to outages. In adding up your extra expenses, please do **not** include expenses that your household would have incurred whether or not the power outage happened. For example, if you decided to dine out during the outage **instead of** another night, the cost of the dinner should **not** be considered as an extra expense because it is simply shifted from another night. However, if you had to dine out during the outage **in addition to** another night, the cost of the dinner should be considered an extra expense.

Case A:
On a <<SEASON1>> weekday, a complete power outage occurs at <<ONSET>> without any warning. You do not know how long it will last, but after 4 hours your household's electricity is fully restored. Note that **all** of the remaining cases occur at **<<ONSET>>**.

SUMMARY:
Conditions: <<SEASON1>> weekday **Start time:** <<ONSET>>
Duration: 4 hours **End time:** <<END1>>

A1. Since you would not know beforehand when the outage would occur or how long it would last, how would your household adjust during and after this outage? (Check all that apply.)

- ☐ There is generally no one home on a summer weekday at this time
- ☐ Stay home and do activities that don't require electricity
- ☐ Go out and eat, shop or visit friends
- ☐ Run a backup power generator
- ☐ Use a propane/gas stove or grill for cooking
- ☐ Reset clocks and appliances after outage
- ☐ Other (please describe) ______________________________

A2. How much do you think it would cost your household in extra expenses **and** in inconvenience or hassle to adjust to this outage? If necessary, please refer to the definitions on page 2.

$ ________ extra expenses **and** inconvenience costs

A3. Of the above amount, how much of it would be **just for the extra expenses**?

$ ________ extra expenses **only**

A4. Suppose a company (other than [Utility]) could provide you with a battery backup service to handle all of your household's electricity needs during this outage. With this backup service, you would not experience the outage and would not have to make any adjustments.

Please indicate the one-time amount you would be willing to pay for this backup service to avoid this particular outage. *(Please circle or specify one amount.)*

$0 $1 $3 $5 $7 $10 $12 $15 $20 $25 $30 $40 $50 $75 $100

Other (please specify) $_________

A4a. **If you circled $0 in question A4**, is that because the service is really worth nothing to you or is there some other reason? (Check one)

- ☐ Worth nothing
- ☐ Other reason (please explain)

____

____

Case B:
On a <<SEASON1>> weekday, a complete power outage occurs at <<ONSET>> without any warning. You do not know how long it will last, but after 1 minute your household's electricity is fully restored.

SUMMARY:

Conditions:	<<SEASON1>> weekday	**Start time:**	<<ONSET>>
Duration:	1 minute	**End time:**	<<END2>>

B1. Since you would not know beforehand when the outage would occur or how long it would last, how would your household adjust during and after this outage? (Check all that apply.)

The rest of Case B is identical to Case A.

There are five to eight cases in total. Typically, most of the other cases are identical to Case A except for the duration of the outage.

And then the last case is typically identical to Case A except that it asks about an outage on the other day type (weekend if Case A asked about weekday, or vice versa) or in a different season.

A Few Discussion Points on "Using Stated Preferences to Estimate the Value of Avoiding Power Outages: A Commentary with Input from Six Continents"

Discussant: Riccardo Boero
Affiliation: Los Alamos National Laboratory

1. Are hypothetical answers <u>valid</u>?

After decades of debate on the validity of hypothetical values in all the different fields of social sciences, no definitive answer has been reached. However, a few results emerged, in particular in the literature about the willingness to pay – WTP – for public good provision:

a) Validity of hypothetical values is a possibility that must be considered in addition to biases. Researchers adopting hypothetical values must deal with the fact that may be not "simply" systematically biased but "true" random values.
b) Beyond usual biases, familiarity with the hypothetical situation should be carefully controlled for. It impacts both the validity of results (i.e., if the hypothetical scenario is credible) and the result itself (e.g., if the respondent has recently experienced a power outage).
c) Results from designs and questionnaires should be compared (correlated) with results coming from other sources (e.g., hedonic price estimates). If this is not possible for power outages, approaches should be compared by applying them to contexts for which the data from other sources are available.

On a similar line (and thus still taking inspiration from problems of public good provision), hypothetical situations could be manipulated to improve realism and thus validity of results. This can be accomplished adopting the induced value theory[13] and thus the standard practice of experimental economics.

2. Are power outages <u>certain</u>?

Usually, WTP is used for the assessment of real, existing goods and services for which there is no market and no price (e.g., public goods such as environmental externalities). Sometimes, the approach is used to assess the value of future but certain goods and services (e.g., a new park in the neighborhood).

In this case, the focus is on power outages that are intrinsically different from the goods and services above because uncertain events. The uncertainty is about every aspect of the event, and it regards the "if", "when", "where", and "for how long". The value of avoiding a power outage is thus uncertain as well.

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[13] Smith, V. L. (1976). Experimental economics: Induced value theory. The American Economic Review, 66(2), 274-279.

Among the many biases discussed in the paper, it is worth adding those associated with uncertainty, which are probably the most impacting. The three most important ones are:

a) heterogeneity in risk propensity;
b) framing, as in standard prospect theory[14], which determines preference inversion;
c) reference points, as in cumulative prospect theory[15], probably determined by respondents' experience of outages and usage of electric power.

3. Are the <u>value</u> of avoiding a power outage, the <u>WTP</u> for that, and the <u>cost</u> induced by the outage all equal?

Section 2 of this paper starts saying: "The present paper deals only with direct costs of residential power outages […] researchers typically use non-market valuation methods […] known as "stated preference" surveys […] to determine the most each respondent would be willing to pay to avoid the outage". In the definitions on page 2 it is also said that costs are "net monetized value of the effects of a power outage".

The paper implicitly assumes that the cost of what is lost, the value of avoiding the loss, and the WTP for that are all the same.This, however, may be imprecise because of three main reasons. First, there is the uncertainty to be considered, as in probabilistic risk assessment. These are usually expected values. Second, decision-making should be based on marginal values and not on average (or total) ones. Third, the WTP is influenced by the cost of risk mitigation. To be more specific, consider a residential consumer that enjoys an electricity-intensive good. The good is not free and its price is determined on the market. We also know that the consumer gets a utility from the consumption of the good that may be approximated by a reservation price. The difference between the two prices determines the customer's surplus.

In this example and assuming that there is only this customer and only this good:

a) the cost of the power outage is the price of the good;
b) the value of avoiding the power outage is the avoided loss of surplus by the residential customer (i.e., = personal reservation price – market price);
c) the WTP for avoiding the power outage has to be less than the value in b) and equal to the amount of risk mitigation in which marginal costs of risk mitigation equal marginal benefits.

These differences are important independently from the approach adopted. It means that even for goods and services for which a market price is known, it is important extending the analysis to price elasticities and other measurements supporting utility and marginal evaluations.

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[14] Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263-292.
[15] Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and uncertainty, 5(4), 297-323.

V. Evaluating Methods of Estimating the Customer Cost of Long-duration Power Outages

Author: Jeffrey D. Roark
Affiliation: Electric Power Research Institute

1. Introduction

Catastrophic natural disasters such as "Superstorm Sandy" in 2012 and other threats to our energy infrastructure have heightened the need to strengthen and broaden our efforts to improve the resilience of our critical infrastructure. Others have recognized the need for increased resilience at various scales—at the community, state, and national levels.

In 2017, EPRI contributed to these deliberations by examining several methods for monetizing the benefits that may result from investments that improve resilience and may collaterally improve reliability. (EPRI, 2017) Parts of that paper are repeated herein. A second study[1] independently released by Lawrence Berkeley National Lab appeared with a strikingly similar intent and similar results (Sanstad, 2016). That two studies independently undertaken concur to such a degree seems to validate the findings as relevant, employing similar comparative modeling frameworks and reaching many of the same conclusions. This white paper draws from those results, and extends it by suggesting several additional criteria for evaluating alternative methods of monetizing the value of resilience.

2. Background

At the request of the federal government, the National Research Council launched a study to address the broad issue of increasing the nation's resilience to disasters (the National Academies, 2012). In addition, there have been several more focused efforts to develop risk-based frameworks to facilitate the measurement of increased energy resilience. Electricity sector resilience emphasis is on the development of analytic methodologies to inform policy decisions regarding electric system infrastructure planning, investment, and operations.[2]

In response to this heightened public interest, EPRI has embarked on efforts to determine how the adverse effects of such events can be minimized. Researchers in EPRI's Energy and Environmental Analysis Group are assessing the policy and research landscape from the perspective of climate change (Diaz, 2016). Their counterparts in EPRI's Power Delivery and Utilization Division are developing ways to harden the electric system to withstand better these events, as well as designing microgrids to meet a variety of resilience needs.

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[1] Sanstad, A. March 2016. Regional Economic Modeling of Electric Supply Disruptions: A Review and Recommendations for Research. Lawrence Berkeley National Laboratory.

[2] See for example, Watson, *et al*. (2014), The National Academies (2014), Electric Power Research Institute (2013), Executive Office of the President (2013). These recent efforts build importantly on earlier efforts including, for example, Congress of the United States Office of Technology Assessment (1990), Gyuk *et al*. (2003).

Part of this latter research is to examine local and customized ways to stay electrified when the electric system is forced out of service. Microgrids are portions of the grid that can form a self-sustaining electric system that can provide, for a limited time, some or all constituents' power requirements when the area grid is out of service. While there may be other benefits to such an arrangement, for example some constituents' may be able to generate some power cheaper than the cost of grid supply, the resilience benefits are likely the largest source of benefit. Can the resilience benefits be monetized sufficiently to justify the expenditure?

To accomplish these objectives, EPRI seeks to develop a framework for evaluating the physical and financial consequences of extended outages to determine how customers value resilience generally, and to monetize the resilience value attributable to investments that support resilience. This framework must be risk-based and consistent with a generally applicable definition of resilience. The framework should include several metrics and "…procedures for analyzing, quantifying, and planning for resilience of energy infrastructure systems" (Watson, *et al*. 2014, p. 11). It is within this framework that one can measure the effectiveness and performance of investments designed to improve infrastructure resilience. It also indicates how the benefits of such investments in resilient electric infrastructure can be compared with their costs.[3]

There are a number of physical components needed in any evaluation of investments in resilient infrastructure that define the source of the benefits and costs. In a recent study, EPRI examined one of the major benefits of such investments: the increased supply security and resilience against the more adverse power outage conditions. To monetize this important benefit of resilience, one must establish the value to customers of a more resilient electric system. After all, electric customers are the beneficiaries, and customers likely will pay for measures undertaken to improve resilience.

Conventional studies of the value of electric service have sought to assign monetary values to reliability, where reliability is defined for relatively localized and short power outages that by practice specifically exclude extreme events, ranging from momentary outages to those lasting a few hours.[4] To value resilience over extended spatial and temporal dimensions, we must first identify the costs customers might incur during such outages and understand how customers and businesses might adjust and accommodate to extended outages lasting several days, or even longer. Conventional outage-cost valuation methods seldom make such distinctions. It is important for evaluating utility resilience investments, recognizing that there are preventive and remedial actions customers can take on their own to realize private benefits (i.e., to limit the adverse outcomes of an extended grid outage).

The need for long-duration outage cost estimates is multi-faceted. Utility-planning methodologies typically consider discretionary investments in terms of costs and benefits specifically for their customer population, who ultimately pay for the investments. There are grid investment alternatives that can harden a local or regional grid and/or facilitate recovery from damage. When transmission investments reduce the duration of widespread interruptions, whether in routine or catastrophic

[3] Watson, et al. (2014) develop one such framework; they provide "…use cases regarding electricity, petroleum, and natural gas to provide tangible examples of how these resilience metrics can be put into practical use" (p. 11).
[4] Utilities typically report reliability statistics for interruptions that are 5 minutes or longer but are not associated with what is considered a major event, which is defined differently across the country based on exposure.

incidents, they produce widely shared public benefits, rendering them a public good. Distribution investments, downstream of the regional transmission grid, have more local benefits, while still being dependent on the regional transmission grid for power. With credible positive value estimates, improved resilience could be driven by utility-planning economics alone, but for this, utilities would require acquiescence of regulators.[5] Policymakers or regulators may consider costs and benefits for a broader population, and may subsequently instruct jurisdictional utilities accordingly, expanding the utilities' non-discretionary obligations (with concomitant expectation of cost recovery).

Expanded service obligations for resilience could take many forms, such as new construction standards or expected-performance metrics, but it seems likely and beneficial that utilities would retain flexibility to develop and decide among technologies to meet the expanded goals, especially in the early phases. If utilities' obligations are flexibly expanded to provide greater resilience, the utilities will likely need to decide, within the bounds of their discretion, among alternative resilience investments, comparing each against the others, in an effort to minimize the cost of meeting their obligations.[6] To follow this path, the industry ultimately needs analysis applicable at a regional population level for policy-making, for resilience measures at the bulk-system level, and at a utility service-territory level for utility decision-making.

3. Review of EPRI's 2017 Measuring the Value of Electric System Resilience

EPRI's 2017 paper examined alternative microeconomic methods to derive estimates of outage costs from customer survey data. One was based on customer damage functions (CDFs) that assign costs based on how customers assign value (loss) to characteristics of specified service outages, how a customer is effected by the outage notice, duration, and frequency of situations that the customer evaluates. The other is based on discrete choice experiments (DCEs). The DCE method is an especially promising approach because it associates weights with outage attributes in a behaviorally consistent manner, thereby producing willingness-to-pay measures that can be extended to a wide range of outage situations over many populations.

That paper also examined macroeconomic impact modeling as a means for estimating the direct (corresponding to outage cost) and indirect costs (additional, cascading costs that result) of electric service interruptions from extreme events. This approach has appeal because it is consistent with the nature of severe events, the impacts are extensive and of long duration, and affect not just those directly impacted. But, those results come at the expense of extensive modeling requirements that are

[5] "Regulators" is here intended to include any governing body with approval authority over government and/or cooperatively owned utilities' planning standards or objectives. Even self-regulated utilities would need to convince themselves through their governing boards, though their perspective may be focused specifically on their customers.

[6] In planning, this is complicated by the fact that the alternative investments may increase resilience in different ways with different probabilities of being invoked for their designed duty. That is, the impacts and the benefits will differ among investments, but the utility must decide among them on comparable value terms. This is a problem of both evaluating different kinds of impacts and defining resilience metrics and goals.

very region specific. Finally, the paper provided a brief look at using insurance data for estimating the outage costs.

3.1 Review of Literature

The EPRI paper reviewed literature in several categories of investigation. The analysis itself was couched in the context of a conceptual framework for developing metrics of resilience for electricity in other energy sectors (e.g. Watson et al., 2014). Consistent with this framework, Watson, et al. adopt the following working definition of resilience:

> "…the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents." (PPD-21, 2013).

Watson, et al. (2014, p. 33) go on to define a resilience metric framework as the probability of consequence X given threat Y. The framework does not specify the specific threat or consequence, and therefore, it can be applied broadly. For immediate purposes, however, these authors focus on high-consequence, low-probability events, such as damage from serious riverine flooding, coastal flooding and wind damage accompanying hurricanes, ice storms, and malevolent attacks. They suggest that resilience metrics should:

1. be useful;
2. provide a mechanism for comparison;
3. be useable in operations and planning contexts;
4. exhibit extensibility;
5. be quantitative; and
6. reflect uncertainty.

The Seven Steps of their Resilience Analysis Process (RAP) are to:

1. Define resilience goals;
2. Define system and resilience metrics;
3. Characterize threats;
4. Determine level of disruption;
5. Define and apply system models;
6. Calculate consequences; and
7. Evaluate resilience improvements.

This seems a logical place to begin an investigation of resilience consequences because the costs and benefits of resilient investments in the electric system are certainly important, quantifiable metrics in such a framework.

The importance of establishing the value of electric service resilience is underscored further in EPRI's 2016 white paper, "Electric Power System Resiliency: Challenges and Opportunities." These values are needed to guide utility expenditures on grid hardening and to analyze microgrid investments from a public service perspective. Another 2017 EPRI white paper, "A Cost-Benefit Analysis Framework for Evaluating Microgrids," points out that some proposed microgrids are to intended provide mostly private benefits for a small number of beneficiaries. It suggests that in cases where one or a few decision-makers consider microgrid investments, limits on their willingness to pay can be sampled directly when they are confronted with the costs for various levels of microgrid "coverage," referring to the amount of time that a microgrid can be expected to operate without a grid connection, an important microgrid design variable. Confronting a decision-maker with the cost of a range of proposals may or not determine the willingness to pay for that individual, but it may bracket it relative to the cost estimates. Though not suggested in the paper, it implies that the same might be said for individuals considering investments in equipment with only private benefits; a cost estimate may provide one or more observations of the only willingness-to-pay relevant to the decision.

Methods of quantifying outages costs were reviewed, where EPRI found that the vast majority of the available studies were found to have focused on estimating the value of electricity service reliability employing a microeconomic approach. In this approach, outage costs are elicited directly from customers, describing outages of different character (estimated or realized), or that are based on estimates of willingness to pay/accept outages, also elicited directly from customers. Customers providing data are generally representative of the service territory of the utility that sponsored the survey. Primary data gathered from customers provide the foundation for modeling the value of service, and hence outage cost.

In the body of available applications, reliability relates to service interruptions that most customers have experienced, either as momentary interruptions or for just a few hours. That approach lends credibility to monetary estimates of the cost incurred during such an event, and makes willingness-to-pay estimates by residential customers a candidate measure of outage cost. The researchers found no experience using the microeconomic approach to measure the costs resulting from high-impact, low-probability events such as extreme weather events or other natural disasters. Implementing an outage-cost study just after a widespread outage might shed light on the value of electric service, but it could simply reflect pent up frustration from going without electricity, not what they would be willing to pay to avoid such an outcome in the future.[7]

The costs of electric service interruptions have been estimated through macroeconomic impact modeling of extreme events such as earthquakes, floods, and total blackouts that might be attributed to massive system failure or terrorist activity. Here, a model of the economy of interest (which might roughly represent a utility's service territory) is constructed to reflect equilibrium conditions (business as usual). It then is shocked by imposing physical, market, and consumer disruptions that could be attributed to a catastrophic event. The difference in the level of economic output (gross product, wages, and profits) before and during the event defines the extent of the outage cost imposed, and presumptively what society would pay to avoid that outcome. The attraction of this approach is that costs are viewed in terms of their collective level, and therefore may be less prone to bias in values elicited from a few individuals.

[7] Strategy bias, respondents offering extraordinary (unsubstantiated by the customer's circumstances) low or very high estimates of the cost of an outage, is a confounding issue in reliability studies. One might expect that this bias would be most extreme when customers are asked to value an outage that has left power lines down all around them, in the same way a drowning man values life preservers more the typical cruise customer.

Most recently, the insurance industry has contributed to ways to estimate the cost of electric grid disruptions by extrapolating insured business loss data for extreme events to the broader population of non-residential and residential customers. This exploratory approach is attractive because it uses secondary data (premiums) that reflect customers' implied estimate of the cost of an outage. As discussed further below, it has several shortcomings that may render it not very useful, at least today, because growing collective concern about extreme events is recent.

EPRI, 2017, considered an alternative microeconomic approach employing discrete choice experiments (DCE). A DCE also elicits data directly from customers, but with another purpose; to construct a theoretically-based behavioral relationship. The model seeks to characterize how the attributes of an outage influence the cost associated with it. Doing so attaches probability weights to the notice, duration, frequency and other physical attributes of an outage. Once such a preference model is fully conformed, outage costs for any set of attribute levels can be calculated. The attraction is its theoretical underpinning in random utility theory that is generally consistent with economic demand theory, and WTP measures can be derived from the estimated model.

The challenge is not to try to find a single method or approach the can be recommended in all cases. Rather, one must identify how these methods can be used singly in their present or appropriately modified form, or in combination, to generate the most useful and reliable estimates of value under the several circumstances that can lead to an extended electric service disruption. For example, we know that the economic impacts of power outages may differ in major ways depending on whether the outage is due to: an isolated failure in the electrical system; a targeted terrorist attack; or a catastrophic natural disaster. In the latter case, damage is likely to be more widespread, so that it is more difficult for businesses to cope during the outage and when power is restored. The recommendations, of course, will depend on the nature of the outage, its cause, and its duration, and who is affected and how. The trail to valuing resilience leads back to electric customer, consumers, and citizens.

3.2 Microeconomic, Survey-Based Outage Cost Methodologies

Survey-based methods are commonly employed for estimating customers' electricity outage costs. Their prominence derives in part from their building up outage-induced damage cost from what customers express as the cost they would incur under stipulated conditions. Before discussing the various statistical methods available to elicit individual's customer outage costs, it is useful to derive the concept of a comprehensive customer damage function.

Most outage cost studies have employed the microeconomic method. They were designed to estimate the value of electric service reliability based on survey data collected from random samples of business owners and residential customers. Typically, business owners are asked to provide estimates of the direct costs of an outage, defined as the value of lost production plus other outage related costs, less any outage related savings. Through a series of contingent valuation questions, residential customers review estimates of their willingness to pay/accept for electricity outages. In these studies, separate outage cost estimates for both business owners and residential customers are derived from statistical analysis of these survey data. These estimates may differ by business type and by residential customer demographics.

3.2.1 Survey-Based Customer-Damage Functions (CDFs)

Outage costs differ depending the character of service interruptions: frequency (how often), amount of advance notice provided, and its duration (how long it lasts), and time of day and year. For residential customers, outage cost is expected to differ by customer characteristics and demographics. An outage at a vacant residential premise has less impact than one where several people are at home during the outage. If someone at home depends on electricity for a critical heath service, then the outage cost may be even higher. Outage costs typically differ across commercial and industrial customer types, depending on the type of business they conduct, the physical plant they operate from, how it operates, and whether there are backup facilities that can partially serve needs during an outage. The last factor determines whether power and operation are fully lost or just more expensive to maintain. Outage cost, as it varies by duration, is typically aggregated by customer type to form a customer damage function (CDF). To use these CDFs for utility-investment decision-making, they are typically normalized based on average interrupted demand or consumption for the customer types, and applied to a customer mix appropriate to a given service area.

3.2.2 Survey-Based Discrete Choice Experiments

A discrete choice experiment (DCE) is an alternative approach offering a long-standing, well-tested theoretical basis in random-utility theory (RUT), and consistent with the theory of economic demand. "A discrete choice experiment … is a general preference elicitation approach that asks agents (consumers or business decision makers) to make choices(s) between two or more discrete alternatives where at least one attribute of the alternative is systematically varied across respondents in such a way that information related to preference parameters of an indirect utility function can be inferred." (Carson and Louviere, 2011, p. 543).[8] RUT is based on a latent construct labeled "utility," which exists in a person's mind, but which is unobservable to researchers. There are two components to latent utility, an explainable, or systematic, component, and an unexplainable, or random, component. The systematic components consist of the attributes that distinguish the differences in the choice alternatives, as well as covariates of individuals that explain differences in the choices individuals make. The random components are unobservable factors that also affect individual choices.

In a DCE, preferences can be constructed for hypothetical or generally unavailable goods and services by eliciting stated preferences (SP) from subjects; if these choices were available, what would they choose? This makes DCE attractive for valuing resilience to protect against the consequences of infrequent outages. DCE is rooted in an established behavioral portrayal that imposes important consistency structure on the parameter estimates. This is particularly important in studies where the objective is to estimate total willingness to pay (WTP) for a good (e.g., WTP to avoid an electric system interruption), rather than just to measure how attributes affect marginal preferences. Thus, a

[8] Put somewhat differently, A DCE must contain two essential elements: "(1) a respondent is asked to make a discrete choice between two or more alternatives in a choice set, and (2) the alternatives presented for choice are constructed by means of an experimental design that varies one or more attributes within- and/or between-respondents to be able to estimate economic quantities tied to preference parameters." (Carson and Louviere, 2011, p. 542-43). To satisfy these conditions it need not be the case that one must provide more than one choice set; a single multinomial choice question will do.

respondent's certainty about a decision will change when asked about larger changes than smaller ones, and a DCE can capture this important effect.

3.3 Macroeconomic Approaches

Outages of extended duration that affect large geographic areas and large populations are the likely result of high-consequence, low-probability events such as damage from serious riverine flooding, coastal flooding, or wind damage accompanying hurricanes, ice storms, or malevolent attacks, and electric outages due to collateral serious failures in infrastructure. On the other hand, cascading power outages from events or damage to facilities in the bulk electric system can radiate to areas remote from the trigger event, and can cause outages that last for days, as in the Northeast Blackout of 2003.[9] In these situations, the costs incurred from a service interruption include direct physical damages and indirect spillover effects in the greater economy. These costs, some of which may be averted, may not be distinguishable in a survey-based outage-cost study, especially if utility service territories (the focus of most outage-cost studies) and regional economics do not fully overlap.

Efforts to estimate these indirect spillover effects and to disentangle the costs due to simultaneous lifeline failures date back at least 25 years. Prior to that time, efforts to estimate losses from disasters such as floods, earthquakes, and hurricanes focused primarily on the physical damage to buildings and structures. Any attempt to measure the costs of such disasters was limited almost exclusively to the capital-related costs of repair and replacement of damaged buildings and lifeline components. Efforts to identify the appropriate modeling strategies were not addressed until the mid-to-late 1990s. Some were developed in detail and embodied in FEMA's HAZUS-MH software, a nationally applicable, standardized method to estimate potential losses from earthquakes, hurricane winds, and floods. The idea was to use the results from direct losses estimated from physical damages to buildings and other structures as input into a regional impact model to estimate the indirect economic losses.[10]

The marriage between HAZUS output and the regional economic impact models has never been as seamless as some had hoped. At best, selected damages estimates, as well as input parameters from HAZUS (in combination from a variety of data from other sources) have been utilized in regional impact models to estimate the indirect economic impacts from natural disasters and electric system outages.

There are two major types of regional impact modeling: Input-Output (I-O) methods and Computable General Equilibrium (CGE) models. The I-O model provides a fruitful way to depict and investigate how the underlying processes that bind an economy together are affected by a shock, a new public policy, or some other substantial change of economic circumstances. I-O is used primarily to evaluate public policies where the interests of all citizens (society) are included, in contrast to investment decisions by private firms that consider only the costs and benefits they realize. The methodology's analytical capacity (and hence, attractiveness) lies in its ability to estimate the indirect and induced economic

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[9] NERC enforceable reliability standards established since that time have been oriented toward making these events less likely or less severe.

[10] See: Multi-hazard Loss Estimation Methodology Flood Model Hazus®-MH MR5 Technical Manual chapter 15, and Multi-Hazard Loss Estimation Methodology Earthquake Model HAZUS®MH MR4 Technical Manual, 2003, chapters 3 and 16.

effects stemming from the direct policy expenditures that lead to additional purchases by final users in an economy. I-O by itself may not be sufficient to estimate resilience value, but it can play an important role as an embedded element of a more generalized characterization of an economy and how it is affected by catastrophic events.

By relaxing many of the more restrictive assumptions of the I-O model, CGE models have proven to be powerful analytical tools for policy evaluations at state, regional, and country levels. Advances over the past 20 years in optimization software and computer speed have created a research environment that allows for the specification of complex interregional models on a truly global scale.

A natural disaster is no more than a special class of an external shock that affects the economy, but in those cases, we must consider changes in the internal environment that are brought about by the external shock from the natural disaster. The direct damage to fixed plant and equipment in the short run is certainly a shock in the spirit of those mentioned above, but there are many other disruptions that are endogenous to the economy, called indirect impacts. The changes in regional or local trade patterns are good examples of these endogenous shocks to the economy after a natural disaster.

The challenge is to determine if a CGE model can be altered to reflect the changes in the economy both before and after a natural disaster and the extent to which all these changes should be incorporated. The answer to these questions depends on how the results are to be used. For example, are the results to be used to measure the effects of the disaster or to predict how the economy will look after it has had time to recover? In the former case, we are trying to measure the value of averting disaster (resilience), while in the latter we are trying to forecast the economic future of the area for recovery planning.

Regardless of which of these perspectives is of interest, when an economy receives an external shock or a policy change is invoked, a new set of prices consistent with equilibrium in the economy will result. A CGE model of the economy will generate these prices and use them to determine new equilibrium levels of production, consumption, employment, income, etc., that are of interest to analysts and policy-makers as they measure the desirability of the outcome.

Finally, in the choice of a CGE model, there is the implicit notion that economic structure matters, meaning, for example, the share of exports in gross domestic product (GDP) or the share of agriculture or manufacturing in total output. In so doing, it is necessary to reproduce, to the extent possible, the detailed structure of the economy in the model. Given the relaxation of many of the assumptions of the I-O model, this implies that the data requirements to construct a CGE are even more extensive than in the case of an I-O structure. The problems of obtaining the data mount rapidly if the model is needed to disaggregate into more distinct production sectors, for example, to distinguish the impact of power losses by business activity or industry sector.

3.4 Estimating from Insurance Data

A recent study of the costs of electric grid disruption was conducted from an insurance perspective. That paper explores four case studies, one of which was the August 2003 Northeast Blackout. The analytical framework exploits insurance loss data, and scales the insured values up to total economic losses for the insured and the uninsured. Economy-wide losses are then approximated by applying per-customer insured losses to all insured households and businesses in the affected area (Mills and Jones, 2016). The authors compare their estimates of dollar losses per customer with those for the 16-hour interruption estimates for summer days from Sullivan, *et al*. (2015). They had no data to distinguish between small, medium, and large C&I customers, but their per-customer outage loss estimates were bracketed by those from Sullivan, *et al*. (2015). They attribute this difference, at least in part, to the larger number of policy holders in their database and perhaps to the availability of more advanced loss-prevention devices such as uninterruptible power supplies, backup generation, and surge protection devices. In contrast, their estimates of per-household losses were 50-to-200 times larger than those in Sullivan, *et al*. (2015).[11] From this, Mills and Jones (2016) conclude that traditional survey methods to estimate value of service reliability seem not to fully capture the costs of grid disruptions to households.[12]

This approach has many limitations. It requires getting data from insurance companies specifically for claims after a catastrophic event, which may limit the scale and scope of the study (will they release policy and claim data). People with insurance to cover extreme, low probability events are likely to be particularly vulnerable to the consequences and therefore not typical of the general population. Extending their situation to all businesses and customers likely results in overestimation of damages to the population in general. Damages are limited to those that are insurance reimbursable, which is not all the cost incurred to many businesses, unless lost production is explicitly covered, and inconvenience to residences is probably not covered.

Insurance claims are not well-suited for estimating how customers value resilience. They may serve a role in providing a useful perspective in verifying (or bracketing) estimates from other methods of the cost of catastrophic events and the derivation of measures with what customers would pay to avoid them.

3.5 Comparison of the Reviewed Methodologies

3.5.1 Reflections on Surveys for CDF Estimation

From the discussion above, it is clear that CDFs derived by aggregating and normalizing outage cost estimates for individual customers may be useful in assessing system reliability as defined by outages of relative short duration, a day at most. Can they also be constructed so that they could also be used in evaluating resilient investments in the electric system?

A central issue for this survey-based method is whether customers' impressions of event cost can be

[11] For the details, see Mills and Jones (2016, Table 6, p. 25), and Sullivan *et al.* (2015, Table ES-2, p. xii).

[12] The authors are quick to point out the preliminary nature of their results. Therefore, it would certainly be premature to jump to such a conclusion based on this single study without knowing the validity of extrapolating losses from insured to those that are uninsured. Are the insured households representative of the uninsured ones? This may be a particularly important question to ask given what we know about problems with incomplete penetration of markets for insurance for high-consequence, low-probability events like the 2016 flooding in Louisiana (adverse selection and moral hazard), such as exacerbated limits, deductibles often in the form of a waiting period) and exclusions in many policies. Does the fact that there are more people working from home affect the results?

relied upon if they never have encountered such an event, whether assigning a WTP to avoid it or constructing a monetary damage cost estimate from their reckoning of the business and operation impacts. Can they place themselves in such a hypothetical situation and provide cost data that are reliable?

3.5.2 Reflections on Survey-Based Discrete Choice Experiments

Discrete Choice Experiments (DCE) are an alternative and perhaps superior approach to eliciting from customers their reckoning of outage costs because they offer a long-standing, well-tested theoretical basis consistent with theory of economic demand. Second, the DCE would ask survey respondents to indicate their preference for alternative service bundles defined in terms of specific levels for each of the attributes, one of which is the premium they would pay (over their existing rate) to avoid such an outcome. By making the premium an attribute, the relative importance to the decision of how much resilience can be derived from the estimated choice function. Planners can explore the implications of acceptance for different levels of various attributes and cost. Consistent WTP estimates can be derived from the characterization of preference of outages specifications, in effect producing the same outage cost metric as a conventional outage cost estimation.

A DCE survey would be constructed to efficiently sample the topology of attribute levels, following established practices (Louviere et al., 2008). Instead of estimating a damage function, a choice model would be developed that links outage attribute levels and customer characteristics, to the cost associated with an outage in such a way as to reveal the underlying preference for resilience. This produces a way to associate preferences for services with different levels of resilience directly. In this way, DCE might also be applicable for estimating outage costs for smaller commercial customers. A feasibility study of this kind is underway as an alternative to collecting outage cost data directly through expensive interviews, and it might be extendable to large customers.[13]

DCEs may better accommodate methods to establish the cost of extended outages (the value of resilience) than those used to estimate damage functions. DCEs provide both the rigor of an underlying economic behavioral characterization and the ability to consider a wider range of attributes than have been achieved through conventional outage-cost methods. DCE reveals the importance of drivers to resilience value that may be influential, including the geographic extent of the electric outage, the extent of outages in other critical services, whether the customer or business has recourse to temporarily move out of the affected area, or has available remedial services from on-site generation or storage.

3.5.3 Reflections on Computable Generation Equilibrium approaches

Both survey-based methods consider the direct cost individuals themselves incur, not the costs experienced by others. The CGE method attempts to estimate the costs of electric service interruptions through macroeconomic impact modeling of extreme events.

[13] EPRI is working with university partners to asses alternative ways to measure consumer and business preferences for service alternative and extensions to valuing service reliability.

Comparing economic output (gross product, wages, and profits) before and during the event defines the extent of the outage cost imposed, and by construction represents what society would pay to avoid that outcome. The attraction of this approach is that costs are viewed in terms of their collective level, and therefore they may be less prone to bias than are values elicited from a few individuals, as in microeconomic approaches. However, methods for applying macroeconomic impact analyses are different from the statistical models used in the microeconomic approaches. The data requirements differ as well. Moreover, to model the impacts effectively, the CGE impact models must be constructed to represent a meaningful economic region. The economic regions may encompass electric customers in more than one utility's service territory, thus making it difficult to assign losses directly to electric customers by utility.

An additional shortcoming of the CGE model is that it is difficult to disaggregate the measures of the indirect market impacts (losses) so that they can be assigned to the several service lifelines (telephone, internet, electricity, water, transportation, and natural gas) that might fail during the disaster. Attempts to disentangle these effects may well be accomplished by systematically comparing the losses, simulating situations where selective lifelines are assumed not to fail. Perhaps more importantly for the electric sector, the CGE model does not distinguish impacts of value to customer classes (residential, commercial, and industrial) as defined by electric rates, since the demand side is represented by a collective agent. This may limit its application because the value of resilience may be different across those classes, and would affect the degree and location of resilience investments made.

4. Practical Comparison Criteria for Methodologies

EPRI's 2017 paper on measuring the value of resilience provided a side-by-side comparison of several of the foregoing methods for evaluating the cost of long-duration interruptions (CDFs, CDEs, and CGE) in terms of their characteristics and components of their derivation. The comparison table from EPRI, 2017, is included in Appendix A. Ultimately, however, criteria for selecting a method for implementation may rest on practical grounds, such as:

- Theoretical basis, including consideration of possible loss of services other than electricity, such as water, sewer, gas, transportation, and communication infrastructure (cellular, wired phone, and internet).

  The theoretical basis is a qualitative judgment, questioning whether the information produced by the methodology represents the breadth of event possibilities in a meaningful way. Loss of electric service may be the beginning of an event, as in a region-wide blackout, but other services may be involved. Losses of essential services may be immediate or accumulate as the event wears on. Backup generators fail or give out of fuel. Transportation fuels become unavailable. Electric trains may stop service, and air travel may suffer delays.[14] Water pressure is lost, and the remaining

[14] On December 17, 2017, Atlanta's Hartsfield-Jackson airport suffered a power outage from fire that defeated its ability to use redundant service feeds or backup generation, resulting in the cancellation of 1,180 flights to/from that airport alone by the time of restoration on the 18th, affecting some 30,000 people directly. (CNN, 2017) The extended reach of the incident was not reported.

supply becomes unsafe. Cellular communications may fail, and citizens lose the ability to charge phones. These impacts can occur whether or not there is local damage of any sort; a scenario with local damage brings recovery demands into the local area, but changes the ability of the population to escape the situation. This is to say that the state-space for interruption scenarios is multi-dimensioned and wide in many dimensions. Further, the state of any selected small area in the universe of possible hazards that might affect it is highly uncertain; it might be involved in damage or it might be only lacking in essential services, beginning with the lack of power. Surveys draw on experience and imagination, but not many populations have experienced the breadth of scenarios that a method needs to cover. This criterion is somewhat aspirational in that regard.

A methodology that deals explicitly with possible failures of multiple utilities and services should be extensible to scenarios that begin with events other than electric service interruption. Loss of water or gas service, for instance, could be analyzed through similar methods.

- Time and cost to produce estimates for a given region.

  The costs of any method can be estimated once the scale and scope of the study are specified. A comprehensive WTP/direct-cost elicitation study can cost $1 million or more for a large service territory and take a year to complete. A CGE uses available Social Accounting Matrix (SAM) data so it might be faster to assemble the base model, but specifying how a disaster affects infrastructure, and hence output, is challenging.

- Consistency of results addressing different needs such as policy-making, regulation, and planning decision-making.

  The needs of regulators and policy-makers may differ from those of utility planners by matters of scope. Policy-makers may be concerned about states, countries, or regions, while a utility is focused on its service territory. The government policy-maker might want to know whether having all utilities construct to a certain resilience standard would provide net positive value overall, considering the likelihood and distribution of hazards within its constituency. A utility considering discretionary investments of the same type might be more interested in the likelihood of a set of more specific hazards occurring in its specific territory. It is worth noting again that long-duration loss of power caused at some distance in the bulk system is a totally different hazard than nature-caused destruction of a distribution system and local sub-transmission. Nevertheless, an evaluation method should be considered in terms of its ability to explicitly “roll up” to the policy level and provide estimates consistent with those the utility would use for planning. Recall that the use by planners might be for prioritizing among alternative ways of meeting a standard set by policy-makers, and the values (and hazard probabilities) should be specific to the utility. For example, a coastal utility might have different exposures than an inland utility, though they might lie in the same region. The resilience benefit side of decisions is needed by utility planners when rationing a resilience budget, as might occur if regulators ask the utility to invest a certain amount in unspecified resilience-promoting technologies. If, however, policies are set in concrete terms such as physical construction standards, then utilities can build to those standards using their established cost-minimization planning methodologies to resolve any planning decisions that remain; the benefit side of such decisions is moot if resilience performance is essentially the same under all alternatives that meet the standard.

- o Extensibility from one region to another

  Clearly the hazards that affect the electric systems vary from region to region, so the subject hazards and all of the probabilities that might contribute to the total risk should reflect that. The values of candidate resilience measures would differ according to these parameters, and a method that can reflect those different hazards and infrastructure parameters would be able to reflect those differences somewhat.

- o Scalability from region to service territories

  As noted above, the methodology not only should scale from region to smaller areas, but should at least reflect the variance in hazard probabilities as the area focuses down to individual service territories. This would reflect the different uses to which the estimates would be applicable for.

- Applicability to interruptions from both natural disasters and man-made catastrophes (such as blackouts)

  Natural disasters may cause serious damage to the bulk and distribution systems in a region or service territory, while blackouts at the bulk level, to use an example, may cause power to be lost without any local damage to the system. A cascade of interruptions of essential services of all types may accompany a long-duration blackout, but the costs of a blackout of the same duration would be different apart from the direct costs of damages in the case of a natural disaster.

5. Closing thoughts and conclusions

For utilities, regulators, and policy-makers, an aspirational goal is to have an expected value to apply to all manner of resilience-supporting measures so as to either decide which ones to undertake or whether they are worth undertaking at all. However, the physical-impact side of these questions, when looking at some investment alternatives is complex, in some cases as complex as determining the value of avoiding long-duration interruptions. That is, the connection between individual components of a resilient system and their expected impact on durations of interruptions and the severity of events is a separate area that planners will need to deal with. Transmission planning standards already enforce a certain level of redundancy to limit contingencies that cause interruptions of customers and to avoid cascading outages. As noted above, investments on distribution systems have local impacts, and may not affect even other feeders emanating from the same substation.

Additional thoughts:

- Before a method can be universally embraced, specific evaluation criteria need to be established and applied to each method.
- That consideration should include needs outside the electric sector because catastrophic events affect many public works and the interdependencies need to be accounted for both in how impacts are modelled and in how investments in different infrastructure elements impact the final cost (set

priorities for investments).

- Scale and scope of the study should be understood so that studies undertaken are most useful, perhaps militating for regional cooperation in studies and sharing results to produce more robust models.
- Consideration should include the useful life of any valuation, how often it should be updated; or can a study have lasting value when embedded in a larger system that can be updated relative easily or as needed.

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Appendix A.

The following table from EPRI, 2017, provides a comparison of the methods discussed herein. Additional details are available in the source paper.

Table A - 1. The Value of Resiliency--Comparison of Approaches

	Methodology		
	Microeconomic		**Macroeconomics**
Methodology Feature	**Customer Damage Function (CDF)**	**Discrete Choice Experiment (DCE)**	**Computable General Equilibrium (CGE) Model**
Event	Event resulting in full outage (typically) or partial outage (occasionally) at single or multiple businesses or residences. Could be in context of extremely localized (a neighborhood(s)) or extremely widespread).		Natural disaster (hurricane, flood, earthquake, snowstorm) devastating a large area.
Events used in analyses	Specify alternative levels (or changes in levels) of outage attributes; primarily notice, but may include, notice, frequency, exposure.		Events are specified in terms of return frequencies (100-yr. flood, 1% yearly; 500-year earthquake, 0.25% yearly)
Valuation Concept	Associates losses (damages) with the attributes of a defined event (notice, duration, frequency) that results in loss of power.		Losses for a defined event are indirect economic losses in the economy.
Common reference terms	<u>CDF</u> Outage or damage cost, value of lost load.	<u>DCE</u> Outage or damage cost, value of lost load.	Direct physical damage, direct and indirect economic losses.
Theoretical Basis	No well-defined behavior theory of choices;	Consistent with Random Utility & demand theory	Consistent with Walrasian general equilibrium theory
Mechanism	• Residential: elicit willingness to pay from individuals. • C&I: ask businesses to estimate costs incurred.	Elicit estimates of attribute importance to outage cost: • Residential customers; • Small C&I businesses; • Perhaps large C&I businesses.	For a defined event, estimate physical damage to buildings, lifelines & other components of built environment.
Research Methods	• Survey residential customers. • Sampling is across alternative attributes levels. • Conduct interviews with business managers /operations staff. • Estimate WTP/outage costs statistically.	• Survey residential, commercial and industrial customers. • Sample from topology of event attribute levels (a wider range of attributes level than in conventional outage cost methods) • Links outage attribute levels & customer characteristics to cost	• Construct a general equilibrium model of economic activity in the effected region. • Shock economy (change structure of model) to account for physical damage to buildings, lifelines & other parts of built environment. • Simulate indirect economic impact.

	Methodology		
	Microeconomic		**Macroeconomics**
Methodology Feature	**Customer Damage Function (CDF)**	**Discrete Choice Experiment (DCE)**	**Computable General Equilibrium (CGE) Model**
		of an outage. • Estimate WTP/outage costs statistically.	
Outage cost estimates	For each customer class, determine number of customers affected & calculate the aggregate outage/damage costs based on average per-customer outage costs.		Costs are defined as changes in economic output, value added, employment, and wages.
Direct cost			Direct Economic Costs are: • Market and/or depreciated value of damaged buildings and contents (by occupancy class) and structures; • Impacts to lifeline system functionality, component costs, & time to recover are considered.
Indirect costs	• Residential: elicited as willingness to pay values. • C&I: Survey and interviews designed to elicit incurred costs categorically.		Explicitly accounts for the direct material cost incurred by the firms effected physically and collateral costs incurred by others as result of lost business transactions
Spatial Scope	Conventionally the context is an outage by the facility/home, no specific reference to its extent, but some respondents might include some of those considerations implicitly.	Can add the extent of an outage as an attribute and measure its importance in determining outage cost.	Accounts for collateral effects upstream & downstream on firms, even those that are incurred by individuals or businesses not directly affected by the event.
Temporal Scope	Conventionally outages of 12 hours or less have been examined.	Potential to examine long duration outages with careful survey design.	Dictated by severity of the disaster and the estimated time to recover.
Granularity by Outage Duration	As currently constructed, outage costs are for: • PQ (momentary or a few seconds to 5 minutes) • Reliability for events from 5 min. to 12 hrs.	Potential to construct a single model that include a wide range of durations (covering PQ to disasters) along with notice, frequency, scale and scale.	Duration is dictated by: • Severity of natural disaster; • The estimates of the recovery time for electric system, and/or other critical lifelines or facilities.
Customer Granularity	Conventionally distinguishes outage cost by customer class: • Residential customers by demographics; • Commercial and	Allows establishing deep interactions of customer characteristics that support segmentation of customer by their distinct demographic and	Aggregate indirect market impacts (losses): • Are not easily disaggregated to be assigned directly to electric customers by service class.

	Methodology		
	Microeconomic		**Macroeconomics**
Methodology Feature	**Customer Damage Function (CDF)**	**Discrete Choice Experiment (DCE)**	**Computable General Equilibrium (CGE) Model**
	industrial firms by 2-to 5-digit NAICS code.	premise's characteristic	• May encompass electric customers in more than one Utility's service territory.
Applications	Standard in electricity sector for estimating outage costs, but administered only occasionally and by only a few utilities.		Applications of the effects of simulated natural disasters have been developed to: • Link estimates of physical damages buildings, structures, and infrastructure to regional economic impact models; • Modify structure of regional model to account for physical damage; Monetize indirect economic impacts of the disaster through counterfactual comparison of what the important economic variables would have been absent the disaster.
Examples of Studies Conducted	Over 25 studies used to construct a meta-study model of outage cost (ICE).	None found	A single simulation of the economic effects of a complete blackout in the LA area resulting in a localized, two-week outage.
Examples of Uses of outage cost estimates by electric utilities	• Generation capacity planning may use VoLL to determine investments. • Used in some wholesale markets as an implicit measure of value. • Used by ERCOT to set the ceiling price on hourly energy, as was the case in the initial England and Wales Power Pool. • Some US utilities use VoLL to set retail hourly RTP prices to derive prices for load curtailment programs.	Same as for customer damage functions but with a greater degree of customer granularity	None was found.

Discussion of "Evaluating Methods of Estimating the Customer Cost of Long-duration Power Outages"

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Introduction

The following is a commentary on Jeffrey Roark's[15] paper, "Evaluating methods of estimating the cost of long-duration power outages." The paper focuses primarily on the value of long duration lost load (VOLDLL) for long duration power outages to customers and indicates microeconomic approaches to obtaining this cost. He also discusses macroeconomic approaches to determining the cost of long duration power outages. Further, he critiques each method proposed. He describes two microeconomic approaches; the survey-based customer-damage functions (CDFs) and survey-based discrete choice experiments (DCEs). In addition, he evaluates the insurance-based actuarial approach. For macroeconomic approaches, he evaluates Input-Output (I-O) models and computable general equilibrium models. I will review and comment on the approach to each method. I would suggest upfront the definition of the items to be valued in long duration lost load need to be clearly separated. Is the paper focused only on the value of customer lost load or is it broader including the resilience of the entire grid? If it is the broader definition, the paper doesn't include all the items necessary to value grid resilience. In addition to customer losses, there are generation, transmission and distribution system losses such as equipment damage, unproductive salaries and un-recouped overheads and revenue losses, to name the most important components. These losses are a part of a broader resilience value function.

The final paper included a review of the literature that provided a resilience metric framework to undertake resilience valuation. Different studies provide different steps but the steps appear to be inclusive of major steps required. One should note however, that the steps are not always sequential; sometimes the steps may need to be repeated until the valuation is complete.

Microeconomic - CDFs versus DCEs

When it comes to the choice between CDFs and DCEs, I would suggest data driven choices. Roark suggests that it might be difficult to get customers to value what they have not experienced, meaning enduring a long-duration service outage. However, I believe that with a well-designed survey that elicits from the respondent the items at risk as the electricity outage becomes longer, most respondents could determine what is at risk. Value may have to be implied, but with enough detail, the value can be estimated. The question would be whether the surveyor could get enough time from the surveyed to accurately determine the impacts of a long-term outage. The choice between CDFs and DCEs, based on

[15] Jeffrey Roark is with the Electric Power Research Institute (EPRI).

a quick look at the literature, indicates that to the extent that data exist, CDFs would be preferred, if the survey data can be collected that accurately reflect the costs of the long duration outages.

Discrete choice experiments would be the choice for when data doesn't exist, as the results appear to be a less reliable indicator of the loss. Thus, an issue for DCEs is the reliability of the results. A study by Rokotonarivo (2016) indicated that 45% of the 107 studies showed different results when small changes were made to the sample design.[16] The study also indicated that 2-90% of the respondents disagreed with the content of the survey. Additionally a large proportion of those surveyed found the results incomprehensible or inconsequential. The authors suggest that DCE results need to be validated with tests of reliability to assure that the results reflect the underlying value. On the other hand, DCEs have become common in Health valuations. Roark indicates that he found no studies of resilience value using the DCE method. Thus, with time and tests to determine reliability for VOLDLL estimation, DCEs may prove valuable in valuing electric customer outages. The last paragraph in the draft final paper indicates that DCE can reveal the importance of drivers to resilience. This section needs more elucidation and some examples to make the point clearer.

My suggestion for the use of the CDFs and DCEs would be to use these according to the ability to conduct surveys to develop the data. To the extent that willingness to pay survey data cannot be developed, the DCE method may be the approach. However, willingness to pay is a well-established approach to obtaining values for non-market quantities. Thus, I suggest choosing the approach that best fits the requirement for which resilience is being valued and for which valid estimates can be developed.

Insurance data

The insurance approach is intriguing because it proposes an actuarial approach to calculating the value of lost load from actual claims data. In order to qualify for insurance, the risk must be quantifiable with an ability to assess the frequency and cost with enough entities willing to participate to spread the risk. My questions when initially thinking through the issue of insurance were what proportion of the population was insured and for what were they insured, how much of the value of lost load is captured and what is not captured. Much of the damages would likely be for property damage.

Business interruption costs would provide an estimate of the consumer and customer related losses. The problem is that only those businesses that are highly dependent on electricity to maintain their revenues would likely purchase insurance. Even this coverage may be bundled with other coverages, making it difficult to disentangle the electricity values from other values. Businesses, for which electricity is a mainstay, may invest in backup generation or micro-grids. The investment in the backup is an indicator that the micro-grid investment costs were less than the long-term value of outages to the

[16] Rakotonarivo, OS, M Schaafsma, N Hockley. Dec 2016. "A systematic review of the reliability and validity of discrete choice experiments in valuing non-market environmental goods." J Environ Manage. 183:98-109. doi: 10.1016/j.jenvman.2016.08.032. Epub 2016 Aug 27.

investor. Thus, there are holes in the data that must be reconciled. In the reviewed paper[17] it was noted that there is a difficulty in separating claims directly related to the outage versus other claims. They found what I noted and Roark notes, as well, that insurance data may not fully capture the cost to households and businesses of long duration outages. In my example, residential losses may or may not be directly related to the costs of long-duration outages. For example, the damage from a hurricane may have destroyed the roof, which would possibly be insured but have nothing to do with the losses associated with the electricity outage. In addition, time of year may change the impact of the outage. Outages during mild weather may have little damage resulting in deaths, while outages in the summer or winter may have heat stress- and hypothermia-related deaths, respectively. Thus, I agree with the paper's assessment that insurance claims are not "well-suited" for valuing resiliency. I would suggest they may be able to provide a component of the information especially that associated with property loss for electric companies. As noted, obtaining the data from insurance companies may be difficult.

Macroeconomic Models

The paper appropriately chooses the Computable General Equilibrium (CGE) model over Input-Output (I-O) models for valuing electric grid resilience. It should be noted that value in macroeconomic models is a value-added concept and may not be directly comparable to microeconomic approaches that value outages for individual entities. Summing values from individuals will not provide the same value as a macroeconomic valuation.

I-O models have some issues in terms of evaluating the impacts of natural or man-made disasters. The fixed coefficients imply that the underlying structure doesn't change with the economic event. I-O models also imply fixed prices which in a damage scenario would not reflect reality. I-O models are also instantaneous in the impact results and don't show the effect of a shock over time. Although I-O models are data intensive, there are extensive datasets that can be purchased for analysis. The I-O model, however, provides a quick and dirty estimate of direct, indirect and induced impacts if the shocks to the system are input correctly. Thus, it can reflect macroeconomic impacts of losses and investments to economy. The model, however, is limited in valuing the non-market impacts of resilience, i.e., the value people place on electricity outages to their lives. Those non-market values would need to be obtained and the model's coefficients would need to be adjusted to account for these values.

The CGE model accounts for both price and quantity changes as the system adjusts to a shock. Thus the CGE provides a more equitable resilience value for the impacts of shock whether it is a man-made or natural disaster. However, CGE also fails in accounting for the non-market values that people place on outages. The direct impacts of loss of electricity to businesses are included in the results of the CGE model, but it doesn't include the non-market values individuals will placed on lost electricity usage. Thus both the CGE and I-O models can only provide a piece of the resilience value. Again, the CGE like the I-O model could be adjusted to reflect these non-market values. All in all, I agree with the premise

[17] Mills, E, RB Jones. Oct 2016. "An Insurance Perspective on U.S. Electric Grid Disruption Costs." In The Geneva Papers on Risk and Insurance – Issues and Practice, October 2016, Vol. 41:4 pp 555-568

of the paper that CGE is the preferred model.

Practical Comparison Criteria

Roark's paper also provides comparison criteria for choosing a method to value resilience. Among the items he evaluates are: theoretical basis, time and cost to develop the estimate, consistency of results, and applicability to both man-made and natural disasters.

Theoretical basis

I agree that the theoretical basis of the approach needs to be adequate enough to capture all the impact pathways that spill out of a shock to the electrical system, and the approach needs to follow all the threads that are indicated by the damage function. The model would indicate that a fragility curve needs to be able to capture the damage that would radiate out from a shock to the electrical system. As electricity has become a primary component of manufacturing, commercial business, and consumer segments, all of the affected entities need to be captured in the damage function. The problem is that fragility curves must be developed for each hazard, infrastructure, and geographic area. That requires a lot of information. My understanding is that some fragility curves exist with respect to electricity demand (load)[18] and for a limited number of infrastructure types for impacts from seismic activity through the Federal Emergency Management Administrations HAZUS model. In additional, there are a number of factors that impact the damage function such as the age of the infrastructure and the state of repair. Thus, all the damage functions need to be estimated and estimated such that they can be adapted to a number of regions, infrastructures, and hazards.

Time and cost

I agree that cost is an important variable in determining what method(s) should be chosen. However, I would suggest that there is an additional variable to cost, which is value. An inexpensive model that provides an incorrect or meaningless value probably has no value, even if it was inexpensive. So the quality of the answer is an important criterion. Thus, cost of the modelling approach needs to be balanced against the value of outcomes.

Consistency of Results

I could not agree more wholeheartedly with the commentary on consistency. The models need to provide the same answer for the value of resilience regardless of whether it is addressing policy-making, regulation, or planning decision-making. The model needs to be able to address the damage function by region and be able to adjust based on the hazard probabilities associated with the locality. These are labeled as extensibility and scalability.

[18] Berscheid, A, R Diao, YV Makarov, Z Hou, Y Zhang, N Samaan, Y Yuan, H Ren, H Zhou, Skorski, D Harkins. Sep 2017. "An Innovative Tool for Forecasting Power Grid Stress Level at Balancing Authorities." Final Project Report. Pacific Northwest National Laboratory. Internally funded project.

Applicability

The last criterion mentioned is the applicability of the model to be able to value both natural disasters and man-made catastrophes. Again, we are in agreement. The models need to be able to distinguish the differences in value between each type of severe event. The fragility curve is likely to differ depending on the hazards, probabilities, and the damage function by region.

Reproducibility

One item that was not included in the practicality of comparison section was reproducibility. The results need to be reproducible by others interested in validating the results. Without the reproducibility of the results, the validity of the results is questionable.

Appendix

The appendix provides a list of features for the CDF, DCE, and CGE models. The theoretical feature for the CDF indicates there is no well-defined theory behind it. Willingness to pay, however, is a well-accepted approach to valuing non-market items. The way the discussion is worded provides a negative connotation to the value of CDF in approaching commercial and industrial entities who well know the value of resilience to their companies.

Other comments

Roark describes, in his introduction, the idea of improving resilience for electric power. I believe a consistent definition of resilience needs to be developed before analysis of the value of resilience can be developed. For example Watson (2014)[19] indicates that Presidential Policy Directive 21 defined resilience as:

> "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from the deliberate attacks, accidents or naturally occurring threats or incidents."

Therefore, the value of resilience would be dependent on the threat and the vulnerability of the underlying system to that threat. For example, a specific electric grid could be resilient to hurricanes, but may not be resilient to the inundation through flooding. The damage function associated with each vulnerability and region is different. Thus, the customer damage function would be directly related to the threat. The value of lost load to the customer could be null or significant. The paper focuses primarily on methods to value lost load, although there may be many other items such as investment

[19] Watson, J-P, R Guttromsom, C Silva-Monroy, R Jeffers, K Jones, J Ellison, C Rath, J Gearhart, D Jones T Corbett, C Hanley LT Walker. Sept 2014. "Conceptual Framework for Developing Resilience Metric for the Electricity, Oil and Gas Sectors in the United States." Sandia National Laboratories, SAND2014-18019

costs, benefits, and other costs that can be directly quantified and are a part of valuing resilience. It is noted that the draft final paper did include the definition of resilience.

I would suggest that the introduction be split into a dialogue on what the paper is laying out and a background section that contains most of what is in the introduction. I would like to know upfront if approaches described are only focused on the value of long-duration lost load. There is nothing wrong with the introductory material, but I am still unsure whether the paper is trying to discuss valuing resilience or just a component of resilience, the value of lost load. The final draft paper notes that the paper is primarily focused on the value of long-duration lost load.

Conclusions

I believe that all the components discussed in this paper are needed to evaluate and provide a value of long duration lost load (VOLDLL). I believe that careful consideration needs to be given to defining exactly what components belong to long duration lost load which are being valued. Is VOLDLL, strictly speaking, only the value to customers of long-duration lost load or is it, more broadly speaking, the value to grid of long-duration loss load. If it is the first case, then the micro-economic approach is probably the better approach. If it is the latter approach, a combination of the micro-economic approaches would be better. For example if it is the broader approach, there may be additional items that are only mentioned in passing in this paper like the generation, transmission, and distribution system's components, such as the value of damaged equipment, lost time, and lost utility revenue that is involved in valuing resilience of the grid overall. Thus, the main issue that needs to be clarified is which definition is being valued. The paper primarily discusses methods for obtaining the VOLDLL for customers. The CDF with a well-designed survey, (I believe) will be able to elicit the value of lost load from commercial and industrial customers. However, a DCE approach may well be needed to value long duration lost load from households. There are many aspects of the household loss function that individuals should be able to value, such as the loss of food from refrigerators and freezers that would not be true of less- than-a-day outages. It is the remaining household value that needs a DCE approach to reveal the value of their preferences. A well-designed CGE model will be able to evaluate either customer VOLDLL or overall grid resilience impacts from an economy-wide perspective, but needs the microeconomic aspects to determine the coefficients to inform the CGE coefficients.

VI. Data Landscape: Challenges and Opportunities

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1. Introduction

At a conceptual level, the economics of widespread, long duration power interruptions are quite simple. Utilities and their regulatory counterparts—the parties primarily responsible for managing the electric system—prioritize resilience investments based on an assessment of the lifetime cost of each investment relative to the risk of widespread, long-duration power interruptions. The costs of resilience investments are relatively straightforward to estimate and track over time. However, assessing the risk over the lifetime of a 20- to 50-year investment is especially challenging due to a variety of data issues at each step in the assessment process, including:

- Identifying relevant power interruption scenarios;
- Forecasting the probability of each scenario; and
- Estimating the economic impact of each scenario.

These data issues arise from the nature of widespread, long duration power interruptions. They are infrequent and have potentially catastrophic impacts across multiple sectors of the economy, including significant indirect costs that extend to areas not directly affected by the outage. Identifying and resolving these data issues has become a pressing policy matter in light of the increasing frequency and cost of extreme weather events in recent years. According to the National Oceanic and Atmospheric Administration (NOAA), the U.S. experienced sixteen extreme weather events with damages exceeding $1 billion in 2017, which is expected to cost a record $300 billion (NCEI, 2018). Furthermore, these events are not confined to a specific geographic area or type of climate disaster (see Figure 1), resulting in the resilience of the electric system becoming a significant policy issue throughout the country.

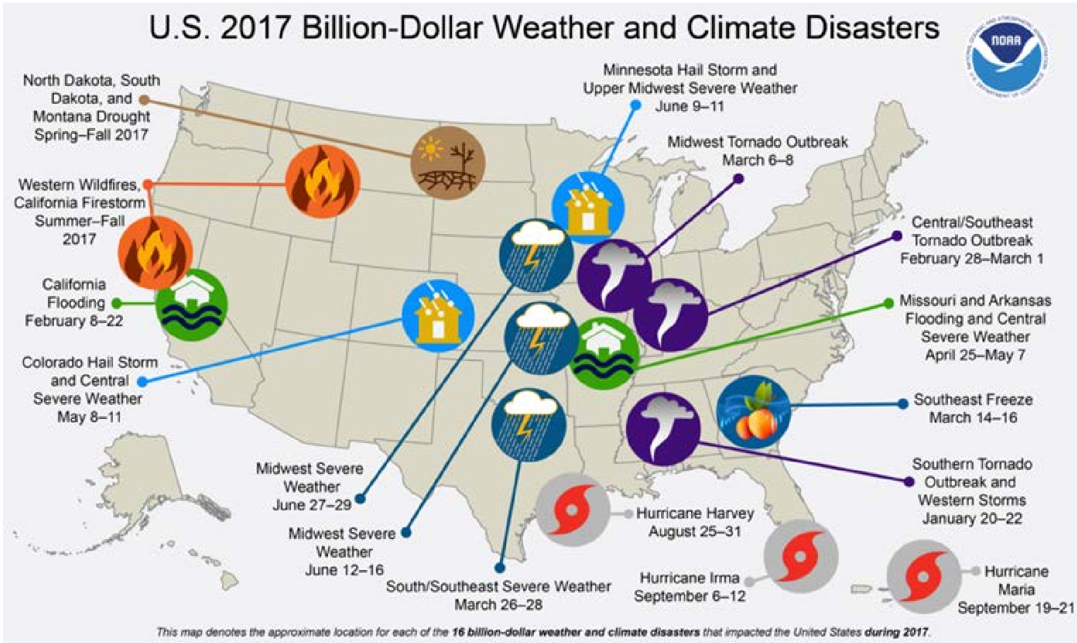

Figure 1. U.S. 2017 Billion-dollar Weather and Climate Disasters (from NCEI, 2018)

Drawing from the authors' experience conducting interruption cost studies and supporting multiple utilities in the development of resilience business cases, this paper identifies key data challenges and opportunities for assessing the risk of widespread, long-duration power interruptions. The remainder of this paper proceeds as follows:

- Section 2 establishes the importance of including estimates for non-residential entities when assessing the value of reliability or resilience;
- Section 3 describes data issues related to critical infrastructure;
- Section 4 provides an overview of various data collection issues related to using surveys to estimate outage costs and the economic value of resilience;
- Section 5 briefly summarizes three additional data challenges outside of the critical infrastructure and surveying issues;
- Section 6 summarizes the conclusions and opportunities for further research to address these data challenges.

2. Importance of Estimates for Non-residential Entities

Over the past decade, the academic literature on estimating the value of electric reliability has grown and now features several studies from outside of North America (mostly Europe and Asia).[1] Even though most of these studies only include results for households, some make significant policy

[1] See Shivakumar et al. (2017) and Praktiknjo (2014) for example studies that also summarize recent academic literature.

conclusions. For example, Shivakumar et al. (2017) found that the annual average value of lost load for the households in the European Union was 8.7 €/kWh (US $10.80), concluding that the results from the study inform key areas of European energy policy and market design. Praktiknjo (2014) also includes the results of a residential survey (in Germany), suggesting that they inform load shedding in the context of intermittent renewable power. However, studies that do not account for the value of reliability or resilience for non-residential entities will most likely have limitations when establishing conclusions and policy implications.

To demonstrate the importance of accounting for non-residential entities when drawing policy-related conclusions, Table 1 summarizes the results of an interruption cost analysis by sector from the Interruption Cost Estimate (ICE) Calculator.[2] The estimated direct cost of a 2-hour power interruption for the entire U.S. is $37 billion. Even though the residential sector accounts for 87 percent of utility customers, it only comprises 2.4 percent of the total interruption cost (under $1 billion). The state-by-state estimates show a similar trend, with the costs for residential customers ranging from 1.4 percent of total costs in Wyoming and 1.6 percent in California to 3.2 percent in Virginia and 3.8 percent in Arizona. While the ICE Calculator has well-documented data issues related to the age and representativeness of the underlying surveys (see Sullivan et al., 2015), the relatively low percentage of overall direct costs for residential customers in the U.S. overall and across states in this example is telling. Even if the residential costs were quadrupled, bringing the cost per unserved kWh to $11.30 (above the E.U. estimate from Shivakumar et al., 2017), the residential sector would still only account for 9% of overall interruption costs, and no state would have a higher percentage than 13.6 percent (Arizona).

Table 1. Estimated Direct Cost of a 2-Hour Power Interruption for All of the U.S. by Sector

Sector	Number of Utility Customers	Cost Per Event (2016$)	Cost Per Unserved kWh (2016$)	Total Cost of Sustained Interruptions ($ Billion)	% of Total Cost
Medium and Large C&I	2,429,795	$7,625.9	$43.9	$18.5	50.1%
Small C&I	15,996,040	$1,097.1	$148.3	$17.5	47.5%
Residential	124,686,620	$7.2	$2.8	$0.9	2.4%
All Customers	**143,112,455**	**$258.3**	**$43.2**	**$37.0**	**100%**

Importantly, the ICE Calculator results only include direct costs to customers who were surveyed by utilities, so it does not account for the indirect costs that extend to businesses not directly affected by an outage. It also does not account for the impacts to broader society when critical infrastructure goes down for an extended period of time. When these indirect costs are taken into consideration, the direct costs to households are even less of a driver of the overall value of reliability and resilience. Therefore,

[2] The ICE Calculator is a publicly-available, online tool designed for electric reliability planners at utilities, government organizations or other entities that are interested in estimating interruption costs and/or the benefits associated with reliability improvements. It is available at icecalculator.com.

the remainder of this paper emphasizes conclusions and opportunities for further research for non-residential entities.

3. Data Issues for Valuing Resilience of Electricity System Serving Critical Infrastructure

3.1 Critical Facilities

Certain types of facilities in a region or community are more critical for the health, safety, security and survival of residents during natural disasters or extreme weather events. These types of facilities are generally referred to as critical facilities, critical infrastructure, or lifelines. These facilities provide for the basic needs of society and include fire service, emergency medical service (EMS), hospitals, police, wastewater treatment, water provision, and others. Electric utilities sometimes face investment decisions where they are looking to prioritize hardening of only certain components of the electricity system which supply power to critical facilities. Alternatively, utilities may install or provide incentives for backup generation or microgrids to power critical facilities in case grid assets fail.

Critical facilities may suffer direct costs from a short duration outage, which could be accurately captured in a survey-based customer interruption cost study. However, for long-duration, widespread outages, society incurs costs from the critical facilities not having power and thus not operating at full (or perhaps even partial) capacity. Regional economic models do not have the level of granularity needed for undertaking this type of analysis. Furthermore, regional economic models assess the impacts to the broader economy, whereas the benefits of maintaining critical infrastructure are generally realized via improved health, safety and security (which can be monetized using cost-benefit analysis (CBA) techniques).

This section discusses the broader perspective of protecting critical infrastructure, the specific case of utilities investing in ways to provide continued service to critical facilities, existing methodological tools for assessing the economic impact of long-duration outages on critical facilities, and data challenges that utilities face. These challenges include identifying the appropriate facilities, collecting data at a granular level, accounting for the importance of electricity to each type of facility, and identifying vulnerable populations.

3.2 Protecting Critical Infrastructure: A Broad Perspective

It is useful to step back and place decisions around electricity service to critical facilities in the broader context of disaster preparedness and infrastructure protection. Utilities face the decision of which assets to harden to ensure that the appropriate critical facilities continue to receive power. But the electricity system is only one component in a holistic perspective of disaster preparedness. The Department of Homeland Security's (DHS) National Infrastructure Protection Plan (NIPP) defines a broader category of "critical infrastructure" as: "systems and assets, whether physical or virtual, so vital to the United States that the incapacity or destruction of such systems and assets would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters" (DHS, 2013). NIPP identifies sixteen critical infrastructure sectors, listed in Table 2. "Energy" is one of the critical infrastructure sectors. Other sectors on the list which play a significant role in generating electricity are "dams" and "nuclear reactors, materials and waste."

Table 2. Critical Infrastructure Sectors from NIPP

- Chemical	- Dams	- Financial Services	- Information Technology
- Commercial Facilities	- Defense Industrial Base	- Food and Agriculture	- Nuclear Reactors, Materials and Waste
- Communications	- Emergency Services	- Government Facilities	- Transportation Systems
- Critical Manufacturing	- Energy	- Healthcare and Public Health	- Water and Wastewater Systems

The different types of critical infrastructure are interconnected and depend on other critical infrastructure for continued operation. Virtually all components depend to some extent on energy infrastructure. Electricity thus plays an important role in the continued operation of various types of critical infrastructure.

In the context of utility investments, the focus on "critical facilities" refers more narrowly to local infrastructure whose continued operation allows communities to persevere through natural disasters and extreme weather. It has less of a focus than the NIPP on economically important facilities. The perspective is which facilities should be reinforced to receive power during a long-duration, widespread outage for the good of the region or community. For example, Consolidated Edison (Con Edison) describes "critical infrastructure" as "public and private facilities needed to support the health and safety of communities." In its storm hardening plan, this category of facilities includes "hospitals, police and fire stations, municipally owned buildings (schools, etc.), nursing homes, adult care centers, subways and commuter rail lines, waste water treatment plants, and tall buildings."[3]

3.3 Examples from Utility Cases

Utilities analyze potential investments and provide business cases to regulators for review and approval. The business case is often a cost-benefit analysis[4], in which the utility compares the impact of resilience investments (such as selective hardening) to the impact of maintaining the status quo or implementing the least cost alternative. Undertaking a resilience project often has the impact of customers experiencing outages less frequently or for shorter periods, such that the number of customer outage minutes is less than it is under the baseline scenario. Many of the benefits of resilience investments are thus discussed in terms of avoided negative impacts relative to the status quo or least cost alternative. When analysts are able to monetize the negative impacts, the benefits are

[3] Tall buildings are considered critical facilities because without power, occupants could face health risks from being stranded in upper floors with non-functioning elevators.
[4] Also known as benefit-cost analysis (BCA).

represented as avoided costs. Selectively hardening assets that provide electricity to critical facilities can avoid costs of lost lives, injuries, and lost time.

Various utilities have addressed the issue of critical facilities in business cases filed with their utility commissions. Commonwealth Edison, in its microgrid application, proposed using a microgrid to power an “oasis” of critical infrastructure (ICC, 2017). Connecticut’s Two Storm Panel recommended several selective hardening efforts in its final report (TSP, 2012). Con Edison prioritized asset hardening investments based on the likelihood of a significant storm occurring, the probability of assets being affected by wind or flood damage, and the impact of damage to utility infrastructure on the population and critical infrastructure (ConEd, 2015). Florida Power and Light (FPL) approached critical facilities from a cost-effectiveness perspective. In its 2013-2015 Electric Infrastructure Storm Hardening Plan, FPL acknowledged the difficulty of quantifying critical facility benefits, but reasoned that its investments for protecting critical infrastructure were cost-effective (FPL, 2013).

3.4 Potential Estimation Methods from FEMA

A review of the relevant literature found no examples of utility business cases where utilities performed a quantitative, monetized analysis of benefits for a resilience investment intended to maintain service to critical facilities in the face of extreme weather or other disruptions. However, the broader literature on infrastructure protection does have some methods for monetizing benefits that the utility industry could apply. In particular, FEMA has developed software for performing cost-benefit analysis for applications submitted under its Hazard Mitigation Assistance Grant Program (FEMA, 2016).

The FEMA software uses a set of standard economic values and the software’s accompanying documentation describes methods employed for estimating impacts from losing critical facilities (FEMA, 2016). The methods could be applicable for estimating impacts from long-duration outages at critical facilities. Some modifications would be necessary to apply the methodology to electricity interruptions. As the methodology is used in the software, it assumes that the critical facilities go offline due to some type of natural disaster. Modifications would allow the analysis to account for only a power interruption at the facilities and not other types of damage; if power is restored to the critical facility, the service would resume.

Value of lost time is an input into FEMA’s software and is applicable for analyzing critical infrastructure. Non-functioning critical facilities cost residents time when residents seek the next available service provider. If a hospital is not functioning due to an outage, people who use the hospital must spend time to travel to the next closest hospital. Time has different quantitative value for everyone, depending on forgone income and other factors. The U.S. Department of Labor’s Bureau of Labor Statistics (BLS) provides average values of lost time, which are useful for performing cost-benefit analysis. The most recent BLS update is $35.64 per hour from September, 2017 (BLS, 2017).

The benefits quantification methods vary by type of critical facility. For fire, EMS and hospital services, the method assumes that the population served by the critical facility will travel to the next closest, similar facility instead. This increased time to travel to the next facility—or for the service to travel to them—results in negative economic, health and safety impacts. For police service, the method assumes a decrease in police presence, which leads to an increase in crime. For water and wastewater, the model estimates the impact to economic activity for the non-residential population and welfare losses for the residential population. Table 3 shows the estimated impacts and data requirements for each critical service.

Table 3. Economic Impacts and Data Requirements for FEMA BCA Methodology

Critical Service	Impacts Estimated	Data Required
Fire Service	Value of fire losses from increased response time (injuries, fatalities, property, indirect losses)	– Distance to replacement (operating) fire station – Pop. served by non-operating fire station (optional)
Emergency Medical Services	Value of lost lives from increased response time	– Distance to replacement (operating) EMS provider – Pop. served by non-operating EMS provider (optional)
Hospital Services	– Cost of traveling to next nearest operating hospital – Cost of extra waiting time at alternative hospital – Value of lost lives due to increased distance to alternative hospital	– Distance to alternative (operating) hospital – Pop. served by non-operating hospital (optional)
Police Services	Value of crime losses due to lower police presence. Includes tangible (direct losses) and intangible (pain and suffering) costs.	– Number of offices working at station before shutdown – Pop. served by station – Number of officers serving affected area after shutdown
Wastewater Services	– Value of economic impact on commercial & industrial plus welfare loss for residential.	Population
Water	– Value of economic impact on commercial & industrial plus welfare loss for residential.	Population

3.5 Data Challenges

Utilities face a number of challenges in identifying critical facilities and assessing the economic impacts of a disruption to their operations caused by long-duration, widespread outages. Key challenges are identifying the appropriate facilities, collecting data at a granular level, accounting for importance of electricity, and identifying vulnerable populations. Working with local stakeholders is a necessary tactic for overcoming these challenges.

3.5.1 Critical Facility Identification

Systematically identifying critical facilities can present difficulties for utilities. Some of the larger facilities likely have dedicated account representatives. The quality of the utility's customer data will determine its ability to identify smaller facilities, such as nursing homes, adult care centers and schools.

Often, industry classification codes (such as NAICS) associated with customer accounts are missing (or incorrect) for a significant portion of customers. Some utilities, such as Public Service Electric and Gas Company (PSE&G) and Con Edison, have worked with community groups or local governments to identify critical facilities (PSE&G, 2018) (ConEd, 2015). This is not a quantitative assessment of economic impacts, but allows them to prioritize asset hardening efforts based on local expertise.

3.5.2 Collecting Granular Data

Collecting data at a granular level is a necessary step for utilizing the FEMA methodology (or other similar methodology) for quantifying benefits of selective hardening investments. As Table 2 shows, utilities would need at least approximate locational data for critical facilities, along with the size of the population served by each facility. For police services, they would need the number of officers working before and during the interruption. Another piece of facility-level data to account for would be the presence of onsite backup generation capabilities. Facilities with full backup capabilities would not face the same negative impact from a long-duration interruption as those with without it.

3.5.3 Accounting for Importance of Electricity

The FEMA model was designed to analyze the impact of a natural disaster on critical infrastructure. If the “disaster” is limited to a power outage—and not a flood or earthquake that could compromise the integrity of the facility—some modifications to the approach would be necessary to account for the importance of electricity to facility operations. FEMA (1991) contains a blueprint for modifying the methods to apply to power loss. It contains “importance factors” of critical infrastructure for different industries and sectors. This type of weighting could provide a means to account for when a loss of power does not result in a complete loss of service for critical infrastructure. For example, a loss of power to a police station may not render it completely non-functional, but may reduce its effectiveness by a percentage that could be estimated from the literature or collected first via survey—even potentially on a facility-by-facility basis. NYSERDA applied the FEMA model to power interruptions to estimate the benefits of microgrids specifically (IEC, 2015). The model based the importance factors on whether or not the facilities have backup generation to make up for the entire lost load or just a portion of the lost load.

3.5.4 Identifying Vulnerable Populations

Vulnerable populations of customers present utilities with a similar challenge of targeting asset hardening investments—or restoration efforts—to prevent adverse health and safety impacts from long-duration, widespread interruptions. The academic literature has identified characteristics of residents that make them more at risk from health impacts from power interruptions (Klinger, et al., 2014). Currently, there are limited examples of utilities using this type of data for planning. Con Edison is working with New York City to use demographic statistics from the city—in combination with the academic studies—to identify areas with larger populations of customers who are most susceptible to power interruptions and mitigate risk accordingly (ConEd, 2018). These types of partnerships with local government will be important for obtaining demographic data at the proper granularity.

Medical baseline rates provide another source of data for utilities to identify vulnerable populations within their service territories. Utilities generally offer a discounted rate to customers who have critical medical equipment powered by electricity. These customers will receive prioritized communications for rotating or planned outages. Some utilities have incorporated the data into their outage management systems and can use it to prioritize restoration efforts if necessary (CenterPoint Energy, 2017).

4. Data Collection Issues when Using Surveys to Estimate Outage Costs and Value Resilience

4.1 Background

Customer surveys have been used for more than two decades to estimate the economic costs that consumers and businesses experience as a result of electric and natural gas service interruptions (Sullivan & Keane, 1995) (Lawton, et al., 2003) (Sullivan, et al., 2015). (See DOE (2017) for a thorough review of the literature.) These surveys have been carried out for representative samples of utility customers in different market segments (i.e., Residential, Small/Medium Commercial and Industrial (C&I), and Large C&I customers) by large electric utilities located on the West Coast, Southwest, Southeast and Midwest. These surveys collected estimates of the direct costs of outages for sampled customers. They did not explicitly collect indirect or secondary outage costs (i.e., costs experienced by parties not connected to the electric services under study). With one exception[5], they have focused on outages lasting no more than 24 hours (i.e. short duration outages).

Most of the outage cost studies carried out since the early 1990s in North America used a common survey measurement framework of sample designs, survey forms, customer contact protocols and analysis procedures. EPRI's 1995 Outage Cost Estimation Guidebook describes this framework in detail (Sullivan & Keane, 1995). Consequently, it was possible to combine the data from the various studies, conduct a meta-analysis of customer outage costs, and produce customer damage functions which can estimate outage costs for consumers and businesses across the US. The results of this meta-analysis are described in Sullivan et al. (2015) and have been incorporated into the ICE Calculator.

The meta-analysis and ICE Calculator have demonstrated the usefulness of interruption cost estimates in assessing the economic value of reliability investments (Avangrid, 2016) (LBNL, 2015). However, the underlying data has certain limitations. The Northeast U.S. and Northern Tier are not well represented in the underlying meta-database and the surveys were conducted sporadically over a 20 year period. These aspects of the data make it difficult to disentangle the effects on outage costs of time and location.

As utilities have expanded their use of customer outage costs for reliability planning, industry stakeholders have shown more interest in using outage costs from catastrophes such as major storms, earthquakes, terrorist attacks, and wildfires to assess the economic value of resilience investments (DOE, 2016) (NAS, 2017) (EOP, 2013). Unlike the conditions that underlie the survey measurements in

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[5] Sullivan & Schellenberg (2013) used survey methods to estimate costs for outages greater than 24 hours.

conventional outage cost studies (outages lasting < 24 hours), these catastrophic events produce outages that can last days, weeks, months and even years, and can affect widespread geographical locations.

The survey designs discussed thus far have been used to estimate the direct costs for short duration outages. Researchers can use similar designs to estimate the direct costs of long duration and geographically widespread outages. (See, for example, Sullivan & Schellenberg (2013)). However, the surveys cannot be used to measure the indirect costs – costs incurred by parties whose electric service was not interrupted but who rely on production outputs from those who were interrupted. To obtain measurements of these indirect costs, it is necessary and appropriate to employ techniques generally referred to as regional economic modeling.

Regional economic models are used to forecast changes in the output of economic sectors for a given geographical region from changes in inputs to sector level production functions defined either theoretically or empirically for the sectors in the model (see Sanstad (2016) for a review of regional economic models). These models project the output of economic sectors not the output of individual firms or other entities that comprise them. While there are certain theoretical and technical drawbacks to using regional economic models to forecast interruption costs for regions (particularly small ones), these models are capable of projecting the indirect costs of electric service interruptions.

Regional economic modeling has been used to estimate the economic costs of catastrophic events such as earthquakes and hurricanes (Rose & Guha, 2004) (Rose, et al., 1997) (Mantell, et al., 2013). However, a recognized weakness in such models is that they are heavily assumption driven (Sanstad, 2016). Model results have been shown to be particularly sensitive to two classes of assumptions -- those regarding what are called substitution elasticities, and those regarding actions firms can take to reschedule production or revise production practices to mitigate damages. These assumptions about the *resilience of firms* to economic shocks can make a large difference in the estimated cost of catastrophic loss of electricity supply (Rose, et al., 2007).

Researchers can use customer surveys to collect information to calculate statistically defensible estimates of substitution elasticities. They may also use them to provide more concrete information regarding the ability of firms in different industries to sustain operations and recover from interruptions. Surveys of commercial and industrial customers designed to collect this information are currently being considered.

4.2 Survey Design Issues for Measuring Outage Costs and Resilience of Firms

Whether a single survey can provide sufficiently granular estimates of customer interruption costs (for use in reliability planning) as well as information needed to support improved regional economic modeling remains to be seen. It may be necessary to bifurcate these efforts because of technical considerations discussed below. Regardless of the actual survey designs chosen to collect these measurements, certain challenges in surveying must be overcome to ensure the collected information is reliable and valid. In general, these challenges involve controlling for a variety of possible surveying errors. The important sources of error in surveying can be grouped into two broad categories: sampling errors and non-sampling errors.

4.3 Sampling Errors

Sampling errors are survey measurement errors that arise during the process of selecting observations for a survey sample. There are two kinds of sampling errors: sampling precision errors and frame management errors. Sampling precision errors are controllable. Frame management errors, while controllable to a large extent, can present very serious threats to the study's external validity—or ability to generalize the survey results to the populations of interest.

4.3.1 Sampling Precision

Sampling errors arise as a result of natural variation among samples that can be chosen at random from a population of interest. They are the easiest errors to control in surveying because the sampling errors can be adjusted by stratifying the sample in a way that minimizes the sample variance and produces the desired level of statistical precision. There are well developed procedures for designing samples to achieve desired levels of statistical precision (Dalenius & Hodges, Jr., 1959) (Neyman, 1934). However, obtaining statistically reliable interruption cost estimates is not necessarily easy or inexpensive (Sullivan, et al., 2018).

It is well established that customer outage costs vary dramatically with customer size and type, producing a statistical distribution of observed costs that is dramatically right skewed, similar to the distribution of income or electricity usage (Sullivan, et al., 2015). The sample sizes required to achieve acceptable statistical precision are typically much larger than those required for data that is normally distributed. Study designers must therefore pay considerable attention to the design of the sampling strata and identification of the numbers of observations that are to be selected for each stratum in outage cost studies. The Interruption Cost Estimation Guidebook provides a detailed discussion of the methods and procedures used to minimize sampling errors in sampling from utility customer populations (Sullivan, et al., 2018).

Utility sample frames offer a number of technical advantages over other sample frames for measuring customer outage costs. They contain a nearly complete representation of the customers receiving electricity service from a given utility (i.e., those who can experience outage costs). Utilities also maintain digital business records containing historical information about customer energy consumption and—to a more limited extent—information about other characteristics of the businesses and residents that are served. This information can be used to support technically sophisticated sample designs that improve survey estimate precision by identifying optimal stratification designs. These designs efficiently allocate observations to sampling cells based on customer size and type[6]. Utility consumption records can also be easily combined with event-based outage cost estimates obtained from surveying to calculate useful utility planning metrics such as $cost/kWh (annual and unserved) and $cost/kW served).

As mentioned previously, the ICE Calculator meta-database has some geographic and temporal gaps. A potential way to fill these gaps would be to conduct a national survey of customer interruption costs (with or without collecting information to support the measurement of business resilience). If such an effort were undertaken, it would involve the participation of major electric utilities throughout the US. They would be asked to supply basic information needed to develop the sample frames for sampling residential and C&I enterprises in their service territories. Utilities could be offered custom reports concerning outage costs and resilience for their customer populations in return for participation. This approach would require some selling and serious issues about privacy and data security would have to be resolved, but in the end this approach would provide a reliable and valid basis for sampling, and may turn out to be less expensive to implement.

In the event that a utility-based sampling frame proves intractable, it will be necessary to develop sample designs that employ other measures of customer size for stratifying samples (e.g., number of full time employees) to optimize statistical precision. Developing a sample frame for consumers (i.e., residential customers) is not a particularly difficult problem because the U.S. Postal Service maintains a more or less complete database of all occupied dwellings and the outage costs for these customers are relatively small and do not vary dramatically from customer to customer. However, the availability of a manageable sampling frame may be a very significant problem for sampling from commercial enterprises – where there is not an exhaustive list of enterprise locations and outage costs vary by orders of magnitude over customers of different size. It is also likely that an objective of any national study of commercial customer interruption costs will include the ability to provide estimates of outage costs for regions and industry types. This requirement will seriously complicate the sample design problem.

Overcoming the above described sample design challenges will require a very thorough sample design process that takes account of the measurement objectives of the study, the available sample frames and the resources available for the study. It will undoubtedly require the development of altogether new and different sample designs that may bear little resemblance to those that have been used in past utility studies.

[6] Moreover, utility information systems provide useful information that, when combined with per event cost estimates, can be used to estimate non-event based interruption costs used in utility planning (i.e., cost/interrupted kWh and cost/kW). In the absence of such information, usage and demand information will have to be obtained from customers or from their serving utilities after the survey with permission from customers

4.3.2 Frame Management Errors

Frame management errors are another class of sampling errors that must be controlled in outage cost surveying. Frame management errors occur during the sample development process when important members of the population are excluded from sampling, installed in the sample multiple times, or when sample elements that are not qualified to be included in the sample are included in it. Frame management errors that commonly occur in interruption cost surveys using sample frames based on utility customer data include:

1. Sampling from a population of premises that contain master meters behind which there may be customers who experience significant customer interruption costs but not be directly sampled into the study. This commonly occurs in commercial office buildings and malls operated by property managers who receive a bulk electric power bill and pass the energy costs on to tenants either through triple net leasing arrangements or sub-metering arrangements. In these circumstances, an effort must be made to sub-sample tenants of such buildings or the estimated outage cost for the facility (and the segment served by such arrangements) will be dramatically underestimated.
2. Sampling from a population of premises that contains multiple sample points for the same basic location. This occurs when multiple meter/address combinations serve the same enterprise location. To correct for this problem, sites for which multiple meters are present must be edited in the sample so that only one sample point represents the premise.
3. Sampling from a population of premises containing premises that are not appropriate for the class of customers. This occurs when high rise residential buildings are classified by utilities are commercial businesses yet the energy consumption for the buildings is residential.

The above three problems are typically resolved during the sample development process by cleaning out duplicate and ineligible customers before they are assigned to sampling strata. In some cases, adjustments to the sample frame are made after the sample has been drawn. The Interruption Cost Estimation Guidebook provides a discussion of protocols for adjusting samples of utility customers to correct for these problems (Sullivan, et al., 2018).

In the event that researchers use sample frames other than utility records as a basis for sampling, they should expect greater difficulty in controlling for framing errors. The quality of data provided in commercially available sample frames (e.g., Dun and Bradstreet) is unknown. For example, the accuracy of the NAICS codes is unknown, as well as whether this information is even available for sites that might be selected for commercial outage cost measurements. If past experience is any guide, data on customer size and business operations for particular sites will not be very reliable. An investigation of the quality of information in commercially available sample frames should be made. It may be that the sample frames available for commercial customers are so incomplete or error prone that some systematic form of sampling based on filling quota cells will be required to complete these surveys. This sample design complexity could be avoided for a national study if utilities could be convinced to participate in the study by providing information needed to develop the sample frame.

4.4 Non-Sampling Errors

Non-sampling errors occur downstream from sampling in a variety of ways. They are the most pernicious and difficult sources of errors in surveying that must be addressed in studying interruption costs using surveying. They fall into three basic categories: non-response errors, response errors and specification errors.

4.4.1 Non Response

By far the most difficult and expensive source of error to control in surveying consumers is non-response bias. Participation in surveys by consumers is typically voluntary and consequently some non-response is to be expected in surveying. Non-response occurs when the target respondent to a survey does not respond to the survey or to some important element of it. The US population has become increasingly resistant to surveying over the past three decades in spite of survey designers' efforts to improve the ergonomics of survey design and reach customers who are difficult to contact. Prior to the turn of the century, response rates in excess of 90 percent could be achieved in surveys (including interruption cost surveys) with survey designs available at the time. Now, response rates between 35 percent and 50 percent can be achieved in surveys of residential customers using modern mixed mode survey designs. For small and medium-sized C&I customers, response rates no higher than 25 percent should be assumed. Surveys of large customers can be expected to vary dramatically depending on the extent of utility support – anywhere from 25 percent to 60 percent. The effect of government sponsorship for such a survey is unknown and should be explored.

Response rates depend heavily on the following important design considerations (Dillman, et al., 1993):

1. The level of difficulty involved in answering survey questions;
2. Perceived length of the survey;
3. Perceived legitimacy of the entity sponsoring the survey;
4. Degree of affect for the sponsor of the survey;
5. Perceived threats arising from frankly answering survey questions; and
6. Perceived benefit arising from answering the survey questions.

Outage cost surveys are difficult to answer, as they require the respondent to think about the answers to questions and provide concrete responses. Residential and small/medium C&I survey forms typically require 20-30 minutes to complete and large customer surveys usually must be conducted onsite requiring an hour or more to complete.[7] Consequently, obtaining high response rates with these designs is a significant challenge. To the extent that respondents are unfamiliar with the sponsoring entity or they view the entity negatively, lower response rates than those described above can be expected. This caution particularly includes commercially available internet panels. Voluntary internet panels should be excluded from consideration for interruption cost surveying.

[7] See Sullivan et al. (2018) for examples of outage cost survey instruments for each customer class.

Non-response causes two kinds of problems in surveying. First, it increases the cost of surveying because it inflates the number of solicitations needed to obtain a given number of completed responses. For example, if the target number of completed surveys is 1,000 and the realized response rate is 50 percent, then the required number of solicitations is 2,000—or, two solicitations for each completed observation. On the other hand, if the realized response rate is 10 percent, the number of required solicitations is 10,000—or, ten solicitations for each completion. Survey solicitations are expensive and are generally at least half the cost of completing an interruption cost study. The cost of solicitations in surveying commercial and industrial customers in outage cost surveys is between $50 and $100 per unit given a clean sample. Thus, the real cost of non-response can become quite significant when sample sizes are in excess of a few hundred.

A second and more serious problem arising out of non-response is the possibility of non-response bias and the uncertainty it sheds on the reliability of the resulting data. If all of the target respondents to a survey complete the survey, then the statistical reliability of the survey estimates is likely to be close to the design criteria set forth in the sample design process. For example, if the sample is designed to provide parameter estimates for the population that are accurate to within plus or minus 10 percent with 95 percent confidence, then if everyone responds to the survey, the resulting parameter estimates taken from the sample are 95 percent likely to be within plus or minus 10 percent of the population parameters. However, when significant non-response occurs (i.e., more than 10 percent), this inference is undermined and the confidence intervals for estimates from the survey may be inflated so much that the survey data become useless.

For this reason, customer outage cost survey protocols have been designed to minimize non-response. However, given recent trends in consumer survey response rates, and despite efforts by surveyors to reduce non-response, it is practically impossible to reduce survey non-response to the point that it does not threaten the validity and reliability of the survey results. Instead, a "belt and suspenders" sort of approach should be used to control for non-response bias. For the belt, intensive efforts must be made to encourage customers to complete surveys, including careful targeting of respondents to ensure they possess the information needed to respond to the survey, repeated reminders to respondents, and economic incentives for completing the survey. For the suspenders, serious efforts must be undertaken to discover whether non-response bias is present in the resulting sample; and correct for it statistically when possible. These efforts, along with survey designs that have been developed to minimize non-response, are described in the Interruption Cost Estimation Guidebook (Sullivan, et al., 2018).

4.4.2 Response Errors

Response errors occur when respondents misinterpret the questions on a survey or provide unresponsive answers. Outage cost surveys are susceptible to such errors because of the nature of the information that is sought. In the end, these surveys are intended to discover the economic losses that consumers and businesses will experience as a result of different kinds of electricity outages. So, why not just ask: "what would be your cost in the event that the power to your home/business was interrupted for four hours?" Researchers do not ask the question that way because there are too many ways consumers and businesses can interpret the words "cost" and "four hours." Surveyors need to be explicit about what kinds of costs the respondents should consider and more specific about the timing of the supposed outage in order to avoid response errors.

In studying the direct cost of outages, the estimation problem has been broken down into relatively discrete cost components and outage impacts. The typical survey forms circumscribe the answers that are appropriate, thereby avoiding response errors. To further ensure that the survey format and interpretation of cost components is properly applied for large commercial enterprises, survey interviews are conducted onsite by an interviewer trained to guide the respondent through the survey. The survey forms presented in the Interruption Cost Estimation Guidebook have been subjected to substantial field testing, so they are unlikely to be susceptible to serious response errors.

The current formats for outage cost surveys are relatively detailed and somewhat difficult for businesses to complete. In the ideal case, a less detailed and more streamlined survey form could be developed that would lower the burden on respondents while obtaining a reasonable level of accuracy in responses. Improvement of the survey forms to achieve this goal should be carefully tested for validity and reliability using advanced survey development techniques including cognitive testing designed to reveal the tradeoffs between survey difficulty, validity and reliability.

Willingness to pay questions pose particularly difficult problems in avoiding and correcting for response errors. These problems are discussed in the next section.

4.4.3 Specification Errors

Specification errors occur when the data elements that are collected in a survey do not correspond well with the measurement objectives of the survey. They occur when surveyors and study sponsors do not have a common understanding of the measurement objectives of the survey and the survey measurements thus do not provide measurements that the survey sponsors need. Most of the specification errors for measuring outage costs have been worked out over the long period of time of their application. This is not true for proposed measurements designed to reveal substitution elasticities and actions that businesses can take that affect their resilience.

Information about substitution elasticities and adaptive actions by businesses could be collected to improve the performance of regional economic models in taking account of resilience. In developing survey data to support this process, researchers should conduct a careful analysis of exactly what data is required to make adjustments to existing regional economic models. For example, it will be necessary to identify the issues the survey must address in order to adequately measure substitution elasticity for a given business segment and then to develop questions that can be asked for businesses in that segment to measure it. This is a process that should be undertaken collaboratively and include model developers, model output users, and surveyors. The survey questions developed through this process should be subjected to cognitive testing and formally field tested before they are used to collect data for an actual study. The modifications to proposed regional economic models should be tested side-by-side with resulting survey data to ensure that the improvements to the model are working as expected. This survey design and development exercise is particularly important if it is part of a broader government-sponsored survey of businesses where the number of questions that can be asked will be very limited.

4.5 Measuring Willingness to Pay in Outage Cost Surveys and Resilience

Historically, different measurement protocols have been used for measuring outage costs for customers in different utility market segments (Sullivan & Keane, 1995). For commercial and industrial enterprises, interruption cost surveys have been designed to measure the direct worth of the economic losses businesses experience under varying outage conditions. The direct worth of an outage is the economic value of products or services that the firm could not produce and deliver to market because of the outage, plus the cost of any damage to the production facilities or feed stocks, minus any savings that might result from curtailing production (e.g., unused feed stocks or labor). It contains all of the cost of production and the profit that might have been made from it as a result of an outage.

Willingness to pay (WTP) measurements are much simpler to formulate and easier for consumers to answer than the elaborate cost estimates obtained through the direct cost estimation process. So why not use WTP questions to measure outage costs for commercial enterprises? It was considered in the early stages of designing the current generation of outage cost surveys, but was discarded for several reasons:

1. Willingness to pay questions are intended to be proxy measurements of the real costs that business customers experience as a result of outages.
2. The accuracy of WTP measurements (however posed) depends on the degree to which the choice options offered to respondents correspond with the real choices that they might experience in a hypothetical market. If the respondent cannot imagine ever being offered the choices they are presented with, their answers are not likely to be a reliable indication of what they might actually be willing to pay (Hanemann, 1994). Being offered the choice of improved reliability at a higher price is not something most commercial enterprises can easily imagine or compute without significant background information, such as an estimate of its current cost of unreliability, a realistic technological solution to the problem and the estimated cost of the solution.
3. As development of a reasonable estimate of the cost of unreliability (our primary objective) is necessary to obtain a reliable estimate of commercial customers' willingness to pay to avoid it, there is no reason to go beyond estimating the direct worth of their outage costs.
4. Businesses can react negatively when asked to state a price they would be willing to pay to a monopoly supplier, particularly when the survey is sponsored by that supplier. They immediately ask: "why are you asking me this?" "Are you looking for a way to raise the price?" "How should I answer in order to protect my interests?" None of these are good thoughts for a respondent to have while formulating a WTP answer. Most utility clients dismissed the idea of asking this question out of hand based on the possible damage it could cause to their business relationships with commercial customers.
5. Decision-making heuristics for business enterprises and consumers are very different. When

consumers are asked to state their WTP, they only need to account for their own tastes and desires and balance those factors against the price they are willing to pay. This is not so when a person is asked to state willingness to pay for a business. Business decisions are generally not made by a single actor within an organization. They are often made by a collection of interests within the organization taking account of a number of factors that may be irrelevant to outage costs. An honest answer to the question what would you be willing to pay, and what would your enterprise be willing to pay often are very different for very good organizational reasons.

5. Additional Data Challenges

This section briefly summarizes some additional data challenges outside of the critical infrastructure and surveying issues. It covers the lack of data in the following areas: granularity in regional economic model inputs and outputs, the point at which indirect costs begin with respect to duration or frequency of interruptions, and identifying relevant scenarios and forecasting associated probabilities with and without investment.

5.1 Lack of Granularity in Regional Economic Model Inputs and Outputs

Unlike reliability investments, which can benefit customers throughout a utility's entire service territory, resilience investments are usually targeted to the specific customers who are most vulnerable to extreme weather or those served by a given substation that the utility plans to upgrade. Therefore, the utility typically prefers to build its business case and resilience CBA based off of the information available for those specific customers. Given that regional economic models rely on macroeconomic indicators for somewhat broad geographic areas as their key inputs, the utility or its regulatory counterpart may have concerns about whether the study is applicable to the specific customers who will benefit from a given resilience investment. Macroeconomic data is usually not readily available for specific areas of a utility's service territory. In many cases, this data may not align with the utility's service territory at all, unless it is a municipal utility that only serves a specific city or county for which macroeconomic indicators are available.

This issue is especially important because the value of a kWh can vary substantially across a utility's service territory. In order to identify areas with high outage costs, Sullivan et al. (2012) analyzed gross domestic product (GDP) per non-residential kWh for each metropolitan statistical area (MSA)[8] in PG&E's service territory. Although GDP per kWh tends to substantially underestimate outage costs, the study hypothesized that it serves as a good proxy for the geographic variation of non-residential outage costs normalized by usage. Figure 2 provides a map of GDP per non-residential kWh for each MSA in PG&E's service territory. GDP per non-residential kWh varies from $2.4/kWh in the Bakersfield-Delano MSA to $15.3/kWh in the San Francisco-Oakland-Fremont MSA. In general, there are extreme

[8] MSAs are the smallest geographic unit for which the U.S. Department of Commerce provides GDP information. In PG&E's service territory, each MSA is made up of a contiguous grouping of one to five counties. Some of PG&E's service territory is not assigned to an MSA because areas with relatively low population density are not assigned to an MSA.

differences between the Bay Area and the remaining MSAs in PG&E's service territory. Among the MSAs comprising the 9 Bay Area counties,[9] GDP per non-residential kWh is $13.9 and no lower than $11.1. Outside the Bay Area, GDP per non-residential kWh does not exceed $10.9 and is $4.7 overall, *one-third* that of the Bay Area. The study found that GDP per kWh is significantly higher in the Bay Area for PG&E and that Bay Area cost per average kW is higher than in the non-Bay Area region for every outage duration among residential, small, medium and large business customers.

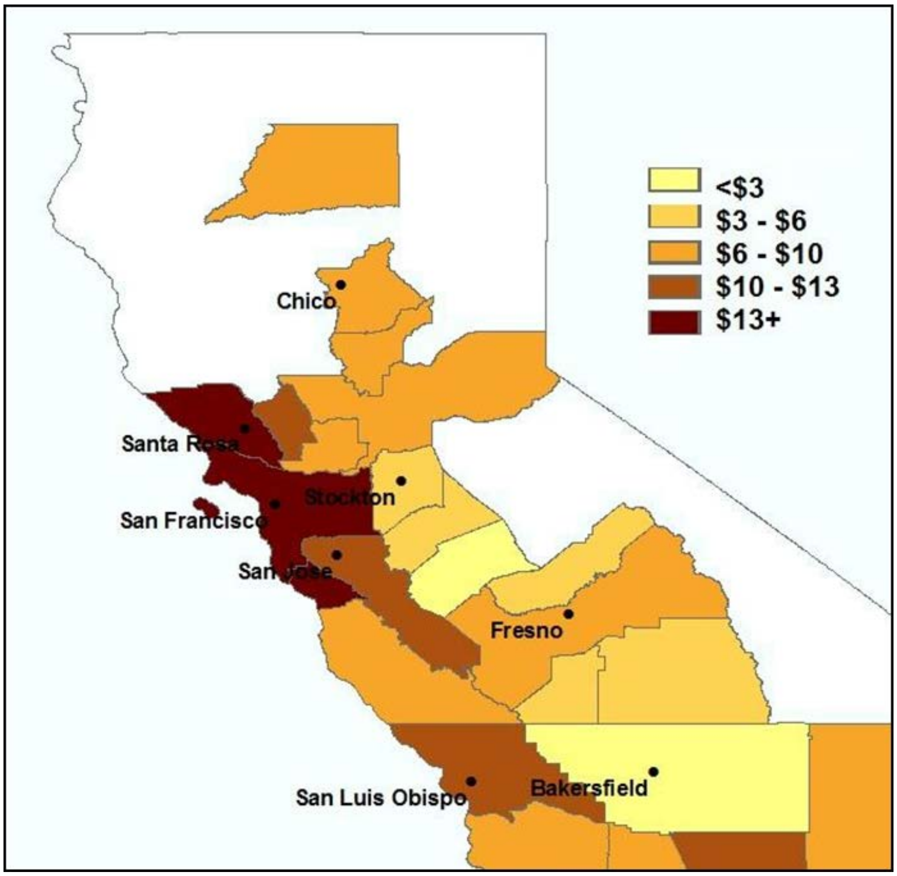

Figure 2. GDP per Non-Residential kWh for Each Metropolitan Statistical Area in PG&E's Service Territory

5.2 Lack of Data on when Indirect Costs Begin During an Outage

The utility industry does not have a common definition for a short-duration versus long-duration power interruption. Furthermore, there is not agreement among researchers on when indirect costs start to become significant. Survey-based customer interruption cost studies measure direct costs from outages, which are generally less than twenty-four hours, and those studies do not include indirect costs. However, there could be indirect costs for even a momentary outage if, for example, a manufacturing facility must be shut down and cannot deliver a product in time for another facility that relies on that product as a critical input. Similarly, repeated short duration outages over several weeks

[9] San Francisco, San Mateo, Santa Clara, Alameda, Contra Costa, Marin, Santa Cruz, Sonoma and Napa

in the context of a rolling blackout scenario may produce indirect costs that are greater than the direct costs that customers in the outage area experience, even if each individual power interruption lasts only one or two hours. Finally, the ratio of indirect-to-direct costs may be quite different in the context of extremely catastrophic scenarios such as the current situation in Puerto Rico. If an outage lasts multiple weeks or months to the point that it causes widespread unemployment and out-migration of the population, the indirect costs to the greater economy could be especially severe and persist for many years.

5.3 Lack of Data for Identifying Relevant Scenarios and Forecasting Associated Probabilities With and Without Investment

In general, there is a lack of data for identifying relevant scenarios and forecasting associated probabilities with and without a given resilience investment. This final challenge applies to both residential and non-residential entities and may be just as critical as accurately estimating the cost of widespread, long duration power interruptions. As discussed in Section 2, the first two steps in assessing the risk over the lifetime of a 20- to 50-year resilience investment are to identify the relevant power interruption scenarios and forecast the probability of each scenario. Utilities that build a microgrid, underground lines, or raise a substation several feet can collect post-event data to determine performance of the resilience measures, assess the accuracy of ex ante performance estimates and improve the decision-making process for themselves and other utilities. It is especially important for utilities to share these case studies and success stories because extreme weather events, while increasing in frequency, are still rare compared to typical outage events under “blue sky” conditions. If a particular investment significantly improves resilience during a major weather event, the industry as a whole can learn from these experiences and use the results to improve and refine future business cases.

A related issue is the lack of accepted industry standards for addressing probability of future extreme weather events. Cost-benefit analysis of resilience investments is dependent upon many variables, including characterizing the probability of future extreme weather events. In contrast to the costs, the benefits of resilience investments, such as hardening assets to avoid hurricane damage, will increase if the probability and severity of extreme weather events worsen. Traditionally, historical information was used to characterize potential events such as future floods. However, using historical experience of a 100 or 500 year flood event may put a utility at risk, considering these types of events are projected to occur more frequently in many regions. To inform resilience planning, it is useful to develop localized probabilistic data on climate and extreme weather and standardized scenarios that can be adopted to address this uncertainty.

6. Conclusions and Opportunities to Address Data Challenges

This paper identifies key data challenges and opportunities for assessing the risk of widespread, long-duration power interruptions. It begins by establishing the importance of including estimates for non-residential entities when assessing the value of reliability or resilience and then summarizes various data challenges with a focus on the critical infrastructure, commercial and industrial sectors. The related opportunities to address these data challenges are as follows:

- **Improve data and methods for avoiding impacts to critical facilities.** Utilities and policymakers have a keen interest in ongoing efforts to prioritize infrastructure for selective hardening (or backup power supply) that would be critical for public health, safety and security during extreme weather events. The data for performing this analysis contains gaps and utilities and researchers could look to FEMA cost-benefit methods for standardized ways to improve existing efforts. Some utilities are already starting to work with municipalities and government agencies to improve the prioritization process and opportunities exist for further collaboration and data sharing.
- **Explore the use of regional economic models in the context of resilience planning in a regulatory environment.** This would include gathering more empirical evidence on the adaptive behavior that businesses and government agencies engage in to mitigate the impacts of extended outages. Further understanding this adaptive behavior helps improve the accuracy of regional economic models and may also help utilities and policymakers further understand ways of mitigating those impacts. Part of this effort could be to explore ways that survey methods could complement regional economic models by providing important inputs from actual customers. Surveys currently obtain economic losses from direct costs of shorter outages, but researchers could adapt them to obtain data on indirect costs, as well as information on what a firm expects it would do to adapt behavior during a long outage. Using the two methods together could speed the development of better regional economic models.
- **Conduct nationwide survey using representative sample.** Such an effort using a consistent approach that produces quality responses and relatively high response rates, especially for commercial and industrial customers, would produce valuable information for utilities and policymakers across the country. However, several questions remain that have to be worked out, including valuation method, recruitment approach, extent of pre-testing and the role of utilities and government in the process. It also remains to be seen whether researchers can develop a data collection approach that both measures direct costs and provides useful information for regional economic modeling of indirect impacts, without over-burdening respondents by including too many questions on the survey.
- **Increase information sharing among utilities regarding forecasts of extreme weather and performance of resilience investments.** Utilities that build a microgrid, underground lines or raise a substation several feet can collect post-event data to determine performance of the resilience measures, assess the accuracy of ex ante performance estimates and improve the decision-making process for themselves and other utilities. It is especially important for utilities to share these case studies. Utilities can also work together to improve forecasting of extreme weather events at a local level.
- **Consider experimenting with alternative decision-making approaches designed for addressing**

problems with deep uncertainty. Decisions related to future extreme weather events present situations where uncertainty is not easily characterized and stakeholders may disagree about the behavior of the system, the nature of the uncertainty, and have different underlying values. Decision-making frameworks have been developed which are specifically designed for addressing these types of issues (Lempert, 2014). These methods address the sources of uncertainty explicitly and seek strategies that are robust across system assumptions and stakeholder values. These decision-making approaches could be useful for evaluating resilience investments which protect the electricity system from extreme weather events of uncertain size and frequency.

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Review of "Data Landscape: Challenges and Opportunities"

Discussant: Vanessa N. Vargas
Affiliation: Sandia National Laboratories

Valuing Economic Impacts and Resilience in the Electric Power System

There is a considerable range of measures and timeframes used to quantify regional and national economic impacts. For some classes of natural and manmade disruptive events, a simple calculation involving the number of anticipated causalities and property damage may be enough to provide the rough magnitude of the economic impact. However, property damage and value of statistical life (VSL) are incomplete for understanding the implications of the total impacts on an economic system, or are not sufficient when the disruption does not result in widespread physical damage and death. Metrics of impact include imports, exports, sales, price changes, and business failures. It is typically the losses associated with employment income and indirect losses that occupy the efforts of economists in the field of disaster and disruption research.

Resilience is not a new concept and has a history within the ecological, engineering, and mental health disciplines, yet there is no common consensus regarding how it should be defined. Beginning in the 1960s, the economic literature began to propose solutions to seismically resistant electric power (EP) generation and transmission solutions. The literature is filled with proposed solutions to identifying the benefits and costs of seismic fragility; nowadays this is referred to more generally as increasing resiliency of critical infrastructure. Resilience has recently emerged as a national and homeland security priority with several efforts in progress at the local and national level with particular interest given to EP systems and long duration outages from natural and manmade disruptions. A unifying theme of many proposed resilience methodologies is the inclusion of economics as a mechanism on which to compare various resilience solutions.

Traditional (macro-) economic impact analysis has a role in the long-run analysis of the effects of changes in resilience, since in the long-run the economy adjusts to the microeconomic impacts through various mechanisms (Kunreuther & Roth, 1998). However, measures of economic health, growth, or expansion are not sufficient for measuring resilience. The majority of infrastructure in the United States is privately owned and operated or is managed through some private-public arrangement. Most effects from changes in resilience should be assessed through short-run microeconomic analysis since the actions of firms will be spurred by internal economic decision-making that will have immediate impacts on local economies. Any forthcoming efforts to include resilience in the economic impacts of long duration EP outages must accommodate the private and simultaneously public nature of the EP infrastructure as well as its role as lifeline infrastructure. Resilience metrics and methodologies will only be helpful to stakeholders if these metrics help them understand the value of improvements to the resilience of communities, infrastructures, or industries.

Summary of Data Landscape: Challenges and Opportunities

In their paper, Schellenberg et al. (2018) have provided a well thought out "lay of the land" of the common methods of estimating the economic costs of EP disruptions, which includes discussion of the difference between costs of outage and regional economic modeling, strengths and weaknesses of methods, the difficulty in incorporating resilience, data collection and availability issues, and recommendations for future research. They identify many difficulties faced by economists in calculating the cost of outages when including non-residential customers and indirect effects. Including resilience valuation adds complexity. They also point out that many of these investment decisions, having impact on resilience of regional economies, are private firm decisions, thereby limiting the role of the public institutions.

The authors outline the importance of the EP infrastructure, especially its role as a "linchpin" infrastructure since it is often the system on which the other 16 critical infrastructures (CI) rely. Without it, many services would cease (or at least perform below optimal levels), resulting in cascading impacts throughout the CI, the economy, and public health. The speed at which the EP infrastructure recovers has both a direct and indirect effect on the overall speed of recovery for a community or regional economy post-disruption further emphasizes its role in ensuring resilience.

The authors present several metrics and methods used by utilities to quantify investments. Resilience has not traditionally been part of their analyses. Some of these analyses have been more focused on the business case for their investments such as cost benefit analysis (CBA), selective hardening, cost effectiveness, and least cost alternatives, all of which are useful for comparisons. Considering catastrophic events, the methods are more focused on consequences such as avoided negative impacts, avoided costs of lost lives and injuries, and negative impacts to infrastructure. Quantifying resilience based on these metrics can be helpful but is largely dependent on the probability and frequency of a catastrophic disruption.

Schellenberg et al. (2018) present their findings from the literature and apply methods to identify potential solutions to the difficulties associated with resilience quantification and these improvements to the family of CI and the community. They present methods from the Federal Emergency Management Agency (FEMA), survey methods and willingness-to-pay (WTP), and regional economic modeling.

FEMA Methods

I had not spent much time reviewing the FEMA software since its previous inception as Summit, which utilized infrastructure models developed by the National Infrastructure Simulation and Analysis Center (NISAC), such as Sandia National Laboratories' (Sandia) Regional Economic Accounting tool (REAcct). I very much appreciated learning the current model details, with its focus on informing CBAs. I think it is an important contribution to assign a monetary value of lost time (VLT) within the context of infrastructure disruptions. It provides a better understanding of how cascading impacts can affect individuals' daily lives, since any infrastructure disruption will increase the amount of time it takes to complete a previously simple task, and how an EP outage, particularly a catastrophic one, will compound any other infrastructure effects. Many current approaches to resilience focus on community/urban resilience as impetus as to why a utility should invest in technology that improves resilience. The VLT has the potential to monetize something many have a difficult time contextualizing in dollars. Many of the other metrics that are part of the FEMA CBA are perhaps less promising given the data requirements. Aside from data constraints, which I'll discuss in more detail later, a major hurdle will be the adoption of "welfare loss" metrics. This is something I've previously proposed to non-economists. While immediately disregarded, the topic of how to measure benefits to individuals from a resilience improvement continues to be discussed.

Survey Methods

The authors highlight survey methods as a potential avenue for measuring EP outages and resilience. There have been proposed WTP surveys in Europe and the U.S. that could offer valuable data on residential users and how individuals think about resilience. However, as Schellenberg et al. discuss, it is a potentially expensive, time consuming, and error prone endeavor. Beyond survey compliance the authors highlighted many of the pitfalls of survey design: sampling precision, frame errors, and non-sampling errors. Surveys are often discussed as the best way to approach how residential and non-residential users value resilience. I've considered it myself, but when considering the non-responses, response errors, and specification errors this paper reminds me why this is often an unappealing proposition.

Regional Economic Methods

I appreciate that the authors have identified the same challenges as myself when considering applying regional economic models to increasingly granular geographic levels. The common models have typically been designed for the state, county, and census tract level. First, this facilitates fairly easy use with federally available and macroeconomic data. Second, there hasn't been much use for regional economic models at a neighborhood level. This is an important point given that many of the proposed EP resilience solutions center around micro-grids, which often service a few city blocks at most. Another difficulty of applying regional economic models is that service territories do not follow predetermined economic geography. The authors discuss the difficulty this presents, a difficulty not often appreciated outside the economics bubble. Often a desire to use a regional economic model is driven by trying to satisfy the stakeholder desire to have a single number to point to, this single number often being gross domestic (or regional) product or jobs.

Potential Solutions

With regard to long duration outages and incorporating resilience into the EP system, many solutions have been proposed as well as how to use past measures of valuing outages to this new concept. The authors provide a useful review of past work and the difficulties in applying the traditional methods of valuing lost load, survey methods, and estimating economic impact to resilience improvements. Data availability is a well-known constraint to many working within this field. However, I think the authors have identified promising solutions and (perhaps previously unidentified) opportunities for collaboration.

The proposition of combining survey data with regional economic models is an exciting path that can be useful to stakeholders in the public and private sectors. I believe surveys and other methods from experimental economics can help fill some of the data gaps in the existing models (this applies to both the FEMA Tool and regional economic models). Two starting places are potentially the NISAC suite of infrastructure tools and Argonne National Laboratory's (Argonne) attribute-based survey for resilience. The NISAC tool suite includes infrastructure-specific models that have been exercised for scenario analysis and real-world events for over 10 years. In the past these tools were used to identify locations of vulnerable populations, hospitals in flood zones, production facilities at risk, and other at-risk infrastructure. Recently, these tools have also been used to co-locate CI with potential locations for micro-grids in New Orleans, LA with the purpose of increasing resilience during extreme weather events. I've recently been alerted to a survey tool out of Argonne that seeks to categorize the level of resilience and resilience needs of specific CI locations, creating a catalogue of attributes by location. Sandia and Argonne are currently working to combine our resilience consequence framework with Argonne's attribute method.

The struggle is especially perilous given the granularity of many proposed resilience solutions. Several of the proposed technologies for the EP infrastructure are applicable at the site level or at most a few blocks, a challenge well-outlined by the Schellenberg et al. (2018). I greatly sympathize with this challenge and have sought potential data solutions with little to no success. The first challenge is financing—that is, identifying a sponsor or funding source to supplement the data purchases. The second is determining how exactly to use such highly granular data. Businesses are born and die quite regularly and could impact relevance of such a granular analysis. The third is considering how useful it is to actually conduct analysis at such a granular level given the overall infrastructure improvements needed throughout the system. It could be that a regional economic impact at this level is not the most helpful pursuit of economists.

Conclusions

I do generally agree with the conclusions of the paper, with varying levels of what I think is possible to achieve.

- **Improvements in valuing avoided impacts to critical facilities.** Highly achievable and resources should be put toward the effort.
- **Explore the use of regional economic models in the context of resilience planning in a regulatory environment.** I think this is a useful and achievable pursuit, but will take funding to accomplish and should be applicable to every type of infrastructure disruption, not just the EP infrastructure.
- **Conduct a nationwide survey using representative sample.** I think this will be a struggle to achieve and, given the survey difficulties outlined in this paper, perhaps not the best use of

funding given the speed at which potential resilience technology could come online and the increasing frequency of long duration power outages. Perhaps it is best to focus on incentive structures for encouraging adoption of resilience.

- **Increase information sharing among utilities regarding extreme weather forecasts and performance of resilience investments.** This seems like a common-sense approach and I am grateful for the hopefulness of the authors. I am, however, doubtful of the achievability of this level of coordination.

I clearly do not have the answer, but this is a common topic I and others wrestle with daily. The answer is likely dependent upon the stakeholder audience and the specific customer.

VII. Speaker and Discussant Biographies

Tim Allison - *Discussant*
Tim Allison is an Energy and Environmental Policy Scientist at Argonne National Laboratory, and has more than 25 years of experience analyzing regional economic and fiscal issues related to energy resource extraction and electricity generation and transmission, with particular regard to disruptions in energy supply and in infrastructure. Recent work includes analysis of the impacts of transportation disruptions on shipping and receiving industries following potential earthquakes in southern California and southern Ohio, as well as the impacts of potential terrorist activity on waterborne commerce in Illinois, on airfreight industries following oil refinery disruption in Memphis, and on regional electricity prices following the loss of generation facilities in North Dakota.

Sunhee Baik - *Speaker*
Sunhee Baik is a PhD candidate at Carnegie Mellon University, the Department of Engineering and Public Policy. She holds a BA in Information and Industrial Engineering from Yonsei University and an MS in Industrial and System Engineering from Korea Advanced Institute of Science and Technology (KAIST). Her interests focus on policy problems where technology, science, and public perceptions play a central role. Her current research focuses on characterizing energy system vulnerabilities from natural disasters and emerging threats, obtaining informed judgments of individuals about their economic and social preferences for reliable electric services in the event of a large blackout of long duration, and enhancing the reliability and resilience of the power system without addressing issues of social equity.

Riccardo Boero, PhD - *Discussant*
Riccardo Boero is an economist at Los Alamos National Laboratory. He specializes in energy, environmental, regional and development economics. Riccardo has a strong modeling background both in equation-based economic models and in agent-based ones, and extensive experience in empirical analyses based on econometric, machine learning, and social networks methods. In particular, he has conducted analyses using computational economics methods including computable general equilibrium, input-output, and micro- and macro-econometric methods and models. Riccardo has also a vast experience in the design and implementation of research studies in the fields of experimental, behavioral, and neuro economics. Dr. Boero received a PhD in economics from the University of Pavia, Italy, in 2004 and a PhD in sociology from the University of Surrey, UK, in 2007.

Myles Collins, PhD - *Speaker*
Myles joined Nexant's Utility Services group in 2016. He has focused on estimating customer interruption costs (CICs) for value-based reliability planning and is currently leading a CIC study for Toronto Hydro. Myles is working with colleagues at Nexant and LBNL to update a guidebook for electric utilities for estimating power system interruption costs. He is also working with LBNL and the U.S. Department of Energy to draft a cost-benefit analysis guide for investments in electricity system resilience. Before coming to Nexant, Myles worked for five years at Southern California Edison, where he led strategy, planning, and analytics projects for the Customer Service organization. Myles holds a

PhD in Policy Analysis from the Pardee-RAND Graduate School and a Master of Public Policy from UCLA.

Alex Davis, PhD - *Speaker*

Alex Davis is an Assistant Professor in the Department of Engineering and Public Policy at Carnegie Mellon University. He is a member of the Behavior, Decision, and Policy Group; the Carnegie Electricity Industry Center (CEIC); and the Center for Climate and Energy Decision Making (CEDM). His research focuses on the behavioral foundations of policy, applied to innovation and entrepreneurship, energy, the environment, health, and information and communication technologies. He teaches graduate courses in applied data analysis (19-704) and stochastic models of choice (19-786). Alex earned his BS from Northern Arizona University in Psychology (2007) and his MS (2009) and PhD (2012) from Carnegie Mellon University in Behavioral Decision Research. He worked as a postdoctoral fellow and research scientist at Carnegie Mellon University prior to joining the faculty at Carnegie Mellon.

Jonathan Eyer, PhD - *Speaker*

Jonathan Eyer is a post-doctoral research associate at the University of Southern California's Center on Risk and Economic Analysis of Terrorism Events (CREATE). He received his PhD in economics from North Carolina State University in 2015. His work utilizes micro-econometric models to analyze individual and firm responses to disasters and climate change, as well as the policies designed to curb their impact. Ongoing projects examine a broad range of climate- and risk-related environmental issues, including the effect of drought on energy systems, the economic capitalization of risks associated with fracking, and the effect of politically motivated job protectionism on electricity markets. He is the Co-PI on a Japan Foundation grant to study how people made their migration decisions following the Fukushima earthquake and the associated tsunami and nuclear disaster. He has participated in a number of CREATE projects, partnering with FEMA, the Department of Homeland Security, and Customs and Border Patrol.

Benjamin F. Hobbs, PhD - *Discussant*

Benjamin F. Hobbs is the Theodore M. and Kay W. Schad Chair of Environmental Management at the Johns Hopkins University, and has been a member of the faculty of that university's Department of Environmental Health & Engineering (formerly Geography & Environmental Engineering) since 1995. His research and teaching concerns the application of optimization and decision analysis to the economic regulation, planning, and operation of electric power systems, and to water and ecosystem management. Since 2010, he has been the inaugural Director of the JHU Environment, Energy, Sustainability & Health Institute. He co-directs the Yale-JHU SEARCH (Solutions for Energy, Air, Climate, and Health) Center, sponsored by the U.S. Environmental Protection Agency. Previously, he was at Brookhaven and Oak Ridge National Laboratories, and on the faculty of the departments of Systems Engineering and Civil Engineering at Case Western Reserve University. He earned a PhD in Environmental Systems Engineering in 1983 from Cornell University. Dr. Hobbs has had visiting appointments at the Helsinki University of Technology, University of Washington, ECN (Netherlands Energy Research Center), Churchill College, the University of Cambridge, CalTech, and Comillas Pontifical University.

Dr. Hobbs chairs the Market Surveillance Committee of the California Independent System Operator. He is a Fellow of the Institute of Electrical and Electronics Engineers (IEEE) and the Institute for Operations Research and the Management Sciences (INFORMS). He has served on the editorial board of the *IEEE Transactions on Power Systems,* was area editor for Energy, Natural Resources, and the Environment for operations research, and deputy editor for Social Sciences and Policy for *Water Resources Research.*

M. Granger Morgan, PhD - *Speaker*
Dr. M. Granger Morgan is the Hamerschlag University Professor of Engineering at Carnegie Mellon University (www.epp.cmu.edu). He holds appointments in three academic units: the Department of Engineering and Public Policy; the Department of Electrical and Computer Engineering; and the H. John Heinz III College. His research addresses problems in science, technology, and public policy with a particular focus on energy, environmental systems, climate change, and risk analysis. Much of his work has involved the development and demonstration of methods to characterize and treat uncertainty in quantitative policy analysis. His most recent book is *Theory and Practice in Policy Analysis: Including Applications in Science and Technology* (Cambridge University Press, 590 pp, 2017). Morgan is a member of the National Academy of Sciences and of the American Academy of Arts and Sciences and a fellow of the IEEE, the American Association for the Advancement of Science (AAAS), and the Society for Risk Analysis.

Bernard Neenan - *Discussant*
Bernie Neenan has been involved in electricity demand and supply issues for over 35 years as a national laboratory researcher, utility rates manager, consultant to utilities and regulatory agencies worldwide, and most recently as Senior Technical Executive at EPRI. A unifying theme in his research is improving electricity supply market performance by providing customers with diverse, marginal-price based services.

Jeffrey Roark - *Speaker*
Jeffrey Roark joined EPRI in 2011 after 35 years in the electric utility industry. His utility experience includes all phases of system and strategic planning in large integrated regulated utilities of both private and government ownership, and market analysis in an unregulated generating and trading company. At EPRI Mr. Roark's work emphasizes cost-benefit analysis within EPRI's Integrated Grid framework, analyzing integration of distributed generation and smart-grid developments in transmission and distribution contexts. Mr. Roark holds bachelor's and master's degrees in Electrical Engineering from Auburn University ('74, '76), and an MBA from the University of Alabama in Birmingham ('85).

Adam Rose, PhD - *Speaker*
Adam Rose is a Research Professor in the University of Southern California Sol Price School of Public Policy, and a faculty affiliate of USC's Center for Risk and Economic Analysis of Terrorism Events (CREATE). Professor Rose's primary research interest is the economics of disasters. He has spearheaded the development of CREATE's comprehensive economic consequence analysis framework and has done pioneering theoretical and empirical research on resilience at the level of the individual business/household, market/industry, and regional/national economy. His other major research area is

the economics of energy and climate change, where he has most recently been involved in modeling and policy analysis of cap-and-trade systems and macroeconomic impacts of climate action plans. Professor Rose is the author of several books and 250 professional papers, including most recently *Defining and Measuring Economic Resilience from a Societal, Environmental and Security Perspective* (Springer), *Economic Consequence Analysis of Disasters* (Springer), and *The Economics of Climate Change Policy* (Elgar). He has been appointed to the editorial boards of *The Energy Journal, Resource and Energy Economics*, *Energy Policy, Pacific and Asian Journal of Energy, Journal of Sustainable Energy Engineering, Journal of Regional Science, Economics of Natural Disasters and Climate Change,* and *Environmental Hazards,* among others. Professor Rose was recently selected a Fellow of the Regional Science Association International and elected President of the International Society for Integrated Disaster Risk Management. He is the recipient of a Woodrow Wilson Fellowship, East-West Center Fellowship, American Planning Association Outstanding Program Planning Honor Award, Applied Technology Council Outstanding Achievement Award, Regional Economic Models Outstanding Economic Analysis Award, IDRiM Society Distinguished Research Award, and DHS/CREATE Transition Product of the Year Award.

Josh Schellenberg - *Speaker*
Josh Schellenberg is Vice President of Advanced Analytics at Nexant. He leads a San Francisco-based data science team that focuses on advancing the use of applied econometrics and machine learning applications for electric and gas utilities. Working with LBNL and DOE, Josh developed the Interruption Cost Estimate (ICE) Calculator (available at icecalculator.com), which utilities have used since 2011 to prioritize reliability investments. He is also working with LBNL and DOE to develop a Cost-Benefit Analysis Guide for Investments in Electricity System Resilience. Finally, Josh has supported utilities in the development of business cases for billions of dollars of proposed grid modernization investments.

Daniel Shawhan, PhD - *Speaker*
Daniel Shawhan's research, teaching, and other work have focused on electricity policy for 20 years. Part of that work has dealt with electricity outage valuation and the related topics of economic survey design and non-market valuation. Shawhan researched and wrote the extensive review of valuation of power outages in DOE's 2017 report to Congress entitled, *Valuation of Energy Security for the United States.* His other current and recent research involves detailed electricity policy simulation modeling (E4ST.com), electricity market design, electricity market learning games, and econometric (statistical) analysis of factors that affect power plant emissions. RFF.org/Shawhan has more information.

Vanessa Vargas, MA - *Discussant*
Vanessa N. Vargas is a Principal Member of the Technical Staff at Sandia National Laboratories (SNL). She is currently the Lead Economist with the Resilience and Regulatory Effects group at SNL and the Department of Homeland Security's National Infrastructure Simulation and Analysis Center (NISAC) at SNL, where she has served for over 10 years. While at SNL Vanessa's research has focused on the development and application of new methods for regional and national economic impact analysis of infrastructure system disruptions and improvements, extension of methods for quantifying economic system resilience, natural resource economics, and policy analysis. Additional research interests lie in

national security, climate effects, and energy economics. Vanessa holds BA and MA degrees in Economics, both from the University of New Mexico.

Mark Weimar, PhD - *Discussant*

Dr. Weimar, Chief Economist at Pacific Northwest National Laboratory, has over 34 years of experience in economics. He has been at the laboratory since 1993. Dr. Weimar has developed program- and project-specific economics and financial analyses for a number of public agencies, primarily for DOE, the California Energy Commission, ISO New England, U.S. Department of Defense (DoD), Federal Highway Administration (FHWA), Montana Department of Transportation, Internal Revenue Service (IRS), U.S. Department of Homeland Security, U.S. Department of Transportation (US DOT), and National Cooperative Highway Research Program (NCHRP).

Ian Sue Wing, PhD - *Speaker*

Ian Sue Wing is Associate Professor in the Department of Earth & Environment at Boston University. He conducts research and teaching on the economic analysis of energy and environmental policy, with an emphasis on climate change and computational general equilibrium (CGE) analysis of economic adjustment to policy and natural environmental shocks. His current research focuses on characterizing the broader economic consequences of climate change impacts in a variety of areas (energy systems, agriculture and forestry, and human health), assessing the implications for society's capacity to mitigate future emissions of greenhouse gases, and simulating the regional economic impacts of natural disasters. Much of this work involves articulating the structural linkages between CGE models and econometric models of climate impacts, or bottom-up science- or engineering-based process simulations of energy systems, agro-ecosystems, and natural hazards. He has been supported by grants from the California Energy Commission, the DOE's Office of Science, the U.S. Environmental Protection Agency (EPA), the U.S. Geological Survey, and the National Science Foundation (NSF). He has been a member of advisory and review panels for the DOE, EPA, National Research Council, and NSF.