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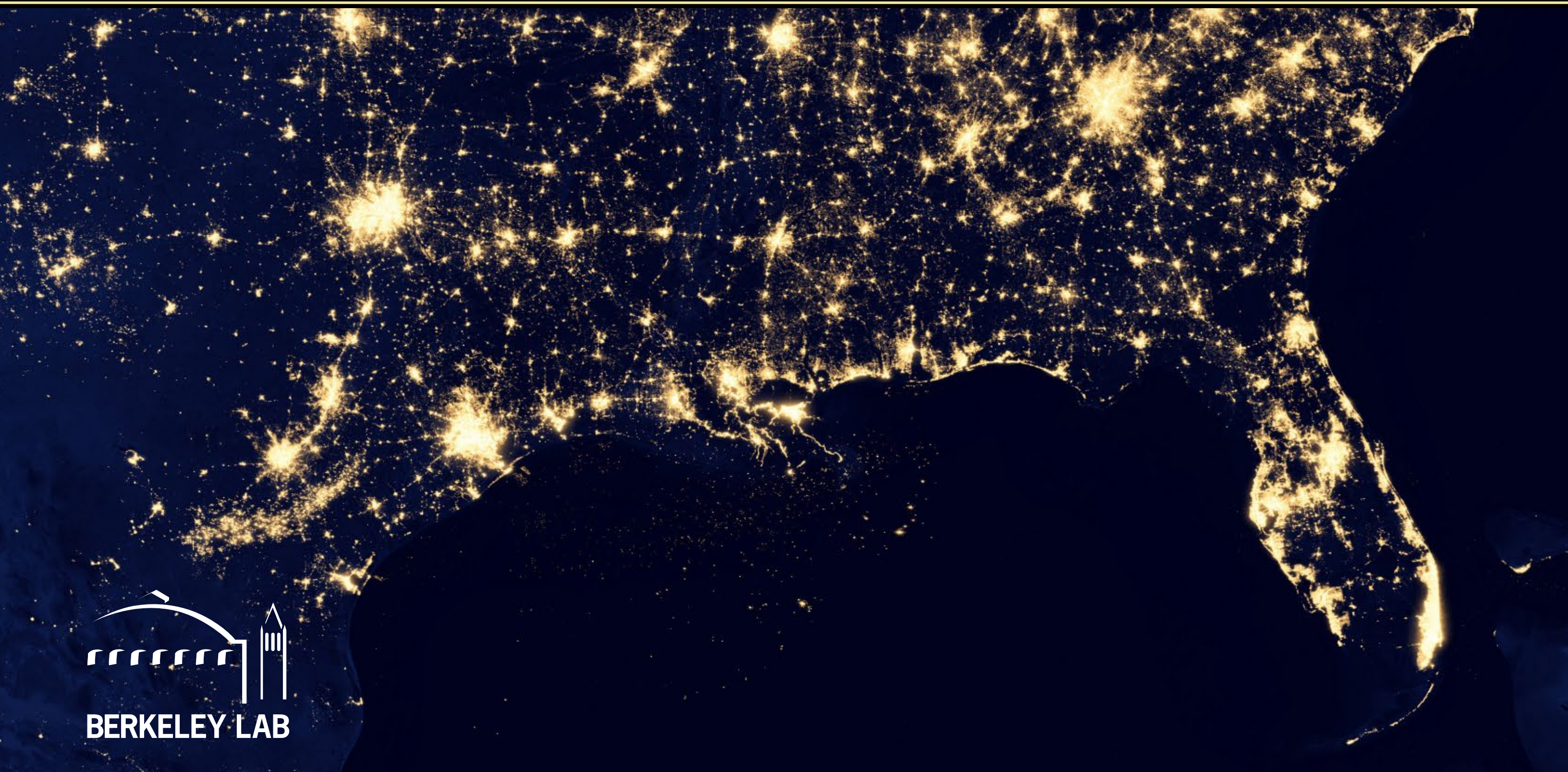

BERKELEY LAB

# A Hybrid Approach to Estimating the Economic Value of Enhanced Power System Resilience

Prepared for the
Office of Electricity
Energy Resilience Division
U.S. Department of Energy

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# Acronyms and Abbreviations

| | |
|---|---|
| CES | constant elasticity of substitution |
| CGE | computable general equilibrium |
| CIC | customer interruption cost |
| CMI | customer minute of interruption |
| ComEd | Commonwealth Edison |
| FEMA | Federal Emergency Management Agency |
| FLQ | Flegg Location Quotient |
| GDP | gross domestic product |
| GTAP | Global Trade Analysis Project |
| HAZUS-MH | Hazards U.S. Multi-Hazard |
| I/C | interruptible/curtailment |
| ICE calculator | interruption cost estimate calculator |
| ICGE | interregional computable general equilibrium |
| I-O | input-output |
| LP | linear programming |
| LBNL | Lawrence Berkeley National Laboratory |
| NAICS | North American Industry Classification System |
| PG&E | Pacific Gas and Electric Company |
| POET | Power Outage Economics Tool |
| REM | regional economic modeling |
| SAM | social accounting matrix |
| SCE | Southern California Edison |
| WLD | widespread and long-duration |
| WTP | willingness to pay |
| WTA | willingness to accept |

# Executive Summary

The costs that power interruptions impose on customers and society have emerged as essential considerations for decision making about power system reliability and resilience. There is a well-established literature on understanding the direct costs of localized and relatively short-duration power interruptions. Utilities are experienced in using tools, like Berkeley Lab's Interruption Cost Estimate (ICE) Calculator, which can estimate the cost of localized, short-duration power interruptions, to justify future investments in reliability. However, far less is known about the costs of widespread and long-duration (WLD) power interruptions, especially the indirect costs and related economy-wide impacts of these events. As a result, the costs of WLD power interruptions are generally not or only incompletely considered in utility planning activities. This paper describes a new approach for estimating the economic costs of WLD power interruptions. Including better estimates of these costs would enhance both the comprehensiveness and completeness of the considerations relied on to support utility planning decisions, especially those on grid-hardening strategies and other capital-intensive investments in electricity sector resilience.

Several methods are available for estimating customer power interruption costs. Customer interruption cost (CIC) surveys are the most common method because they can estimate direct costs for a variety of power interruption scenarios. These scenarios can range from previous interruptions experienced by customers to different, but closely related, hypothetical interruptions. CIC surveys are particularly well-suited for gathering information on the costs that result from shorter duration, localized power interruptions because respondents have experienced these types of interruptions in the past and because the costs consist largely of the direct costs that are borne solely by the respondents. However, CIC surveys might be less suitable for estimating the impacts of WLD power interruptions because respondents may have no past experiences to draw upon in estimating the direct costs they might bear. Thus, without substantial help, respondents may not be able to fully consider the various implications of hypothetical WLD power interruptions, and may have difficulty estimating WLD power interruption costs. Moreover, they are unlikely to have knowledge of the indirect costs borne by others, such as the cascading economic impacts of power interruptions throughout supply chains.

Regional economic modeling (REM) is another source of information on the costs of power interruptions. A specialized form of REM, called computable general equilibrium (CGE) modeling, is thought to be especially well-suited for analyzing the costs from WLD power interruptions because it can take explicit account of both direct and indirect economic impacts, including the adaptive behaviors that customers can and do take to reduce these impacts.

CGE models simulate the behavioral responses of consumers and producers to changes in prices, regulations, and external shocks in interrelated multiple markets within the constraints of available labor, capital, energy, and material resources. They use mathematical descriptions to represent and analyze entire economies, including interactions among households and firms, as mediated through markets.

CGE models contain exogenous parameters for which modelers must specify numerical values prior to computations. The hybrid valuation approach we propose focuses on two key parameters, which are directly related to firms' and households' inherent/adaptive behaviors: (1) *elasticity parameters*, which govern the ability to change the relative values of inputs in response to relative price changes or economic environment changes; and (2) *productivity parameters* of electricity, which represent firms' resilience actions or changes in technology taken by firms in response to power interruptions. Despite the importance of these parameters, most modelers are candid in acknowledging that the empirical basis for the specified numerical values is often weak.

REM, in general, and CGE, in particular, are not currently relied on by utility planners despite their potential advantages. The reasons include unfamiliarity with the use of these types of models to support utility planning studies, the large data requirements of the models, the complexity of the models, the reliance of the models on assumptions that are subject to significant uncertainties, and the technical expertise required to run them. For these reasons, there are no field-tested example applications of them to demonstrate their value for utility planning.

This report is a scoping study that outlines a new approach for improving the information on the costs of WLD power interruptions so that it can be used to support utility planning studies. This document is intended for technical staff at regulatory bodies, utility planners, and academic researchers. It also helps set the stage for conducting a field-test that would demonstrate the value of this new approach. Specifically, this paper proposes a hybrid method that combines the strengths of CIC surveys and CGE modeling in ways that seek to overcome their known weaknesses for estimating the costs of WLD power interruptions (see Table ES-1). The hybrid method we propose involves: (1) using CIC surveys to collect empirical region- and sector-specific data to ground the assumptions and key parameters used in CGE modeling, especially about firms' and households' adaptive behaviors during and after a power interruption; and (2) estimating both the direct and indirect costs of power interruptions throughout a regional economy using the calibrated CGE model.

**Table ES-1. Pros and cons of CIC surveys, CGE models, and hybrid valuation model for estimating economic impacts from power interruptions**

| Model Type | Pros | Cons |
|---|---|---|
| CIC surveys | • Can estimate CICs of various power interruption scenarios without relying on other data<br>• Can produce estimates that are easy to understand even for a lay audience | • Significant effort and resources required to conduct CIC surveys<br>• Possible cognitive biases in respondents' cost estimates because of the hypothetical nature of surveys and the characteristics of elicitation techniques<br>• Potential lack of awareness among respondents of the consequences of hypothetical interruptions, especially for larger geographic regions and/or for longer-duration power interruptions<br>• Cannot estimate cascading economic effects of power interruptions between businesses and industries |
| CGE models | • Can measure sector-level impacts<br>• Can estimate indirect impacts of power interruptions<br>• Can generate revised prices for electricity and other purchased goods and services, as well as shadow prices for unpriced goods | • Significant data requirements<br>• Significant computational resources needed<br>• Involve a complex mathematical formulation that is difficult to analyze and interpret by a lay audience<br>• Without further calibration, limited insight from model results because of initial assumptions about existing backup generation, known inventories, and substitution parameters<br>• Understanding mathematical techniques challenging for non-specialists |
| Hybrid valuation models | • Same pros as CIC surveys and CGE models, plus:<br>• Reflect customers' actual behaviors to adapt to and reduce the impacts of power interruptions<br>• Can estimate both direct and indirect impacts of power interruptions throughout a regional economy | • Significant effort and resources required to conduct CIC surveys<br>• Data intensity, demanding computational resources, and modeling complexity of CGE remains<br>• Not yet validated in the field |

The hybrid approach relies on CIC surveys to collect information directly related to elasticity and productivity parameters that change during and after power interruptions. Also, surveys collect ancillary information to help utilities and policy makers understand resilience tactics that have been implemented by electricity customers and develop long-term investment plans to further enhance power system resilience. This information is then used to adjust or calibrate these parameters to improve the accuracy of a CGE model's representation of how power interruptions affect an economy, including the effect of actions taken by households and firms to reduce the impact of interruptions. By combining the cost-estimation capabilities of CIC surveys and CGE models, we believe that the proposed hybrid method will be able to improve estimates of the direct and indirect impacts of longer-duration (days, weeks, or longer) power interruptions that are wide in geographic scope (affecting utility service territories or multi-utility, and possibly multi-state regions).

In this paper, we describe what information should be collected with CIC surveys and how it should be used in a CGE model. It provides both the motivation for pursuing a demonstration of the proposed hybrid approach and a roadmap outlining how such a demonstration could be conducted.

# 1. Introduction

Society depends on electric power for virtually all individual, household, commercial, industrial, and government activities, making our individual and collective vulnerability to power disruptions a key issue for electric utility planning. Most electric power interruptions occur at the distribution system-level and cause relatively short and localized disruption. Although less frequent than short interruptions, widespread and long-duration (WLD) power interruptions occur more often than one might expect (National Academies of Science, 2017). WLD power interruptions can have substantial economic and social impacts, not only on electricity customers and utilities that are directly affected but also on regional economies. The Northeast Blackout of 2003, for example, left more than 50 million people without power and caused 11 deaths and $4-10 billion in damages (U.S. Canada Power System Outage Task Force, 2004). The federal government, state regulators, and the electricity industry are increasingly concerned about the vulnerability of the power system to more frequent and severe weather events (Karl, Melillo, and Peterson, 2009; National Academies of Science, 2017), emerging threats including extraordinary solar mass ejections (for instance, the solar storm of 2012; Foster et al. 2004; National Research Council, 2008; EPRI, 2012), and coordinated physical and cyberattacks on the grid infrastructure (NRC, 2012).

Historically, generation and transmission planning studies of electricity reliability have been based on engineering criteria. These studies determined the amount of capacity that needs to be installed to meet the desired reliability target, such as loss of load expectation of 1 day in 10 years (NERC, 2011). Economic analysis using such criteria has typically focused solely on utility costs, including the cost-effectiveness of reliability improvement measures. Over time, techniques have been developed that include consideration of customer power interruption costs when evaluating reliability investments. Munasinghe (1979) developed the concept of value-based reliability planning, which holds that the optimal level of power system reliability is the level of reliability associated with the minimum combination of both utility and customer power interruption costs. Many U.S. utility reliability improvement projects have incorporated this value-based reliability planning approach, including projects undertaken by Pacific Gas & Electric (PG&E) (Burns and Gross, 1990; Sullivan et al., 2012), Southern California Edison (SCE) (Collins et al., 2019) in California, and Duke Energy in the southeastern U.S. (Dalton et al., 1996).

To support the use of the value-based reliability planning approach, U.S. utilities have conducted numerous surveys of their customers in order to estimate their customer interruption costs (CICs). Lawrence Berkeley National Laboratory (LBNL) and Nexant, Inc. aggregated a large number of utility-sponsored CIC studies to estimate CIC functions for general use in utility planning (Lawton et al., 2003; Sullivan, Mercurio, and Schellenberg, 2009).

That work was the basis of the Interruption Cost Estimate Calculator (ICE Calculator; Sullivan, Schellenberg, and Blundell, 2015).[1]

Unfortunately, CIC surveys are not well suited for estimating the costs of WLD power interruptions for several reasons, including customer unfamiliarity with long-duration power interruptions and the fact that surveys are not designed to estimate regional-scale economic impacts of such events. Previous survey-based estimates are, therefore, not viewed as directly applicable to estimating customer costs of power interruptions that affect utility service territories and last for days or weeks. These survey-based estimates are even less applicable for estimating customer costs of power interruptions that last weeks or months and affect larger, multi-utility, and possibly multi-state regions (Stockton, 2014; EPRI, 2017; Sanstad et al*.,* 2020).

As an alternative to survey-based approaches, regional economic modeling (REM) has been used to estimate the impacts of WLD power interruptions caused by natural disasters and other extreme events. There are three commonly used REM approaches in this field: (1) macro-econometric modeling, (2) input-output (I-O) modeling, and (3) computable general equilibrium (CGE) modeling. We review the history and characteristics of each of these REM methods in Section 2. We identify CGE modeling as particularly useful in modeling economic impacts of WLD power interruptions, as they can not only estimate economy-wide effects of power interruptions and their direct impacts on customers but can also take account of adaptive responses and measures that businesses and households may take to reduce the impacts of power interruptions (Sanstad, 2016; Sue Wing and Rose, 2020a). However, utilities and regulatory bodies have seldom used CGE modeling to estimate economic impacts of power outages for a number of reasons, including: (1) the models are subject to stringent and comprehensive requirements regarding system information and regional economic data (Schellenberg et al., 2019); (2) CGE models are complicated and have been characterized as "black boxes" (Sue Wing, 2004; Böhringer et al., 2003); (3) decision makers may find it hard to interpret model outputs and incorporate them into existing decision making processes (Sanstad et al*.,* 2020); and (4) the models rely on critical parameters describing customer behavior that are not well-grounded empirically (Beckman et al., 2011; Koesler and Schymura, 2012; Sanstad et al., 2020).[2]

[1] See https://icecalculator.com/home. The current ICE calculator version contains CIC data from 34 studies (a total of 105,000 customer surveys) completed by 10 utilities between 1989 and 2012. The ICE calculator has been used by electric utilities, public utility commissions, government organizations, and other entities for estimating interruption costs and/or the benefits associated with power system reliability improvements.

[2] Sanstad et al. (2020) reported an effort to estimate regional economic impacts from investments in reliability and resilience for the City of New York (by using gross city product as the economic value metric to assess the potential impacts of future super storms; Tsay et al., 2014). However, they could not find other utilities or regulators using REM for estimating utility service territory-wide economic impacts.

In this report, we build on and extend previous work (including Rose et al., 2005 and 2007) and propose a comprehensive hybrid valuation approach that combines state-of-the-art surveying techniques and CGE modeling to estimate the economic impacts of power disruptions, especially those of long-duration and wide geographic scope.

This hybrid valuation method addresses some limitations of both CIC surveys and CGE modeling by using survey data to improve the models' empirical foundations for this type of analysis, parameterizing how the models represent the effects of power interruptions. The hybrid approach aims to (1) improve utilities' and regulators' understanding of how firms and households reduce or adapt to and recover from the impacts of power interruptions of various durations and geographic scope; (2) increase confidence in CGE modeling of power interruptions by grounding it in credible data that are familiar to decision makers; and (3) enable an economic analysis of power disruptions on larger geographic and temporal scales than has traditionally been the norm.[3]

The hybrid valuation method helps utilities and policy makers understand the resilience tactics that have been implemented by electricity customers and also allows them to develop long-term investment plans to further enhance power system resilience. Therefore, we are considering two types of resilience in this paper. The first type of resilience tactics is those referring to economic resilience, defined by Rose (2017). These tactics are further classified as *static* or *dynamic* resilience. *Static* resilience involves utilizing remaining resources efficiently to maintain the functionality of a household, business, industry, or entire economy after a disaster strikes. *Dynamic* resilience involves effectively investing in repair and reconstruction to promote accelerated recovery. The second type of resilience we refer to in this paper, power system resilience, is related specifically to engineering solutions that utilities make to shorten restoration times after a power outage occurs. Rose and Liao (2005) were the first to combine survey data and CGE modeling to assess water service disruptions. Rose et al. (2007) expanded this hybrid approach to study the economic impacts of electric power disruptions. Indeed, these studies represent the most comprehensive approach to-date; however, they only apply their hybrid approach to assess the effectiveness of two economic resilience tactics taken by firms: substitution and conservation. Our hybrid valuation method helps utilities and policy makers understand the benefits of resilience tactics taken by firms/households as well as engineering resilience tactics taken by electric utilities.

This report develops a theoretical framework for the hybrid approach by answering the following research questions:

[3] "Direct" refers to impacts experienced by utility customers as result of losing power, and "economy-wide" refers to impacts of a power interruption propagating throughout an economy and affecting inter-industry supply chains and the availability of goods and services to households.

- How do the two leading methods – CIC surveys and CGE modeling – estimate the costs of power interruptions for purposes of informing planning studies? What are the strengths and limitations of CIC surveys and CGE modeling for estimating power interruptions of varying geographic scope and duration?
- How might a hybrid approach estimate the direct and economy-wide impacts of power interruptions, especially interruptions of long-duration and wide geographic extent? Why would such a hybrid method be expected to yield improved estimates of the economic costs of power interruptions compared to either of the other methods alone?
- What kinds of information must be collected to inform CGE models? How would survey data be used to calibrate CGE models?

The answers to these questions will help technical staff at regulatory bodies and utilities as well as academic researchers and industry consultants develop new methods to value resilience. The remainder of this report is structured as follows: In Section 2, we review previous studies on the economic impacts of power interruptions that used surveys and REM and describe these studies' major limitations in assessing power interruption costs, especially for WLD power interruptions. In Section 3, we review the theoretical basis of CGE modeling, specify the information that needs to be identified by surveys in order to inform CGE models, and describe how to calibrate CGE models using survey results. Finally, we conclude in Section 4 with a discussion of policy implications, limitations, and future research needs related to the hybrid valuation approach.

# 2. Previous Studies on the Economic Impacts of Power Interruptions

WLD power interruptions often result from natural disasters that impact critical infrastructure and have multi-faceted economic impacts. In general, natural-hazard and electricity-specific costs can be divided into five categories: (1) costs of damage to utilities' physical infrastructure; (2) costs of interruptions to residential and non-residential customers, including lost production; (3) indirect costs, which are "ripple" or "spillover" effects on local or regional economies; (4) intangible costs, which can be monetized, including health risks, environmental damage, and legal liabilities resulting from power interruptions and natural disasters (see, for example, Zamuda et al., 2019); and (5) costs of risk reduction and resilience enhancement, which may be incurred prior to an actual power interruption (Meyer et al., 2013). Figure 1 illustrates the cost components related to direct customer power interruption cost assessments, total power interruption cost assessments, and damage assessments for power interruptions along with natural disasters. The *power interruption costs for electricity customers* (the green box in Figure 1), which are the main focus of this report, only incorporate the costs that result directly from power interruptions.

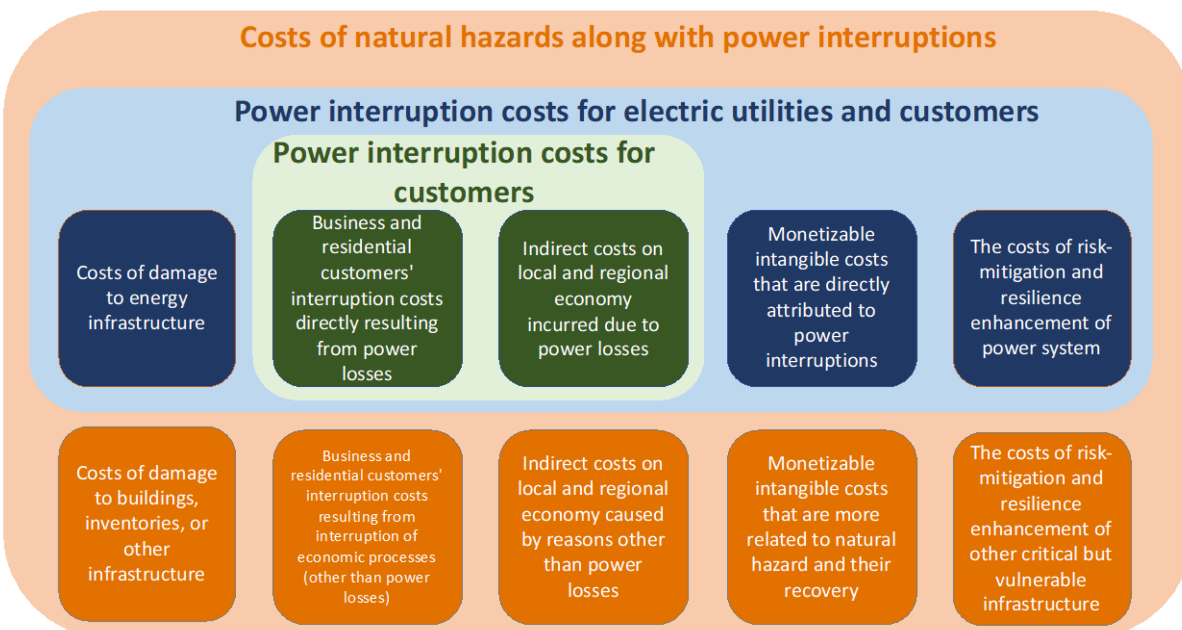


**Figure 1. Venn diagram of natural hazard and power interruption cost components**

WLD power interruptions impose direct costs on firms and households in a manner similar to the manner in which shorter-duration and more geographically circumscribed power interruptions impose costs. However, WLD power interruptions also impose substantial indirect costs that can be far greater than the direct costs, especially for businesses and industries. These costs result from effects that spill over to other sectors in the supply chain that may not be directly impacted by the power interruptions. For example, a direct cost might be loss of production in a company's facilities, and an indirect cost would be another company being unable to procure the inputs it needs to manufacture its product because of the lost production at the first company. Although there is no objective time or geographic threshold at which indirect costs become significant, they clearly increase with the duration and scale of a power interruption as the impacts arising from connections among businesses and industries in markets for goods and services spread through a local and regional economy.

Most studies generally adopt one of five methods to estimate customer power interruption costs: (1) CIC surveys, which measure non-residential customers' costs and savings from (hypothetical) power interruptions or use stated preference techniques to elicit the amount that residential customers are willing to pay to avoid (hypothetical) power interruptions; (2) the revealed preference method, which observes how much respondents have paid for backup equipment or other risk-mitigating strategies;[4] (3) REM, which analyzes the impacts of power interruptions on an entire economy; (4) a production function approach that produces interruption cost estimates based on either microeconomic data (e.g., firms' production and costs and annual household income) or macroeconomic data (e.g., gross domestic product — GDP); or (5) case studies of historical blackouts. Among these methods, CIC surveys are the most popular because they can estimate the direct economic impacts of various power interruption scenarios across all customer segments, including events that have never happened in the past. In addition, interest in REM is growing because regional economic models can capture both direct and indirect economic impacts. For these reasons, the remainder of this paper focuses on CIC surveys and REM.

[4] Although revealed preference method is useful for roughly estimating some portions of large industrial customers' interruption costs, the method is not useful for other customer segments because many residential and small and medium size commercial and industrial customers do not use sized backup generation or interruptible/curtailment (I/C) programs even though they experience CICs. In addition, revealed preference method cannot capture some portions of interruption costs, for example incremental labor costs to deal with outages and damage to inventory, stock, or materials.

## 2.1 Estimating customer interruption costs using customer interruption cost surveys

Many utilities in the U.S. have conducted CIC surveys. In this section, we review the survey-based cost estimation methods for different electricity customer segments, including a brief summary of a recent SCE value-of-service study conducted by Collins et al. (2019). Table A.1 in Appendix A summarizes additional CIC surveys that have been conducted across the U.S.

CIC studies typically segment electricity customers into three classes based on their consumption characteristics and the magnitude of interruption impacts they experience: (1) residential, (2) small and medium non-residential, and (3) large non-residential.[5] Surveys of non-residential customers typically elicit direct costs, which are the sums of costs incurred and savings realized during power interruptions, because business and industrial customers' economic losses are tangible and measurable. Surveys of non-residential customers often begin with an introductory section that describes hypothetical interruption scenarios, including conditions, duration, start time, end time, and whether or not advanced warning was given. Next, the surveys ask a series of open-ended questions associated with the value of lost production, interruption-related costs, and interruption-related savings. Finally, the surveys ask respondents to estimate the overall interruption cost using a range of possibilities: best case, typical case, and worst case (see Sullivan et al., 2018).

However, residential customers' interruption costs cannot be estimated using the direct cost elicitation technique because a significant portion of these costs are intangible. Intangible costs include those associated with inconvenience or lack of comfort (e.g., inability to use appliances, lack of air conditioning on a very hot day) and cannot be inferred using existing market data. Instead, these interruption costs are often estimated using stated preference techniques, including the willingness-to-pay (WTP) elicitation approach.[6] Surveys of residential customers often start by introducing a hypothetical power interruption scenario. Next, the surveys ask respondents to elaborate on how the power interruption leads to extra expenses and/or inconvenience costs. Finally, respondents are asked to identify the maximum amount

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[5] The segmentation of electricity customers is coincidental with the original purpose of CIC surveys, which was to establish the value of reliability for customer classes in utilities.

[6] There are a few value of lost load studies using different elicitation strategies, including discrete choice experiments (for instance, Layton and Moeltner (2005)). Although discrete choice experiments are well-suited for estimating customers' preferences for electric service reliability, they are not well-suited for assessing the costs of power interruptions, especially for WLD power interruptions, because 1) individuals' preferences for resilient electric services are uncertain and incomplete, so it is difficult to use a single cardinal utility function to express their preferences for complex and unfamiliar alternatives; 2) studies need to abstract away significantly from what will actually happen during a power interruption because the method requires many repeated choices from respondents, taking time away from helping respondents understand the time dynamics of lost electricity-dependent services; 3) respondents' value of resilient electric services is determined by many factors, and the differences among people will be washed out by aggregating over individuals; and, 4) testing axioms of probabilistic discrete choice models, for example stochastic transitivity and quadruple condition, requires many repeated pairwise comparisons (Boxall et al., 1996; Davis-Stober, 2009; De La Maza et al., 2018; Baik et al., 2019; Baik et al., 2020).

they would be willing to pay for a backup service that would reduce the impact of the interruption (see Sullivan et al., 2018).

CIC surveys have been the most widely used method to estimate direct CICs. CIC surveys are still utilized by many utilities and are generally understood by regulators. For instance, Collins et al. (2019) recently performed a value-of-service reliability study for SCE – one of the nation's largest electric utilities – to update earlier CIC estimates. Between December 2018 and June 2019, the research team conducted three rounds of surveys with each of the electricity customer classes. The respondents were presented with a range of hypothetical power interruptions lasting from five minutes to 24 hours, along with four other interruption attributes (season, time of week, onset time, and advance warning). Collins et al. (2019) used direct cost elicitation and WTP elicitation approach for the non-residential and residential surveys, respectively. The results suggest that on average, electricity customers directly lose: $0.07 per customer minute of interruption (CMI) (residential), $21/CMI (small and medium non-residential), and $710/CMI (large non-residential).

The survey-based method is a bottom-up approach that can estimate the direct impacts of power interruptions on a specific target group or general population for a wide variety of power interruption scenarios and reliability levels without relying on other data or assumptions (Sullivan et al., 2018). However, surveys suffer from several well-known limitations, including the inability to estimate the full economic impact from longer-duration interruptions affecting larger geographic areas. First, electricity customers may have difficulties in providing precise interruption cost estimates for WLD power interruptions if there is no adequate assistance for respondents to fully consider the various aspects of the consequences they may suffer (Baik, Davis, and Morgan, 2018; Baik et al., 2020). Second, electricity customers may not be fully aware of the cascading consequences of power interruptions throughout supply chains.[7] Third, cost estimates are subject to possible biases introduced by the hypothetical nature of surveys and the characteristics of elicitation techniques. Researchers have shown that some amount of potential bias can be avoided by systematic efforts to design survey instruments carefully, provide required information, and properly conduct surveys (Mitchell and Carson, 1989; Arrow et al., 1993; Boyle, 2017; Johnston et al., 2017). However, it is very difficult to eliminate all the

[7] Sullivan and Schellenberg (2013) assess the total economy-wide impacts of WLD power interruptions lasting from 24 hours to 7 weeks in downtown San Francisco using customer surveys and a range of cost multipliers, but the multipliers may provide inaccurate results because the multipliers were derived from case studies of previous blackouts and regional economic modeling studies, and historical data may not reflect future outcomes.

cognitive biases, especially in practical situations (Arrow et al., 1993; Alberini, 1995; Carson, Flores and Meade, 2001; Venkatachalam, 2003; Johnston et al., 2017).[8]

For the above reasons, it would be relatively difficult to use surveys to estimate the economic impacts of various WLD power interruptions on larger economies. However, surveys are still useful to obtain information on customers' behavior preparing for, mitigating, and recovering from power disruptions. The information collected through surveys can be critical for estimating the indirect impacts of power interruptions, and therefore, for calibrating regional economic models. Section 3.2 discusses surveys in more detail as an approach to collecting important information on resilience tactics/preparedness.

## 2.2 Estimating customer interruption costs using regional economic modeling approaches

Another approach to modeling economic impacts from power outages is to develop a regional economic model of a hypothetical interruption scenario using economic data, which is often publicly available. In this section, we review the history of REM methods and provide summaries of selected REM studies that illustrate each method's unique strengths and limitations. See Appendix Table A.2 for a summary of additional REM studies conducted in the U.S.

REM methods that focus on disentangling direct and indirect (i.e., spillover) impacts from severe supply chain disruptions began appearing in the 1990s. These included development of the Federal Emergency Management Agency (FEMA) Hazards U.S. Multi-Hazard (HAZUS-MH) software, which has several versions for estimating losses from major types of natural hazards (FEMA, 2020). Around this time, FEMA began asking economists for direct assistance in exploring methods for estimating economic impacts resulting from natural or manmade hazards. FEMA's initial intention was to use the direct loss outputs from HAZUS to inform other regional economic models; however, the comparison of direct and indirect impacts across REM approaches remains incommensurate in many cases. As a result of FEMA's call to action, there are now three commonly used approaches to modeling the economic impacts of WLD power interruptions: (1) macro-econometric modeling, (2) I-O modeling and linear programming (LP) modeling, and (3) CGE modeling. For each model type, we summarize a representative study (see Table 1). In our review of REM methods, we determined that CGE modeling is the most

[8] In addition to the inherent hypothetical nature of stated preference studies, each elicitation techniques suffer from several biases and issues. For instance, the payment card method, which was adopted by Sullivan and Keane (1995) for their residential customer surveys, suffers from range and centering bias; dichotomous choice studies suffer from low efficiency, starting point bias, and yes-saying bias; and open-ended questions which are adopted by Sullivan and Keane (1995) for their non-residential customer surveys suffer from strategic bias, respondents' difficulty in providing a precise number, and lack of confidence with estimates especially for things that are not familiar (Kealy and Turner, 1993; Alberini, 1995; Cameron and Quiggin, 1994; Cameron et al., 2002).

appropriate approach for our hybrid method, and this type of modeling will remain the focus of this paper.

**Table 1. Summary of selected REM studies**

| Author | Customers Studied | Outage Duration | Study Region | Method | Results |
|---|---|---|---|---|---|
| Greenberg et al. (2007) | Economy-wide | A couple of days to a couple of months | New Jersey | Macro-econometric | "Middle" scenario (50% power restoration in one week, 100% in two weeks): 1.6% reduction in annual gross state product relative to baseline in the first year following disruption, 3.3% reduction in the second year, and 1.8% reduction in the fifth year |
| Rose et al. (1997) | Economy-wide | 15 weeks | Memphis, Tennessee | I-O/LP[9] | Direct losses of 2.3% of baseline gross regional output, indirect losses of 6.3%. Direct losses can be reduced to 0.58% with optimal restoration and allocation of power. |
| Sue Wing & Rose (2020a) | Economy-wide (electricity sector vs. rest of economy) | Two weeks | Bay Area, California | CGE | Losses to the gross regional output of $1-2B (without resilience strategy), $127-663M (with additional investment in infrastructure or capacity-preserving backup), and $15-16M (with supply-preserving investment) |

### 2.2.1. Macro-econometric models

The first type of economic model we discuss is a "macro-econometric" model, a system of statistical forecasting equations with parameters estimated using historical time series data (Bodkin et al., 1991). Macro-econometric models are commonly used to represent national economies and corresponding macro-economic metrics, such as inflation and employment. They are suitable for performing scenario analysis on a national scale by positing hypothetical future trends or by changing the values of key inputs (Sanstad, 2016).

Greenberg et al. (2007) illustrate the strengths and limitations of using a macro-econometric model to estimate economic impacts on the New Jersey economy after a hypothetical cyberattack resulting in power outages of varying duration during the summer of

[9] This work also included a LP analysis of optimal power restoration and allocation.

2005. Key model variables are employment by industry, personal income of New Jersey residents, gross state product, and total tax revenues. Although Greenberg et al. (2007) detailed fluctuations in gross state product and other macroeconomic variables, their analysis did not explicitly represent grid resilience because their models could not measure impacts at the sector- or county- level. Measuring grid resilience requires estimating the reduction in economic losses from strategies such as substitution, backup generation, and conservation. Macro-econometric models cannot demonstrate how power outages and resilience tactics heterogeneously impact sectors and regions. Access to this information would benefit utility planners and policy makers.

### 2.2.2. Input-Output models

I-O models use systems of linear equations to represent all inter-industry relationships or flows in an economy, depicting the structure of industry transactions in matrix form (Leontief, 1973). Unlike macro-econometric models, I-O models can differentiate effects by sector. The major assumption in I-O models is that of fixed coefficients, or proportions, determining I-O relationships between industries (Sanstad, 2016). Therefore, I-O models do not represent changes in I-O relationships across sectors that might result from scaling, substitution of different inputs, or technological change. Ultimately, this rigid inter-industry representation is simple and computationally efficient, but it mostly ignores the adaptive actions that firms may take during a power interruption. Rose (2005) presents some instruction on how to model a subset of economic resilience tactics firms may take in I-O models, mostly through adjusting input coefficients. Moreover, the I-O model's limited ability to analyze only demand-side multipliers (i.e., indirect and induced impacts on suppliers) renders it only meaningful as an upper-bound estimate of direct and indirect impacts (Rose and Guha, 2004; Rose and Liao, 2005).

Still, modelers use I-O models with regionally downscaled IMPLAN[10] data to estimate local, sector-level disruptions resulting from WLD power interruptions. Rose et al. (1997) use a 21-sector I-O model to represent a 15-week power outage from an earthquake in the New Madrid seismic zone near Memphis, TN. Rose et al.'s model enhances the simple LP formulation that maximizes gross regional production by clarifying indirect effects, general input supply bottlenecks, resiliency of production technology to electricity curtailments, and spatial differentials in electricity use/availability. The emphasis of Rose et al.'s work is to estimate the subsequent loss of production of goods and services by businesses directly cut off from

[10] IMPLAN is a commercial economic assessment database and software system that contains 546 sectors representing all private industries in the U.S. (anything from grain farming to surgical appliance manufacturing) as defined by the North American Industry Classification System (NAICS) codes. IMPLAN relies on assumptions that are viewable and can be edited by users to customize to their areas of interests (Clouse, 2020). IMPLAN data are ideally suited (and, in fact, constructed specifically) to inform I-O models. IMPLAN provides many of the data needed for constructing a CGE model for regions across the U.S.

electricity service. Here, they assume resilience factors that offset some of the production output loss resulting from a power disruption. In the second phase of their study, Rose et al. (1997) extend the I-O model to use LP formulation to optimize the sequencing of re-powering industries to optimize regional economic output. Rose et al. (1997) define “direct” effects as output losses attributable to electricity disruption at the production site (measured at the industry level). They estimate the total direct reduction in gross output from all industries for the duration of the outage to be 2.3% of the annual baseline output. The researchers define “indirect” effects as decreases in industry output resulting from bottlenecks. Rose et al. (1997) find that these indirect, bottleneck effects cause 15-week gross output losses of 8.6% of the annual baseline, nearly four times greater than the direct losses.

#### 2.2.3. Computable General Equilibrium models

CGE models are comprehensive numerical representations of economies in the form of non-linear algebraic equations or mathematical structures, based on microeconomic principles (Sue Wing, 2009). Unlike macro-econometric models, CGE models explicitly represent all supplies and demands in an economy across all sectors, including both direct and indirect market interactions (Arrow and Debreu, 1954). Unlike I-O models, CGE models can account for market flexibility in technology adoption, substitution effects, and other factors. In fact, the most common functional form used to numerically represent production functions in a CGE model is constant elasticity of substitution (CES), in contrast to I-O models’ rigid fixed-coefficient assumption. CGE models estimate a new set of prices consistent with equilibrium given a shock or policy change. These prices are used to estimate the new equilibrium levels of production, consumption, employment, income, etc. (EPRI, 2017). CGE models can analyze demand-side multipliers as well as supply-side multipliers (impacts on customers) within a non-linear framework and left unmodified for the specific circumstance. Thus, they can yield estimates representing over-resilient responses[11] that one should interpret as lower-bound estimates of economic impacts (Rose and Guha, 2004; Rose and Liao, 2005). Table 2 details the strengths and limitations of the basic CGE models.

[11] Over-resilient behavior in a CGE model could result from if the model includes inaccurate assumptions of optimizing producer behavior in the face of increased uncertainties, assumes a facile return to equilibrium, or if the model exhibits excess flexibility during a brief time period of response. These modeling errors occur when the modeler does not properly tune the parameters given what is learned from the survey. A basic example of modeling over-resilient behavior in a CGE model is making a perfect substitution of a production input hours after the outage, even if it is simply not possible for those materials to be delivered to the production site within that timeframe.

**Table 2. Strengths and limitations of the basic CGE models**

| Strengths | Limitations |
|---|---|
| • Allow for substitution and a flexible characterization of production activities<br>• Include more than one class of customer<br>• Can model disequilibria relating to imbalances in labor and capital markets; can also incorporate trade<br>• Can adjust to reflect a range of resilience options<br>• Are appropriate for analyzing longer-duration events<br>• Are capable of modeling disjoint change and non-linear damage functions<br>• Can readily accommodate engineering data and are good at modeling lifelines and infrastructure | • Have relatively demanding data requirements (e.g., substitution elasticities)<br>• Have general issues with model validation and uncertainty quantification<br>• Lack of forecasting ability; often supplemented with exogenous forecasts and a recalibration<br>• Include assumption of optimizing behavior in the face of increased uncertainties (which is sometimes inaccurate)<br>• Include assumption of facile return to equilibrium<br>• Without model refinements, sometimes exhibit excess flexibility during a brief time period of response<br>• Assume perfect knowledge of all variables although several key parameters rely on informal or heuristic data (e.g., substitution of elasticity) |

As illustrated above, CGE models offer great flexibility and, aside from interpretability limits, are often constrained only by data availability and limitations on computational resources. These models are powerful analytical tools for policy evaluation at state, regional, and national levels. Advances in data availability and computational power/optimization methods now allow for interregional models at a global scale. For example, the Global Trade Analysis Project (GTAP), a worldwide network of researchers and policy makers, develops CGE models to examine, at a global scale, issues related to international trade policy, environment/energy, and poverty (Corong et al., 2017).

As noted earlier, the use of CGE models to estimate economic impacts at a state and regional levels began in the 1990s when FEMA approached economists for assistance in exploring methods for estimating direct and indirect economic losses from natural hazards. Since then, Rose and his colleagues have led most of this research and made important contributions to the economic impact modeling literature, especially for regional CGE modeling (see Appendix A.2 for a list of Rose et al. publications that employ CGE models to estimate economic damage from power outages). To avoid redundancy with other publications, we refer readers to Sanstad (2016) and EPRI (2017) for detailed reviews of more CGE model studies, including their corresponding data sets and nuanced assumptions.

To provide perspective on the latest methodology, we summarize the most recently published CGE study by Sue Wing and Rose (2020a) that simulates the impacts of a two-week power outage on California's Bay Area economy using a stylized two-sector analytical general equilibrium model that elucidates mechanisms of adjustment to WLD power interruptions. Their analysis examines two sectors, electric power and the rest of the economy, and assumes CES production. Using algebraic solutions, Sue Wing and Rose (2020a) specifically investigate how mitigation and resilience measures (producer and consumer input substitutability and investment in backup capacity) affect the economic consequences of large-scale disruptions of electric power infrastructure. The authors' central argument is that the parsimonious two-sector model with stylized inputs/parameters can yield similar zero$^{th}$-order estimates of the economy-wide impacts of electric power disruptions as a more granular, computationally intensive model. To solidify this point, they compare the results of the two-sector model with the output of an 18-region, 46-sector interregional CGE (ICGE) model of the California economy that resolves producer and consumer behavior in the nine Bay Area counties and the rest of the state. In both models, gross output declines across all downstream (non-electricity) sectors by $1-$2B; the more complex ICGE model yields more severe impacts. Results highlight the role of substitution as an inherent resilience mechanism and the ability for deliberate investments in mitigation to dampen price and quantity changes and ultimate welfare losses. This study underscores how targeted survey information related to substitution of elasticity, backup generation, and preferred resilience strategies yields behaviorally realistic results.

## 2.3 REM comparison and motivation for CGE models

Table 3 provides a high-level summary of the pros and cons of using various types of regional economic models to measure the direct and indirect economic impacts of power interruptions. Modelers must ask themselves which insights they wish to derive from their economic representations and, thus, which trade-offs they are willing to make.

For a hybrid modeling approach (CIC surveys with REM), we identify CGE models as the most appropriate for estimating sector-level consumer/producer impacts with an empirically validated, behaviorally realistic economic framework. We rule out macro-econometric models because they are not well suited to analyzing sector-level impacts at a regional scale. We eliminate I-O models as an option because they assume fixed coefficients and are difficult and less accurate in modeling adaptive industry behavior. Ultimately, macro-econometric and I-O models do not provide the nuance that we seek in estimating direct and indirect economic impacts from WLD power interruptions. By contrast, CGE models can account for market flexibility in technology adoption, substitution effects, various production functions (e.g., CES), backup generation, and known inventories. Although some key assumptions of CGE models traditionally rely on informal or heuristic data, surveys can help verify these assumptions and improve the behavioral accuracy of the model.[12] These characteristics make CGE models ideal candidates for coupling with survey data that can be used to customize and calibrate otherwise elusive CGE parameters.

**Table 3. Pros and cons of each regional economic model type for estimating economic impacts of power interruptions**

| Model Type | Pros | Cons |
|---|---|---|
| Macro-econometric | • Is suitable for forecasting trends across macroeconomic metrics (e.g., inflation and employment) | • Cannot measure sector-level impacts across consumers and producers |
| I-O | • Can measure sector-level impacts<br>• Is simple and computationally efficient | • Assumes fixed coefficients (or proportions) to represent I-O relationships between industries<br>• Their basic models are not able to represent adaptive reactions that firms can take during a power interruption |
| CGE | • Can measure sector-level impacts<br>• Produces new prices and shadow prices for unpriced goods<br>• Can make adjustments, empirically informed by surveys, to reflect adaptive behaviors | • Has demanding data requirements<br>• Is computationally expensive<br>• Lacks forecasting ability<br>• Without recalibration, provides little insight on existing backup generation, known inventories, and substitution parameters |

[12] For instance, Sue Wing and Rose (2020a) make several assumptions, such as setting the backup technology's share of infrastructure capacity in the baseline equilibrium at 15% and factor-to-backup transformation elasticity values in the range of 0.5 and 1.25 to consider the possibilities of highly inelastic to highly elastic without using empirical data to verify these assumptions.

# 3. Calibrating Computable General Equilibrium Models for Power Interruption Cost Analysis Using Survey Data

As discussed earlier, the two leading approaches for estimating the economic costs of power interruptions and informing planning studies are CIC surveys and CGE modeling. CGE models can be used to estimate direct and economy-wide power interruption costs, but the default values of CGE models' elasticities and productivity parameters are generally not closely tied to empirical data (Beckman et al., 2011; Koesler and Schymura, 2012). We propose a hybridization of CGE modeling and CIC surveys that uses survey information to provide an empirical basis for these elasticities and other parameters in power interruption analysis, thus improving CGE modeling's representations of households' and firms' economic impacts from, and mitigation responses to, power interruptions. Our hybrid modeling approach aims to take the intrinsic region- and sector-specific CGE models (described in Section 2.2) and calibrate them with CIC surveys that measure costs and savings resulting from previous or hypothetical interruptions and resilience tactics (described in Section 2.1).[13] The hybrid model will combine the advantages and address the limitations of both methods by collecting survey information to ground assumptions and key parameters used in CGE, thus constructing more empirically based CGE models.

In this section, we provide additional background on CGE models, summarize the key details of how survey data would be linked to the models, and describe how to recalibrate CGE models' elasticities and productivity parameters using survey data. Appendix B presents a detailed theoretical analysis of our approach, building on work by Rose et al. (2005), Rose and Liao (2005), Dormady et al. (2019b), and Sue Wing and Rose (2020a, 2020b).

## 3.1 Theoretical background on computable general equilibrium models

### 3.1.1 Overview

CGE modeling mathematically represents and analyzes an entire economy. Its key aspects can be summarized as follows:

- *Modeling:* CGE modeling is based on an abstract mathematical/theoretical description of an economy.

[13] Economists have developed hybrid modeling approaches to reduce costs and delays associated with strictly survey-based approaches, improve the regional accuracy of REMs, and customize electricity endowments of certain sectors in CGE models (Lahr, 1993; Flegg and Tohmo, 2013). A recent addition to the hybrid modeling literature is the Flegg Location Quotient (FLQ), which updates the standard I-O model by taking into account regional size and the proportion of regional employment in each supply sector compared to the corresponding national employment of that sector (Flegg and Tohmo, 2013). However, these surveys typically do not aim to collect empirical information that captures electricity customers' coping behaviors or substitution elasticities.

- *Equilibrium:* This is the assumption that supply equals demand in all markets (i.e., markets clear).
- *General:* All economic agents—households and firms—their decisions, the markets in which they transact, and the links among markets are explicitly represented in some form in CGE models. This includes savings and investment decisions. Governments can be included in CGE models, but they are not often represented in a simplified form.
- *Computable:* In CGE models, explicit mathematical descriptions of each type of agent, each agent's decision processes, markets, and other components are used to write software code that ingests data to enable a numerical realization of the model. Several different computational techniques are used for this purpose, but the basic mechanism in solving a CGE is to find vectors of prices that match supply and demand in all markets simultaneously, though typically indirectly in the course of optimizing an objective function.

The following diagram depicts the different parts of the economy's general equilibrium model and how they are connected in an overall "circular flow."

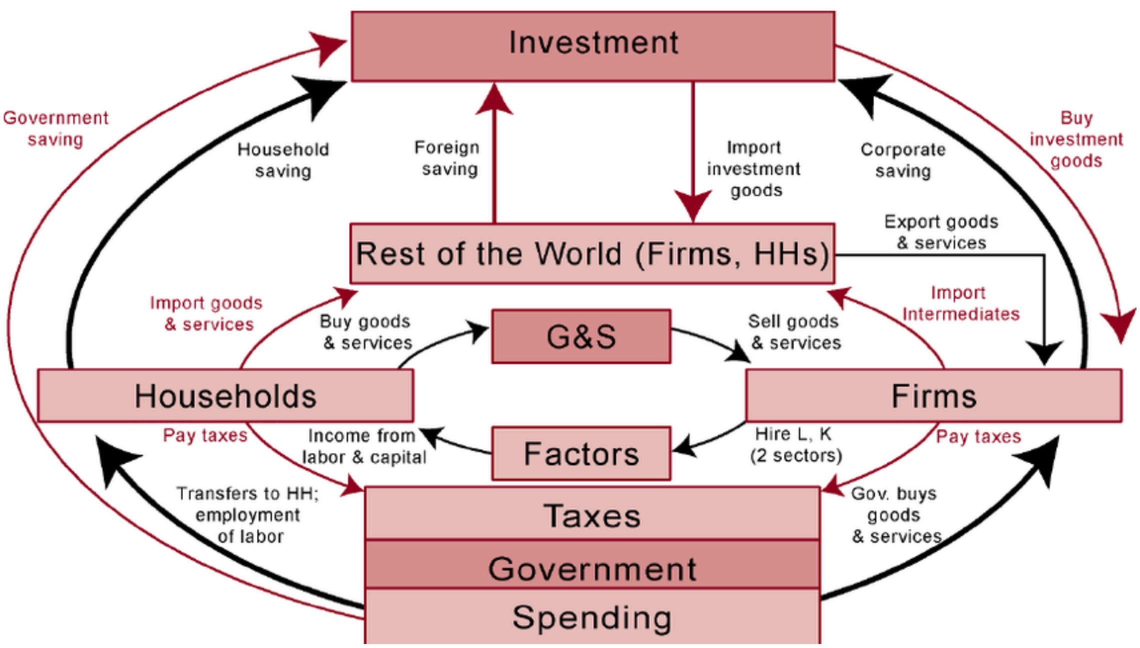


**Figure 2. Simplified circular flow model that represents the relationship among the representative actors of the economy; arrows indicate the flows of money, goods, and services. Figure adapted from Tuerck et al. (2007).**

### 3.1.2 Household and firm behavior

CGE models incorporate "representative" firms and households, which are mathematical models of hypothetical decision makers that capture the behavior of entire industries and types of households (e.g., defined by income classes). Theoretical CGE models are built upon the fundamental microeconomic paradigm of *rational behavior*, i.e., that, broadly speaking, households and firms make their choices about the consumption or use of goods and services through optimization. In other words, these agents make optimal trade-offs among these commodities by comparing the benefits of consuming or using the commodities while taking into account their costs. These models reflect the basic microeconomic concept of equating marginal costs and marginal benefits. A household's optimization is based on a "utility" function, which determines the household's well-being based on its consumption of combinations of goods and services. Analogously, a firm's decisions are based on "production" functions, which yield output based on the use of factors, for example, capital, labor, and other inputs like electricity and, in the case of manufacturing, component parts.[14,15] In this framework, there are two equivalent ways of modeling decision making. One way is to assume that households minimize the expenditures required to obtain a given level of utility subject to a budget constraint and that firms minimize the costs of purchasing factors and inputs necessary to produce specific quantities of output commodities, determined by market demand. Alternatively, households can be assumed to maximize utility subject to a budget constraint while firms maximize profits in producing a market-determined level of output. These two approaches—minimization and maximization—are equivalent in the sense that, given certain mathematical properties of utility and production functions and the optimization problems, they yield identical outcomes: expenditures and utility for households, costs and outputs for firms. These properties hold in essentially all applications of standard microeconomic theory, including CGE models.

The trade-offs mentioned above are a hallmark of the microeconomic theory of behavior, on which CGE models are based. In both utility and production functions, given levels of well-being or output can be produced by many different combinations of inputs. An example related to electricity is energy efficiency. Reducing fuel use (including electricity) by purchasing efficient appliances, equipment, and other devices while obtaining the same level of energy services (e.g., lighting, heating, or cooling) involves not just engineering but economic trade-offs. If equipment efficiency is increased to lower fuel use and thereby minimize the cost of procuring energy services, then the substitution is both economically and physically efficient. The same principle applies, in business, to the use of capital and labor as well as other quantities that can be substituted for one another. This principle also characterizes the

[14] Several other important characteristics of CGE models are as follows: 1) they are deterministic, in the sense that there is no explicit representation of uncertainty on the part of agents in the model or in their economic environments (part of this assumption is that agents have full information); 2) market-clearing includes the labor market, so there is by design no involuntary unemployment In a CGE model; and, 3) money is not represented, so monetary phenomena, for example inflation, cannot be analyzed.

[15] Under certain mathematical assumptions, utility and profit maximization are equivalent to expenditure and cost minimization, respectively: a household's optimization is minimizing the expense of purchasing goods and services to meet a specified level of utility, and a firm's is minimizing the cost of inputs necessary to produce a specified amount of output.

behavior of individuals and firms and potentially changing input combinations in advance of or in coping with and input disruption, such as a power failure.

## 3.2 Key information for calibrating computable general equilibrium models

### 3.2.1 Parameters in computable general equilibrium models

The mathematical production and utility functions described above contain exogenous parameters whose numerical values must be specified by the modeler prior to computation, a process known as "calibration." We discuss these parameters in turn below.

#### *Share parameters*

For industry, share parameters are used to match the model's representation of inputs, outputs, and inter-industry flows of goods and services to empirical data for a particular year. For households, share parameters are used to match the allocation of households' consumption among different goods and services to empirical data for a particular year. These parameters are part of the specifications of the production and utility functions of representative firms and households. "Shares" refer to the proportions of costs of particular goods and services with respect to a firm's or household's overall optimal (minimum) costs. For example, if the data indicate that a representative household spends 10% of its budget on electricity, the corresponding share parameter of 0.1 would be assigned. Although the details vary according to the structure and complexity of individual models, in all cases, these parameters are assigned numerical values (calibrated) in this fashion.

The empirical data used for this purpose are primarily drawn from or based on I-O information collected by the U.S. Department of Commerce. The commercially-available IMPLAN I-O database is built primarily upon these I-O data. In practice, CGE modelers use these types of data to construct "Social Accounting Matrices (SAMs)" as the basis for model calibration of input shares to a base-year economy for whatever area or region is being modeled.

#### *Elasticities of substitution*

Elasticity parameters are also a part of production and utility functions. These parameters govern firms' and households' ability to change the relative amounts of goods and services used to produce output or utility—that is, to shift among these inputs—when the relative prices of these inputs, or some other aspects of the economic environment, change. Higher values indicate greater flexibility in this respect. In the current context, substitution elasticities among electricity and other inputs govern the degree to which firms can adapt to power interruptions by relying on other inputs.

As we have mentioned, the numerical values of substitution elasticities in CGE models are generally not directly grounded in specific empirical data. This includes, but is not limited to, the substitution elasticities that affect or are related to electricity. The values are chosen by modelers mostly through a combination of heuristic reasoning and drawing from related literature–studies in which elasticities may have been empirically estimated in different contexts but usually not for the particular functional forms used in a given CGE model. In the following sections, we explore potential changes in these parameters for the particular purpose of improving the accuracy of CGE models' treatments of power interruption costs.

#### *Productivity parameters*

Productivity parameters in CGE models represent drivers or factors that are not explicitly represented in the models but have the effect of increasing the contribution of inputs to either production or utility. For example, in inter-temporal CGE models that project over decades or more extended periods, energy productivity parameters result in overall economic output—for example, GDP—growing at faster rates than energy inputs, thereby "decoupling" energy from economic growth. In this report, we are implicitly addressing static CGE models, but electricity productivity parameters can be used in this context to represent factors such as backup generation or energy storage that might reduce the costs of power interruptions.

### 3.2.2 Information that needs to be collected through customer interruption surveys

As previously described, elasticity and productivity parameters are particularly important because they represent the possibilities for adaptive behavior by firms and households during a power interruption (i.e., actions and/or measures that dampen the impact of the interruption on the firm's or household's capacity to function). By contrast, the default values of CGE models' elasticities and productivity parameters, which represent behavior under "normal," or average, conditions in an economy, are typically set informally and/or heuristically.

Default values of elasticities and productivity parameters are described by Dormady et al. (2019a) as representing decision makers' "inherent" resilience to power interruptions—their capacities to respond to such events without special or unusual actions or measures. Results from surveys could support changing the values in order to capture adaptive steps that might be taken to reduce an interruption's impact, for example, rescheduling or temporarily relocating production or using backup generation (Rose and Liao, 2005). Table 4 summarizes the resilience actions that electricity customers can take to reduce the impacts of power interruptions. The details of such actions are not represented in CGE models; the goal of using surveys in this way would, thus, be to approximate these actions within existing model structures. We provide additional details in Section 3.3.

**Table 4. Inherent and adaptive resilience tactics that electricity customers employ to absorb and recover from the impacts of power interruptions; adapted from Rose et al. (2007) and Dormady et al. (2019a)**

| Resilience tactic | Definition | Type of resilience | The time when the tactic is used | Classes of customers that can use the tactic |
|---|---|---|---|---|
| Backup generation | Use backup generators with stored fuel to resume at least partial operation | Inherent | Immediately after an outage | Residential, Small/medium non-residential, Large non-residential |
| Use of inventories | Continue business operations by using buffer (finished goods) stock to reduce the impacts of production/operation disruptions | Inherent | Immediately after an outage | Small/medium non-residential, Large non-residential |
| Input substitution | Replace production inputs that are in short supply; for example, replace electricity with alternative energy resources or materials require less or no electricity in processing | Inherent/ Adaptive | Shortly after an outage occurs | Residential, Small/medium non-residential, Large non-residential |
| Activity or production rescheduling | Delay use of household appliances, make up for lost production by working overtime or extra shifts | Adaptive | Introduce gradually as electricity and/or productive capacity is restored (mostly implemented for recovery) | Residential, Small/medium non-residential, Large non-residential |
| Physical relocation | Physically move affected household, organization, or facility to a new location, either temporary or permanent, to where electricity is available | Adaptive | Introduce gradually after an outage occurs | Residential, Small/medium non-residential, Large non-residential |
| Operation transfer | Transfer some operations (work and/or employees) to other locations | Adaptive | Shortly after an outage occurs | Small/medium non-residential, Large non-residential |

In the case of businesses, three key pieces of information are directly related to CGE models' elasticities and productivity parameters. First is information on the decrease in production resulting from the power interruption. Although most operations relying on power shut down immediately after an interruption occurs, electricity customers would be able to resume partial operation if they have invested in inherent resilience strategies. These strategies might include using backup generation with enough fuel on site. Second, surveys can collect information about adaptive actions that firms can readily undertake to reduce the impacts of a power interruption. Taking these actions, which include replacing unavailable inputs with more expensive but readily available inputs may increase the production cost but allow the firm to reduce the impacts of a power interruption. Third, the surveys can collect information about adaptive actions that require a longer-term perspective and that help electricity customers recover from the impacts of a power interruption over time. See Table 5, which includes the type of information collected and example questions. See Appendix C.1 for the full set of sample survey questions designed to be asked of firms.

In the case of households, researchers need to collect two pieces of information. First, information is needed about the impacts of a power interruption on the household sector in terms of economic "welfare" (well-being), including changes in household income levels. Second is information detailing the range of adaptive strategies that households can take to sustain some portions of their activities and reduce the impacts of power interruptions. See Table 5 for more detail on the information collected and example questions. See Appendix C.2 for the full set of sample survey questions designed to be asked of households.

In addition to the key information identified above, surveys can gather ancillary information that helps policy makers, utility planners, and other stakeholders develop investment plans that can effectively reduce the impacts of power interruptions building on what electricity customers have implemented already. Examples of such ancillary information for non-residential customers are: (1) whether their facility can generate any of its own electricity; (2) what percent of their operations their backup generation equipment can sustain and for how long; (3) how they have coped with previous WLD power interruptions; (4) whether their previous experiences influence their planning for risk-mitigation and resilience investments; and (5) how they would respond to future WLD power interruptions of different durations. In addition, ancillary information about the impacts of power interruptions on residential customers, including the income losses and strategies they might implement during the events and operations that could be sustained during power interruptions, can help better understand the consequences of power interruptions on individuals. See Appendix C.3 for the full set of sample ancillary survey questions.

**Table 5. Relationships among customer segments, behavioral strategies, CGE parameters, and sample survey questions**

| Customer segment | Type of information | Related key CGE parameters | Sample survey questions |
|---|---|---|---|
| Non-residential | Inherent resilience strategies and immediate adaptive resilience strategies | Elasticity parameters, Productivity parameters | • What percentage of your business can function without electricity from the utility?<br>• Does your firm generate any of its own electricity using emergency backup generation system?<br>• What percent of electricity can you replace with alternative fuel sources?<br>• What percent of electricity can you replace with backup generators? |
| | Consequences of the suppliers | Supply disruption | • Would the power interruption affect your key supplier?<br>• Please estimate the expected impacts on your operations due to the supply chain disruptions. |
| | Consequences to the customers | Demand loss | • Would the power interruption affect the demand for goods or services your business provides?<br>• Please estimate the expected demand increases/<br>decreases due to the power interruption. |
| | Gradual adaptive resilience strategies | Productivity parameters | • Are there any locations that are available for you to quickly transfer business or other activities?<br>• Approximately what percent of the normal operations can you sustain for how long?<br>• What inputs do you need to implement the strategy, and what would it cost? |
| | Recovery strategies | Productivity parameters | • How much output can you recoup by working overtime or extra shifts? |
| | Previous WLD power interruption experiences | Ancillary information | • What did your organization do to manage the impacts of the power outage? |
| | Strategies or plans to reduce the impacts of (future) WLD power interruptions | Ancillary information | • Did you make any changes in your facility or operating procedures as a result of lessons learned from the previous outage? |

| | | | |
|---|---|---|---|
| | Respondents’ own backup generation capacities | Ancillary information, Elasticity parameters | • Does your organization have some form of emergency backup electric power?<br>• Does your organization perform any processes using electricity that can utilize an alternative fuel source during an outage? |
| Residential | Respondents' and their household members’ Income losses due to power interruptions | Elasticity parameters | • If the power goes out for *<duration>*, will your employer/your household members’ employers pay you?<br>• If not, how much will you/they lose? |
| | Strategies that residential customers can implement at home during and after power interruptions | Elasticity parameters | • How would your household adjust to this power interruption?<br>• If you implement *<strategy>*, what portion of your activities can be sustained for how long? |
| | Previous WLD power interruption experiences | Ancillary information | • How long was the longest power interruption you have experienced?<br>• What major tactics did you use to cope with the interruption?<br>• How effective were these tactics in reducing interruption losses?<br>• What was the cost of implementing these tactics? |
| | Respondents’ own backup generation capacities | Ancillary information, Elasticity parameters | • Do you have a small portable backup generator that needs refueling?<br>• How much fuel to you typically have on hand in case of a power interruption? |

## 3.3 Details of recalibrating substitution elasticities and productivity parameters using survey information

A general equilibrium approach embeds representative firms and households in a framework where their decisions are interconnected through markets. The computational core of CGE modeling is solving the firms’ and households’ optimization problems. From these solutions, so-called cost and expenditure functions can be derived, which give the minimal costs to firms and households, respectively, to use or consume goods and services. These functions depend on the same parameters and inputs as the production and utility functions.

The effects of policies or other changes are typically analyzed in incremental, or “marginal,” terms—technically, by differentiating cost and expenditure functions, most commonly with respect to changes in relative prices of goods or services, perhaps resulting from a tax on one of them. Such a change causes both firms and households to change their decisions, shifting production or consumption from the more to the less expensive inputs. The derivatives indicate the marginal changes in minimum cost or expenditure resulting from the price shift.

Conceptually, there are different ways of introducing power interruptions into CGE models. Sue Wing and Rose (2020b) employ a parsimonious technique of representing power interruptions as "shocks" to the electricity supply by exogenous reductions to electricity services in production and utility functions. The functional forms and parameter values determine the effects of these reductions. The economic impacts of power interruptions can be analyzed in terms of how they change firms' and households' optimal (minimum) costs, along the lines sketched above for policy interventions.

As noted previously, adjusting the default values of model substitution elasticities and productivity parameters to represent adaptive behavior that lessens these impacts has been studied in previous work including Rose and Liao (2005) and Rose et al. (2005, 2007). An approach building on and extending this and other research is described in detail in the technical appendix; we next summarize the basic idea.

A simple cost function with two inputs–electricity E and another factor X–illustrates how empirical interruption cost data can be linked to economic models. A generic two-input minimum cost function can be represented as:

$$Cost = C(\sigma, \gamma, p_X, p_E, W, I) \tag{1}$$

where $\sigma, \gamma$ are the elasticity and productivity parameters, $p_X, p_E$ are the prices of X and E, respectively, *W* represents either a firm's level of output or a household's budget, depending on which type of agent is being modeled, and *I* is a parameter representing power interruption. When $I = 0$, this is simply the minimum (optimal) cost function described above. Giving $I$ a value greater than zero means that power is reduced by the corresponding percent; e.g., $I = 0.05$ means a power loss of 5%.[16]

The incremental or marginal cost of a power interruption of magnitude $\Delta I$ can then be represented as a differential:

$$\Delta Cost = \frac{\partial}{\partial I} C(\sigma, \gamma\ p_X, p_E, W, I)\Delta I > 0 \tag{2}$$

Empirically, we assume that the numerical value of (2) corresponds to what the model would predict with its default parameterization. Survey data on how firms and households respond to power interruptions (i.e., their inherent and adaptive behavior) would then enable us to calibrate the CGE model's estimate of how much this behavior reduced the firms' and households' interruption costs. For example, survey respondents could be asked: "by how much were your overall costs from the power interruption reduced by having backup

[16] CGE models are typically calibrated to annual average data on consumption, production, etc. So, a power interruption will be represented as an event that reduces the averages of these variables by some amount. For instance, given that there are 8,760 hours in a calendar year, an interruption lasting, say, one week (40 hours), would be represented as a reduction of 0.46% of the baseline electricity supply.

generation?" If we call their responses "$Reduced\ \Delta Cost\ from\ backup$," then to calibrate $\gamma$ to capture this effect, we would solve this problem:

$$\begin{aligned}&Choose\ \bar{\gamma}\ so\ that\\ &Reduced\ \Delta Cost\ from\ backup = \frac{\partial}{\partial I} C(\sigma, \bar{\gamma}\ p_X, p_E, W, I)\Delta I\end{aligned} \tag{3}$$

That is, the numerical value of $\bar{\gamma}$ would be chosen so that the right-hand side of this equation (the model's output) matched the left-hand side (the survey response).

Similarly, the substitution elasticity for firms could be calibrated by asking survey respondents, for example, "by how much were your overall costs from the power interruption reduced by shifting the timing or location of your production?" If their response was "$Reduced\ \Delta Cost\ from\ rescheduling/relocation$," then to calibrate to capture this effect, we would solve this problem:

$$\begin{aligned}&Choose\ \bar{\sigma}\ so\ that\\ &Reduced\ \Delta Cost\ from\ rescheduling/relocating = \frac{\partial}{\partial I} C(\bar{\sigma}, \gamma, p_X, p_E, W, I)\Delta I\end{aligned} \tag{4}$$

In summary, we have discussed the fact that CGE behavior parameters are generally not well-grounded in empirical data. Our overview of CGE modeling provides details on how they represent firms' and consumers' economic choices using production and utility functions, and how the parameters are defined. We then described survey information that could be used to set numerical values for these parameters to improve the accuracy of CGE's representation of power interruptions, including the behavioral, adaptive responses that may serve to reduce their economic impacts. Finally, we presented a mathematical synopsis of how this calibration would be implemented. A detailed description of this approach is presented in Appendix B.

# 4. Summary and Conclusion

This report is a scoping study that has outlined a new approach for improving the information on the costs of WLD power interruptions so that it can be used to support utility reliability and resilience planning studies. It is intended to set the stage for conducting a field-test with a utility that would demonstrate the value of this new approach. Specifically, this paper proposes a hybrid method that combines the strengths of CIC surveys and CGE modeling in ways that seeks to overcome their known weaknesses (see Table ES-1). The hybrid method we propose involves: (1) using CIC surveys to collect region- and sector-specific information to ground empirically the uncertain assumptions and key parameters used in CGE modeling, especially about firms' and households' adaptive behaviors during and after a power interruption; (2) estimating both the direct and indirect costs of power interruptions throughout a regional economy using the calibrated CGE model; and (3) helping utilities and policy makers better understand the benefits of resilience tactics taken by firms/households as well as resilience tactics taken by electricity utilities.

The overview of CGE modeling has provided details on how these models represent firms' and households' economic choices, how the parameters are defined, and what their functions are in the model. We have described the survey information that should be used to set numerical values for these parameters to improve the accuracy of CGE models' representation of power interruptions, including adaptive behavioral responses that may reduce the economic impacts of interruptions. We presented a mathematical synopsis of how this calibration would be implemented. A more detailed description of our approach is contained in Appendix B.

## 4.1. Policy implications of the hybrid valuation approach

Until very recently, CIC surveys focused on power interruptions lasting less than 24 hours. These estimates have been used as the economic value of reliability in planning for generation, transmission, and distribution investments under *normal* operating circumstances. The normal operating circumstances exclude low-probability, high-consequence events, including major storms, earthquakes, wildfires, cyberattacks, and other catastrophes. As the number and the average cost of extreme weather events have increased, utility planners and policy makers have become increasingly interested in obtaining CICs under a wide range of scenarios, including the possibility of long-duration interruptions of a wide geographic extent.

Utilities and regulators have a long history of supporting CIC surveys that estimate the customers' direct costs of relatively short-term and local power interruptions. Unfortunately, very few studies have analyzed the regional impacts of WLD power interruptions, and almost no utilities or regulators have incorporated regional economic impact modeling into their decision making processes for power system resilience (Sanstad et al., 2020). This paper proposes a hybrid method that combines the strengths of CIC surveys and CGE modeling in ways that overcome their weaknesses when estimating the costs of WLD power interruptions. The results from this hybrid approach would not only provide valuable input to reliability planning studies, but also to resilience investment decision making. For example, it may be the case that a particularly expensive component of a utility system is prone to risks from natural hazards (e.g., a substation susceptible to flooding). The costs of replacing this substation may significantly outweigh the reliability benefits—i.e., the costs of avoiding shorter duration, localized interruptions. However, investing in a new substation may be justified if it can demonstrate that it will avoid direct and indirect economic impacts of WLD power interruptions.

WLD power interruptions can cause widespread economic damage extending to multiple utility service territories. Furthermore, spillover effects can impact regions that were not directly affected by either the natural or manmade disaster or any associated power outage (Sue Wing and Rose, 2020a). For these reasons, power system resilience decision making problems are not confined to specific geographic areas or types of extreme events. Rather, resilience is a significant policy issue requiring enhanced coordination among utilities, government agencies, regulators, emergency management personnel, and other stakeholders. Results from REM, calibrated with CIC survey data, can help facilitate these important policy discussions.

To that end, Berkeley Lab has partnered with Commonwealth Edison (ComEd) to pilot the development of a Power Outage Economics Tool (POET) that uses survey-based information to calibrate a regional economic model. POET will estimate the impacts of WLD power interruptions within and beyond the ComEd service territory. More specifically, the research team is tasked with (1) developing a reduced-form model to assess impacts to regional economies from power disruptions; (2) calibrating the model using empirically-based approaches to account for producer/consumer behavior; (3) running simulations/scenarios for a recent or hypothetical disruption event(s); and (4) publishing a high-visibility, policy-relevant manuscript.

Finally, the results from the hybrid valuation approach can be readily coupled with other resilient (reliability) planning tools. Electric grid modeling tools and system restoration tools have been used to project electric outages through modeling at generation, transmission, and distribution levels with restoration timelines (e.g., Argonne's HEADOUT, EPFast, EGRIP, and RESTORE). Using the estimated impacts of power outages, the modeling tools can simulate the *avoided* direct and regional economic impacts resulting from proposed electric grid resilience enhancement technologies and restoration strategies. These combinations would help decision makers better understand the efficiency and effectiveness of resilience-enhancing strategies and make more informed decisions around power system reliability and resilience.

## 4.2. Limitations and future research

Although we believe the hybrid valuation approach described in this report is a needed improvement, we recognize that it has not yet been demonstrated. We are hopeful that, when demonstrated, additional critical issues that we cannot address will be addressed. These issues include, but are not limited to, concerns about the complexity of CGE models and their data intensity and the cost of surveys and model development. We have sought to develop a practical guide, including an example, that can (1) assist users in understanding the process; (2) identifying the key data that users need to collect; (3) help inform survey design and administration; and, (4) provide a basis for cost estimates to conduct surveys run CGE models.

The hybrid method provides a more comprehensive approach than most utilities and planners currently take to incorporating cost estimates into decision making processes like Integrated Resource Planning and procurement of new resources. Ensuring practical usefulness of the approach would require working closely with utilities and planners to administer the surveys, calibrate the CGE models, and interpret the output to ensure this information is useful for their long-term planning.

It is important to note that there is additional important research still needed on this topic, including a field demonstration of this concept (e.g., POET project with ComEd). Another necessary piece of analysis is the quantitative comparison of survey-based and CGE-generated interruption cost estimates. Although this issue has not been studied in detail, there is some evidence to indicate that there may be a systematic gap between the two (Sue Wing and Rose 2020a). Understanding the general magnitude of this kind of difference, and the degree to which it might be reduced by the hybrid approach, is an important topic for research. The relationship and gap between the two methods will be further explored in our upcoming study with ComEd. Other important questions for additional research include:

- What are the consistencies and inconsistencies among CIC surveys, CGE modeling, and the hybrid approach?
- How do electricity customers' responses to power interruptions change with duration and geographic scope?
- When is it more appropriate to use the hybrid approach than to use CIC surveys or CGE modeling alone and vice versa?
- How generalizable CIC survey data is to other service territories?
- What are the differences in procedure and results between the simplified functional form and a fully-specified CGE model?

There are also a number of closely-related issues that should be considered in parallel with a future demonstration of the proposed approach. First, regional planners may be interested in incorporating the broader costs to society of extreme weather and other events that cause

WLD power interruptions in the first place. This study only considers residential and business CICs as well as indirect costs to the local and regional economy. However, some types of catastrophes, such as hurricanes, impose broader social costs, including injuries and deaths, especially in vulnerable segments of the population. Such societal costs can be calculated separately (for example, using the FEMA Benefit-Cost Analysis Re-Engineering method; FEMA, 2009) and combined with the hybrid valuation model's customer power interruption cost estimates. It is important to note, however, that there are societal impacts associated with power interruptions, which may or may not have been precipitated by a natural disaster. Morbidity- or mortality-related benefits or the value of enhanced national security—from avoiding (mitigating) the power interruption—are not included in estimates produced as part of the method described here. For example, the extreme heatwaves in Chicago in 1995 resulted in 700 deaths, mostly to vulnerable people who did not have air conditioning or could not afford substantially increased electricity costs to cool their dwellings (Kunkel et al., 1996; Palecki, Changnon, and Kunkel, 2001).

The second category of costs that is similar to societal costs but deserve their own consideration are the monetized damages to utility and other inter-dependent infrastructure systems from disasters. WLD power interruptions often result from natural disasters, which also damage the power system and other interconnected critical infrastructure (e.g., wastewater treatment plants). For example, Superstorm Sandy caused extensive damage to power system infrastructure, including many downed overhead lines and flooded electrical substations (Hoffman and Bryan, 2013). These damages can be assessed and monetized using engineering-based, or life-cycle cost modeling approaches calibrated for electric power or other interconnected critical infrastructure (e.g., see Larsen et al., 2008 and Melvin et al., 2017). Similarly, these damage costs can be calculated separately and combined with the results of the societal cost estimation and hybrid valuation approach to enhance power system resilience.

Finally, additional research should be undertaken to explore the feasibility of coordinating surveying and regional economic modeling across the country using consistent approaches and, where applicable, consistent assumptions. Therefore, results from these coordinated studies could be used to inform resilience valuation efforts across the country under a wide range of interruption and restoration scenarios as well as system conditions.

In conclusion, we describe what information should be collected with CIC surveys and how it should be used in a CGE model. We provide both the motivation for pursuing a demonstration of the proposed hybrid approach and a roadmap outlining how such a demonstration could be conducted.

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# Appendix A. Previous studies on valuation of power disruptions in the U.S.

## *A.1. Survey studies on estimating power outage costs*

**Table A.1. Previous studies on valuation of power disruptions in the U.S. using survey-based approaches, organized chronologically.**

| Author | Types of customers studied | Outage duration | Study region | Elicitation method | Estimated cost in 2020 dollars |
|---|---|---|---|---|---|
| Burns and Gross (1990) | Residential, Commercial, Industrial, and Agricultural | Details not available | Regions served by PG&E between 1983-1989 | Direct cost estimation for commercial and industrial, WTP for residential | \$8.9/kWh (Residential), \$86.9/kWh (Commercial), \$14.8/kWh (Industrial), \$7.8/kWh (Agricultural) |
| Caves, Herriges, and Windle (1990) | Large commercial and industrial participating in interruptible/ curtailment (I/C) programs | 1 hour | Regions served by an undisclosed U.S. utility from Caves, Herriges, and Windle (1988) | Discrete choice econometric modeling using I/C program data | \$2.5-14.39/kWh (volunteer), \$1.96-5.64/kWh (non-volunteer) |
| Hartman, Doane, and Woo (1991) | Residential customers | Momentary-12 hours | Regions served by PG&E | WTP, willingness-to-accept (WTA), and choice modeling | \$13.8/hour (WTA), \$4.4/hour (WTP), \$100/hour (choice modeling) |
| Sullivan et al. (1996) | Residential, Small and Medium Commercial and Industrial (C&I), and Large C&I | Momentary-4 hours | Regions served by Duke Power Company | Direct cost estimation for commercial and industrial, WTP for residential | \$3.4-3.8/kWh (Residential), \$38.8-84.7/kWh (Commercial), \$6.7-14/kWh (Industrial) |
| Lawton et al. (2003) | Residential, Small and Medium C&I, and Large C&I | Momentary-4 hours | Northwest, Midwest, West, Southeast U.S. | Direct worth or direct cost estimation for commercial | \$2.6-3.1/kWh (Residential), \$5.7-143/kWh (Small-medium C&I), |

| | | | | | |
|---|---|---|---|---|---|
| | | | | and industrial, WTP or WTA for residential | $22.4-35.1/kWh (Large C&I) |
| Chowdhury et al. (2004) | Residential, Commercial, Industrial, and Public/Social | Momentary-8 hours | Regions served by MidAmerican Energy (Midwest U.S.) | Direct cost estimation for non-residential, WTP for residential | $0.77/kWh (Residential), $54/kWh (Commercial), $33.7/kWh (Industrial), $30.4/kWh (Public/Social) |
| Layton and Moeltner (2005) | Residential | Momentary-12 hours | Regions served by an undisclosed U.S. utility | Repeated dichotomous choice valuation | $3.26-8.46/kWh |
| Sullivan, Mercurio, and Schellenberg (2009) | Residential, Small C&I, and Medium and Large C&I | Momentary-12 hours | Northwest, Midwest, West, Southeast, Southwest U.S. | Direct cost estimation for commercial and industrial, WTP or WTA for residential | $3.1/kWh (on average, Residential), $449/kWh (on average, Small C&I), $30/kWh (on average, Medium and large C&I) |
| Sullivan et al. (2012) | Residential, Small and Medium Business, Large Business, and Agricultural | 5 minutes-24 hours | Regions served by PG&E | Direct cost estimation for business and agricultural, WTP for residential | $16.8/kWh (on average, Residential), $221/kWh (on average, Small business), $360/kWh (on average, Large business), $56.8/kWh (on average, Agricultural) |
| Sullivan and Schellenberg (2013) | Non-residential | 24 hours, 4 days, 3 weeks, and 7 weeks | Regions served by PG&E's Embarcadero substation | Direct cost estimation for commercial and industrial with multipliers | $209-418M (24 hours), $677M-$1.35B (4 days), $2.60-5.20B (3 weeks), $5.36-10.7B (7 weeks) |

| | | | | | |
|---|---|---|---|---|---|
| Sullivan, Schellenberg, and Blundell (2015) | Residential, Small and Medium C&I, and Large C&I | Momentary-24 hours | Northwest, Midwest, West, Southeast, and Southwest U.S. | Direct worth or direct cost estimation for commercial and industrial, WTP or WTA for residential | $3.3/kWh (Residential), $298/kWh (Small-medium C&I), $22/kWh (Large C&I) |
| Baik, Davis, and Morgan (2018) | Residential | 24 hours | Pittsburgh PA | WTP elicited by multiple-bounded discrete choice method with a follow-up question | $0.36/kWh (non-critical demands), $1.2/kWh (critical demands) |
| Collins et al. (2019) | Residential, Small and Medium C&I, and Large C&I | Momentary-24 hours | Regions served by SCE | Direct cost estimation for commercial and industrial, WTP for residential | $1.90-76.11/kWh (residential), $45.51-832.60/kWh (Small and medium C&I), $26.11-259.65/kWh (Large C&I) |
| Baik et al. (2020) | Residential | 240 hours | Northeastern U.S. | WTP elicited by multiple-bounded discrete choice method with a follow-up question | $1.7-2.3/kWh (critical private demands), $19-30/day (supporting their communities) |

## A.2. REM studies on estimating power outage costs

**Table A.2. Previous studies on valuation of power disruptions in the U.S. using regional economic modeling, organized chronologically.**

| Author | Types of customers studied | Outage duration | Study region | Method | Results |
|---|---|---|---|---|---|
| Rose et al. (1997) | Economy-wide | Over 15 weeks | Shelby County, TN | I-O model | Direct losses of 2.3% of baseline gross regional economic output, indirect losses of 8.6%; reduced to 0.58% with optimal restoration and allocation of power |
| Rose and Lim (2002) | Business | Up to 36 hours | Regions served by Los Angeles Department of Water and Power | I-O modeling | $9.2-227M |
| Rose, Oladosu, and Salvino (2005) | Business | Up to 96 hours | Los Angeles, CA | CGE modeling | Direct losses, without adaptive (resilience) responses: 7.1% of baseline regional output; direct & indirect losses, with adaptive responses: 1.3% reduction in regional gross output |
| Anderson et al. (2007) | Aggregated | 16-72 hours (depending on region) | Regions affected by Northeast blackout of 2003 | Macroeconomic analysis and I-O modeling | $8.2B in total ($2.6B direct loss, $5.5B indirect loss) |
| Greenberg et al. (2007) | Economy-wide | Couple days to couple months | New Jersey | Macro-econometric | "Middle" scenario—5.5% reduction in baseline electricity use, 50% restoration in one week, 100% in two weeks, one-half restoration of employment: 1.6% reduction in annual gross state product relative to baseline first year following disruption; 3.3% reduction in second year; 1.8% reduction in fifth year. |
| Rose, Oladosu, and Liao (2007) | Aggregated | 336 hours | Los Angeles CA | CGE modeling | $25.2B without any resilience adjustment, $3.5B with resilience adjustment |
| Industrial Economics (2018) | Commercial and medical facilities | 24-168 hours | Rockville Centre NY | I-O modeling | $5.5M (1 day without microgrid), $16M (3 days without microgrid), $26M (5 days without microgrid), $36M (7 days without microgrid) |

| | | | | | |
|---|---|---|---|---|---|
| Sue Wing and Rose (2020a) | Business | 336 hours (up to 2 weeks) | Bay Area CA | CGE modeling | $1.0B (without resilience strategy), $127-663M (with additional infrastructure capacity-preserving backup investment), $15-16M (with supply-preserving investment) |

# Appendix B. Technical Appendix

## B.1. Introduction

This appendix provides technical details on key aspects of incorporating a power interruption in a microeconomic framework, applicable to CGE modeling. Specifically, we show how the effects of an interruption can be represented in terms of firms' and households' optimizing behavior and their consumption of electricity and other commodities. This work builds on Rose et al. (2005), Rose and Liao (2005), Dormady et al. (2019a, 2019b), and Sue Wing and Rose (2020a, 2020b). We also provide a template for linking survey information on utility customers' costs of interruptions to parameters of CGE models for calibration.

A typical CGE model includes multiple industries, household types, and regions and represents decision making in multi-level nested structures. In the following, we use simple and non-nested representations of agents' optimizations with two inputs, electricity and a composite. Although the details would be more complex than illustrated here, our approach is, in principle, applicable to the complex and nested function forms used in computational models.

### Baselines and costs

Standard microeconomic welfare analysis using cost, expenditure, and indirect utility functions is based on marginal analysis and maintained optimal choice by agents, typically in response to changes in prices and/or income. However, the nature of power interruptions is

that they cause discrete, not marginal, changes to agents' economic environments. From a microeconomic standpoint, interruptions can be seen as resulting in an initial disequilibrium in affected economies – meaning not only temporary disjunctions between demand and supply but also possibly suboptimal behavior by agents.

In contrast, CGE models are typically calibrated on annual data so that a complete loss of power for some interval is represented as a percentage reduction in firms' and households' annual electricity use. For example, a one-week outage would constitute a 2% reduction using the simple assumption of constant daily average electricity load. It would be reasonable to consider such an impact an incremental or marginal effect.

Below we consider both interpretations, analyzing power interruptions using both an initial disequilibrium and a pre-outage baseline as starting points. In the disequilibrium case, we then assume that households and firms re-optimize following the interruption. As expected, the results – the impacts on firms and households – differ, but both are informative and can be used for calibration. At the same time, the post-disequilibrium re-optimization case may more closely correspond to the manner in which power interruptions are represented in a CGE model. For example, Sue Wing and Rose (2020a) incorporated power disruptions in a CGE model as secular shocks to technology represented as a particular capital endowment – in essence, a form of exogenous technological regress in the provision of electricity. Their analytical strategy is to solve the model twice – once in a baseline without the shock, then with the shock introduced – yielding pre- and post-shock equilibria, which are then compared.

Our analysis uses a variation on Sue Wing and Rose's technique but is more consistent with the technique used by Rose et al. (2007). We use a shock parameter to represent power disruptions, but we do not explicitly treat electricity in terms of capital endowments. In any case, because costs are necessarily relative to some initial state or baseline, the differences among the baselines described above raise the question of which cost metrics are appropriate. We use revenues and expenditures for firms because these will be concordant with the responses to survey questions. For households, we use indirect utility. As we show, however, this entails making direct and indirect utility a function of the shock parameter in addition to prices and income. Depending on one's point of view, this may complicate welfare comparisons. One could argue that with respect to the conventional definition, the exogenous parameter results in a *family* of utility functions, and, therefore, different values of the parameter define different welfare metrics. Contrarily, one could simply make what amounts to a redefinition and view the parameter as equivalent to prices or income, an input to a given utility function. One way or the other, our analysis should clarify what issues are involved in defining costs in the current context.

### *Customer surveys and partial vs. general equilibrium*

The critical difference between partial and general equilibrium microeconomic descriptions of the costs of a power interruption is the set of assumptions about which of the inputs and factors in a firm's or household's cost minimization change between the baseline and the outage scenario. In a partial equilibrium analysis, the prices of goods and services and the firm's output commodity are held fixed, and there is no exogenous change in the demand for the firm's output or the household's budget constraint. By contrast, in a general equilibrium analysis, all prices, the output demand, and the budget constraints may change.

Sue Wing and Rose (2020a) characterize CIC surveys as yielding partial equilibrium estimates. However, this is not necessarily the case: If surveys of firms include questions about, for example, supply chain interruptions and responses to price changes, and surveys of households ask about price changes as well as, for example, losses of income due indirectly to a WLD power interruption, there is no reason not to interpret the responses as reflecting general equilibrium impacts. Of course, it would be best if survey questions were specified in a manner so as to distinguish partial and general equilibrium effects.

### *Previous work*

In a CGE analysis of the impacts of the year 2001 California rolling power outages on greater Los Angeles, Rose et al. (2005) compared partial and general equilibrium effects and used adjustments to model parameters to capture adaptive responses (see below). Rose and Liao (2005) pursued this approach in a CGE study of water system disruptions in metropolitan Portland, Oregon, and presented a mathematical optimization procedure for calibrating productivity and elasticity parameters for two resilience tactics on the basis of the survey data. Dormady et al. (2019a) discussed the use of survey data to estimate businesses' costs resulting from natural disasters, and Dormady et al. (2019b) developed a detailed theoretical microeconomic framework of a firm's resilience responses following a natural disaster; this analysis is revised and extended in Dormady et al. (2020). Sue Wing and Rose (2020a) developed a simple analytical model to study the effects of a WLD power disruption caused by an earthquake in the San Francisco Bay Area, complemented by a detailed CGE analysis. They described the use of "shock" parameters affecting endowed fixed-factors representing electricity services to incorporate electricity outages into their model.

### *General approach*

In this appendix, we build on the above-described work to study the impacts of a power interruption on households as well as firms. We adopt Sue Wing and Rose's (2020b) power shock parameter to represent power interruptions. We solve our simple two-input model in closed form and provide analytical expressions for parametric resilience adjustment in the form of partial derivatives and elasticities. We present a framework for using CIC survey data to calibrate these model parameters governing adaptive responses by firms and households.

In the main text, we use an abstract cost function to summarize our approach to linking survey data and behavioral models. In this appendix, cost minimization is the behavioral model of the firm, but we instead use the production function to assess power interruption impacts; similarly, we use a utility function for the household. The reason is that we consider it more intuitive to think of a sudden power interruption as reducing levels of activity rather than as increasing costs. Among other things, from this perspective, because customers do not pay for electricity not delivered, the first effect of a power interruption might be a reduction in expenditures. However, *mutatis mutandis*, the derivations could be carried out with cost functions instead. As mentioned, the two inputs to these functions are electricity $E$ and a composite $X$.

We focus primarily on partial equilibrium analysis, analyzing the impacts of a power interruption holding prices and a household budget constraint fixed while allowing a representative firm's output – exogenously set in the baseline – to decrease. For both the firm and a representative household, we first examine the shock-induced disequilibrium state, then the agents' re-optimization with electricity in effect rationed by the interruption, and compare the two; this can be interpreted as reflecting what Rose et al. (2005) call “inherent resilience.” We then use the initial baseline instead of the disequilibrium state to calculate marginal impacts from this starting point.

### *Parameter changes and their interpretation*

We take baseline or default values of elasticities (and share parameters) as “correct,” or at least as given. As in the previous work, we use changes in productivity parameters and substitution elasticities to represent adaptive behavior by economic agents following a power supply shock.

In this simple framework, inherent resilience, as defined by Rose and Liao (2005), can be interpreted as the degree to which a firm can adapt to the power interruption by optimally substituting the composite input for electricity without any unusual actions or measures. Adaptive resilience then refers to emergency responses that the firm would only take under extreme conditions. In the current context, the assumption is that these capabilities are not captured by the standard production or utility function, and adjusting the parameters is a way of approximating emergency responses.

There are several complementary ways of interpreting these changes. On the one hand, they may approximate the use of inputs or factors not explicitly represented in the model, such as inventories or possibly a backup generation, that are used or deployed only under emergency circumstances. On the other hand, they may reflect behavioral changes that are either not represented or are only approximated in a model’s structure and baseline parameterization, such as emergency responses and other adaptive actions. These two categories are not mutually exclusive. For example, agents’ capacities to move the location or change the timing of activities (production and consumption) on time scales that are short relative to the underlying calibration (hours, days, or weeks) involve both “omitted factors” and behavioral changes that are not explicitly represented.

### *Productivity parameters and backup generation*

We interpret changes to $X$ productivity as capturing the use of, for example, inventories or household goods on hand that would enable a firm or household to offset the possible unavailability of input supplies.

Rose et al. (2005) manipulated energy productivity parameters to represent “conservation” actions by firms in response to power interruptions or extreme weather. With regard to electricity, however, it is not clear exactly what such actions might be. In particular, energy-efficiency measures such as installing efficient lighting are characteristically very time-consuming and often costly to implement and are not relevant to an emergency situation such as a power outage. If present, they would have already been implemented by the firm or household, and therefore, be reflected in the default parameterization of the production function or utility function.

One specific action firms and households might take that affects electricity consumption is to activate existing backup generation capacity. Sue Wing and Rose (2020a) incorporated backup generation as an additional factor that can be substituted for the regular power supply. Here, we take the simpler approach of representing it directly through an increase in the productivity parameter that represents both backup generation and fuel that are already purchased and installed by a firm or household. That is, the costs of both are assumed to have already been incurred. This does not allow us to assess backup generation from a direct cost-benefit standpoint. However, our framing of the problem can provide utilities and/or regulators with an estimate of the benefits of existing backup generation in a power outage by estimating the reduction in interruption costs resulting from the backup generation, relative to the case with a model's default parameterization.

### *Substitution elasticities*

In Rose et al. (2005), firms' substitution elasticities are first lowered to represent reduced the decision making capacity of a firm following the onset of a power interruption, then raised to reflect firms' adaptive resilience. By contrast, we interpret the initial disequilibrium prior to any behavioral responses to be the state in which a firm's or household's decision making is impaired, and the re-optimization, without any changes to behavioral parameters, to be the first decision making "recovery."

### *Outline*

The remainder of this technical appendix is outlined as follows:

- Section 2: Firms – partial equilibrium
  - 2.1. Cost minimization by a representative firm
    - Basic behavioral model and its solution
  - 2.2. Incorporating a power interruption and analyzing the firm's responses
    - Disequilibrium impact
    - Inherent resilience adjustment – re-optimization
    - Marginal impacts with respect to pre-shock optimum
  - 2.3. Adaptive resilience
    - Adjusting productivity parameters
    - Adjusting the substitution elasticity
- 3. Households – partial equilibrium
  - 3.1. Utility maximization by a representative household
    - Basic behavioral model and its solution

3.2. Incorporating a power interruption and analyzing household responses

- Disequilibrium impact
- Inherent resilience adjustments – re-optimization and welfare changes
- Marginal impacts with respect to pre-shock optimum

3.3. Adaptive resilience

- Adjusting the productivity parameters
- Adjusting the substitution elasticity

4. Incorporating general equilibrium effects

- Gradient of indirect utility
- Total derivative of power shock propagated through an economy

5. Calibration with survey data

- Calibration equations
- Table of calibration cases, assumptions, and metrics

## *B.2. Firms – partial equilibrium*

### *B.2.1. Cost minimization by a representative firm*

A representative firm has a constant-elasticity-of substitution (CES) production function and solves the problem

$$\begin{aligned} &\min_{X,E} p_X X + p_E E \\ &subject\ to \\ &Y_{Base} = F(X,E) = \left(\alpha(\gamma_X X)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E E)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \end{aligned} \tag{1}$$

where $< \alpha < 1, \sigma > 0, X$ and are the composite input and electricity, $p_X$, $p_E$, and $\bar{Y}$are exogenously-determined prices and the production level, respectively $\gamma_X$ and $\gamma_E$ are productivity parameters, and $Y_{Base}$ is exogenous demand for the firm's product. The first-order necessary conditions for this problem are

$$\begin{aligned} &\lambda \frac{\partial F}{\partial X} = p_X \\ &\lambda \frac{\partial F}{\partial E} = p_E \\ &\lambda\big(Y_{Base} - F(X,E)\big) = 0, \end{aligned} \tag{2}$$

where $\lambda$ is a Lagrange multiplier, and the optimal values of the inputs are

$$\begin{aligned} &X^* = \frac{\alpha^\sigma {p_X}^{-\sigma} Y_{Base}}{(\alpha^\sigma {\gamma_X}^{\sigma-1} {p_X}^{1-\sigma} + (1-\alpha)^\sigma {\gamma_E}^{\sigma-1} {p_E}^{1-\sigma})^{\frac{\sigma}{\sigma-1}}} \\ &E^* = \frac{(1-\alpha)^\sigma {\gamma_B}^{\sigma-1} {p_E}^{-\sigma} Y_{Base}}{(\alpha^\sigma {\gamma_X}^{\sigma-1} {p_X}^{1-\sigma} + (1-\alpha)^\sigma {\gamma_E}^{\sigma-1} {p_E}^{1-\sigma})^{\frac{\sigma}{\sigma-1}}}. \end{aligned} \tag{3}$$

The firm's cost function, which gives the minimum expenditure required to produce $Y_{Base}$, given the input prices and the firm's technology, is

$$\begin{aligned} & C(p_x, p_E, Y_{Base}) = p_x X^* + p_E E^* \\ & = Y_{Base}\left(\alpha^\sigma \gamma_X{}^{\sigma-1} p_X{}^{1-\sigma} + (1-\alpha)^\sigma \gamma_E{}^{\sigma-1} p_E{}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \\ & = Y_{Base} C(p_x, p_E, 1), \end{aligned} \tag{4}$$

where $C(p_X, p_E, 1)$ is the minimum unit cost function.

### *B.2.2. Incorporating a power interruption and analyzing the firm's responses*

Following Sue Wing and Rose (2020b), we incorporate power interruptions by adding a parameter to the production function as follows:

$$Y(\Phi) = F(X, E) = \left(\alpha(\gamma_X X)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi)E)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where $0 < \Phi < 1$. As can be seen from (5), $\Phi = 0$ corresponds to the standard case described above, while a value $\Phi > 0$ will cause a drop in output.

### *Disequilibrium effect of an interruption*

Suppose that a power interruption is imposed on the optimal solution in (3) as what Sue Wing and Rose call a "shock" of magnitude $\Phi_1 > 0$. Absent any other changes, including actions by the firm, output will fall to

$$Y_{Shock}(\Phi_1) = \left(\alpha(\gamma_X X^*)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E^*)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} < Y_{Base}. \tag{6}$$

This can be interpreted as a *disequilibrium* impact because the firm has not re-optimized or otherwise adjusted to the interruption other than simply reducing production. If we assume that the price of the firm's output does not change, then a measure of the firm's economic loss is the decline in its revenue $p_Y(Y_{Base} - Y_{Shock})$.

Equation (6) also enables us to see the difference between a microeconomic and what might be called an "engineering" perspective on the economic effects of power interruptions. From an engineering perspective, the interruption might be expected to cause a simple proportional reduction in output:

$$Y_{Shock,Eng.}(\Phi_1) = (1-\Phi_1)Y_{Base}. \tag{7}$$

Because $F(X, E)$ has constant returns-to-scale, (7) can be written as

$$\begin{aligned} & Y_{Shock,Eng.}(\Phi_1) = (1-\Phi_1)Y_{Base} \\ & = \left(\alpha(\gamma_X(1-\Phi_1)X^*)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E^*)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{8}$$

that is, a proportional reduction in output is equivalent to reducing both inputs. Because $F(X, E)$ is increasing or decreasing in both inputs, however, the reduction in (7) and (8) is greater than the reduction in (6), i.e.,

$$\begin{aligned} Y_{Shock,Eng.}(\Phi_1) &= \left(\alpha(\gamma_X(1-\Phi_1)X^*)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E^*)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \\ &< Y_{Diseq}(\Phi_1) \\ &= \left(\alpha(\gamma_X X^*)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E^*)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \end{aligned} \tag{9}$$

### *Inherent resilience adjustment – re-optimization*

We next suppose that the firm adjusts to the shock $\Phi_1$ by re-optimizing, specifically, changing its use of the $X$ input to produce output at the level $Y_{Shock}(\Phi_1)$ at minimum cost. Because the utility does not charge for unused electricity, the budget constraint changes in this case, and the firm solves the problem

$$\begin{aligned} &\min_X p_X X + p_E(1-\Phi_1)E^* \\ &subject\ to \\ &Y_{Shock}(\Phi_1) = F(X,(1-\Phi_1)E^*) = \left(\alpha(\gamma_X X)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E^*)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \end{aligned} \tag{10}$$

The first-order conditions for this problem are

$$\begin{aligned} &\frac{\partial F(X,E^*)}{\partial X} = p_X \\ &\lambda'\big(F(X,E^*) - Y_{Shock}(\Phi_1)\big) = 0, \end{aligned} \tag{11}$$

where $\lambda'$ is a Lagrange multiplier. The optimal value of $X$ is

$$X^*_{Opt.}(\Phi_1) = \frac{1}{\gamma_X}\left(\frac{1}{\alpha}\left(\big(Y_{Shock}(\Phi_1)\big)^{\frac{\sigma}{\sigma-1}} - (1-\alpha)(\gamma_E(1-\Phi_1)E^*)^{\frac{\sigma-1}{\sigma}}\right)\right)^{\frac{\sigma}{\sigma-1}} \tag{12}$$

From (12), we can calculate the reduction in expenditures resulting from re-optimizing – that is, how much the firm saves relative to its expenditures in the disequilibrium state:

$$\begin{aligned} &(p_X X^* + p_E E^*) - \big(p_X X^*_{Opt.}(\Phi_1) + p_E(1-\Phi_1)E^*\big) \\ &= p_X X^* - p_X X^*_{Opt.}(\Phi_1) + p_E\Phi_1 E^* \\ &= p_X\left(X^* - X^*_{Opt.}(\Phi_1)\right) + p_E\Phi_1 E^*. \end{aligned} \tag{13}$$

We can combine this with the previous value of the firm's lost revenue to obtain the firm's net loss from the shock, $p_Y(Y_{Base} - Y_{Shock}) - \left(p_X\left(X^* - X^*_{Opt.}(\Phi_1)\right) + p_E\Phi_1 E^*\right)$.

We can interpret (10) through (13) as reflecting what Dormady et al. (2019b) call "inherent resilience," which is the firm's *existing* capacity of the firm to respond to the power outage in an optimal way (i.e., prior to any adaptive responses).

### *Comparing the use of different baselines*

In the introduction to this appendix, we mentioned that the question of using different baselines against which to compare costs and the issue of exact disequilibrium vs. approximate marginal estimates of power interruption effects. We next compare the results of these two calculations.

The marginal impact of a shock on the firm's initial optimum is:

$$\frac{\partial Y(\Phi)}{\partial \Phi} = -(1-\Phi)^{\frac{-1}{\sigma}} F(X^*, (1-\Phi)E^*)^{\frac{1}{\sigma}} (1-\alpha)(\gamma_E E^*)^{\frac{\sigma-1}{\sigma}} < 0. \tag{14}$$

The usual linear approximation of the change in output, in units of output, is then

$$\Phi_1 \frac{\partial Y(\Phi)}{\partial \Phi} = -\Phi_1 (1-\Phi_1)^{\frac{-1}{\sigma}} F(X^*, (1-\Phi_1)E^*)^{\frac{1}{\sigma}} (1-\alpha)(\gamma_E E^*)^{\frac{\sigma-1}{\sigma}}, \tag{15}$$

and, recalling that baseline output $Y_{Base}$ is equal to $Y(0)$, the approximate new output is

$$Y_{Base} - \Phi_1 \frac{\partial Y(\Phi)}{\partial \Phi} = Y(0) - \Phi_1 \frac{\partial Y(\Phi)}{\partial \Phi}. \tag{16}$$

This differs from the disequilibrium value $Y_{Shock}$ because of the nonlinearity of $F$.

#### *B.2.3. Adaptive resilience*

### *Representing adaptive behavior through the productivity parameter*

As just discussed, the re-optimization solution to the firm's cost minimization problem with shock-reduced output represents the firm's "first line responses" to the outage. We therefore start with the partial equilibrium solution in (11) – (13), which reflects re-optimization. We differentiate $F(X,E)$ with respect to $\gamma_E$ at $(X^*_{Opt.}(\Phi_1), (1-\Phi_1)E^*)$, with output level $Y_{Shock}(\Phi_1)$:

$$\begin{aligned} \frac{\partial}{\partial \gamma_E} F(X,E) &= \frac{\partial}{\partial_E} \left( \alpha(\gamma_X X)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\ &= F(X,E)^{\frac{1}{\sigma}} (1-\alpha) \left((1-\Phi_1)E\right)^{\frac{\sigma-1}{\sigma}} \gamma_E^{\frac{-1}{\sigma}}. \end{aligned} \tag{17}$$

We can represent this effect in terms of elasticity of $\gamma_E$,with respect to which is the unitless percentage change in $F$ resulting from a percentage change in $\gamma_E$ and calculated as

$$\begin{aligned} \frac{\partial F(X,E)}{\partial \gamma_E} \frac{\gamma_E}{F(X,E)} &= \frac{\partial}{\partial \gamma_E} \left( \alpha X^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \frac{\gamma_E}{F(X,E)} \\ &= \frac{(1-\alpha)(\gamma_E(1-\Phi_1)E)^{\frac{\sigma-1}{\sigma}}}{F(X,E)^{\frac{\sigma-1}{\sigma}}}. \end{aligned} \tag{18}$$

Similarly, the elasticity of $F$ with respect to $\gamma_X$ is

$$\frac{\partial F(X,E)}{\partial \gamma_X}\frac{\gamma_X}{F(X,E)} = \frac{\partial}{\partial \gamma_X}\left(\alpha X^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi_1)E)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}\frac{\gamma_X}{F(X,E)}$$
$$= \frac{\alpha(\gamma_X X)^{\frac{\sigma-1}{\sigma}}}{F(X,E)^{\frac{\sigma-1}{\sigma}}}. \tag{19}$$

To calculate the impact-reducing effect of this parameter starting at the baseline solution, we instead start with the marginal impact of the power interruption given in Equation (14). Letting $\Delta\gamma_E$ be the incremental change in the productivity parameter, the corresponding differential is $\frac{\partial^2 F(X,E)}{\partial \gamma_E \partial \Phi}\Phi\Delta\gamma_E$. This gives the joint effect of the power shock and the countervailing increase in $\gamma_E$ in units of output; i.e., it measures the extent to which the adaptive measure(s) represented by the productivity parameter offsets the impact of the power shock with respect to the initial optimum. The analogous result for the composite is $\frac{\partial^2 F(X,E)}{\partial \gamma_E \partial \Phi}\Phi\Delta\gamma_E$.

### *Representing adaptive behavior through the substitution elasticity*

As we discussed, changing the elasticity parameter is another option for capturing actions and measures that a firm might take to reduce the effects of a power interruption. It can be shown that

$$\frac{\partial}{\partial \sigma}F(X,E) = \frac{1}{\sigma-1}F(X,E)\begin{pmatrix}\frac{1}{\sigma-1}\ln\left(F(X,E)^{\frac{\sigma-1}{\sigma}}\right) \\ +\frac{1}{\sigma}\frac{\alpha(\gamma_X X)^{\frac{\sigma-1}{\sigma}}\ln X + (\gamma_B(1-\Phi_1)E)^{\frac{\sigma-1}{\sigma}}\ln(\gamma_E(1-\Phi_1)E)}{F(X,E)^{\frac{\sigma-1}{\sigma}}}\end{pmatrix} \tag{20}$$

which is strictly positive unless $X = E = 1$ (in which case it is zero). The elasticity of output with respect to $\sigma$ is

$$\frac{\partial F(X,E)}{\partial \sigma}\frac{\sigma}{F(X,E)} = \frac{\sigma}{\sigma-1}\begin{pmatrix}\frac{-1}{\sigma-1}\ln\left(F(X,E)^{\frac{\sigma-1}{\sigma}}\right) \\ +\frac{1}{\sigma}\frac{\alpha X^{\frac{\sigma-1}{\sigma}}\ln(\gamma_X X) + (\gamma_E(1-\Phi_1)E)^{\frac{\sigma-1}{\sigma}}\ln(\gamma_E(1-\Phi_1)E)}{F(X,E)^{\frac{\sigma-1}{\sigma}}}\end{pmatrix} \tag{21}$$

which is also strictly positive unless $X = E = 1$.

Analogous to the case of the productivity parameter, when evaluated at the point $X^*_{Opt.}(\Phi_1), (1-\Phi_1)E^*)$, corresponding to output level $Y_{Shock}(\Phi_1)$, this quantity would measure the extent to which an increase in "flexibility" would enable the firm to partially offset the production impact of the interruption. If we instead began with the baseline solution, the differential $\frac{\partial^2 F(X,E)}{\partial \sigma \partial \Phi}\Phi\Delta\sigma$ would measure the reduction-offsetting effects of a change in the elasticity with respect to the initial optimum.

### *B.3. Households – partial equilibrium*

As with firms, we will examine a series of problems for households, first disequilibrium and then several cases of partial equilibrium with different assumptions regarding an electricity supply shock, the productivity parameter, and the substitution elasticity. For households, we will first create a notational template that contains all the parameters, in effect defining a family of optimization problems with a series of special cases.

In the current context, it was natural to define the firm's problem as cost minimization with exogenous demand. For households, we will work with utility maximization with an exogenous budget constraint.

#### *B.3.1. Utility maximization by a representative household*

Consider the parametric problem

$$\begin{aligned} &\max_{X,E} U(X,E) \\ &subject\ to \\ &U(X,E) = \left(\beta(\gamma_X X)^{\frac{\tau-1}{\tau}} + (1-\beta)\left(\gamma_E(1-\Psi)E^{\frac{\tau-1}{\tau}}\right)\right)^{\frac{\tau}{\tau-1}} \\ &p_X X + p_E(1-\Psi)^i E \leq W, \end{aligned} \tag{22}$$

where and are again a composite commodity and electricity, $W$ is the household's budget, $\gamma_X, \gamma_E \geq 1$ are productivity parameters, $\Psi$ is a power shock with $0 \leq \Psi < 1$ and $i = 0\ or\ 1$. The special cases of this problem we will discuss are:

1) $\gamma_X = \gamma_E = 1, \Psi = 0, i = 0$, defining a baseline;
2) $\gamma_X = \gamma_E = 1, \Psi > 0, i = 0$, defining a disequilibrium power interruption case without an adjustment in the budget constraint;
3) $\gamma_X = \gamma_E = 1, \Psi > 0, i = 1$, defining an equilibrium power interruption case with an adjustment in the budget constraint;
4) $\gamma_X, \gamma_E \geq 1, \Psi \geq 0, i = 1$, and either of the productivity parameters, and the substitution elasticity $\tau$, are allowed to vary.

The first-order necessary conditions for this problem are

$$\begin{aligned} &\upsilon \frac{\partial U(X,E)}{\partial X} = p_X \\ &\upsilon \frac{\partial U(X,E)}{\partial E} = p_E \\ &\upsilon\left(\overline{W} - \left(p_X X + p_E(1-\Psi_1)^i E\right)\right) \geq 0, \end{aligned} \tag{23}$$

where $\upsilon$ is a Lagrange multiplier. The optimal solutions are

$$X^*(i,\Psi,\gamma_X,\gamma_E,W)=\frac{\beta^\tau p_X{}^{-\tau}W}{\beta^\tau\gamma_X{}^{\tau-1}p_X{}^{1-\tau}+(1-\beta)^\tau\gamma_E{}^{\tau-1}(1-\Psi_1)^{\tau-1+i}p_E{}^{1-\tau}}$$
$$E^*(i,\Psi,\gamma_X,\gamma_E,W)=\frac{(1-\beta)^\tau\gamma_E{}^{\tau-1}(1-\Psi_1)^{\tau-1}p_E{}^{-\tau}W}{\beta^\tau\gamma_X{}^{\tau-1}p_X{}^{1-\tau}+(1-\beta)^\tau\gamma_E{}^{\tau-1}(1-\Psi_1)^{\tau-1+i}p_E{}^{1-\tau}}. \quad (24)$$

(In this section we omit prices from these variables because they are assumed exogenous.) Note in (24) that the exponent of the power shock term corresponds to the budget constraint as follows: When $i=0$ and the electricity expenditures are $p_E E$, the term is $(1-\Psi)^{\tau-1}$; when $i=1$ and electricity expenditures are $p_E(1-\Psi)E$, it is $(1-\Psi)^\tau$.

To represent the unit expenditure and indirect utility functions for these problems, we use the following notation. The unit expenditure function is

$$C(p_X,p_E,i,\Psi,\gamma_X,\gamma_E)=\left(\beta^\tau\gamma_X{}^{\tau-1}p_X{}^{1-\tau}+(1-\beta)^\tau(1-\Psi)^{\tau-1+i}\gamma_E{}^{\tau-1}p_E{}^{1-\tau}\right)^{\frac{1}{1-\tau}}. \quad (25)$$

Note that when $\Psi=0$, then $(1-\Psi)^{\tau-1+i}=1$ for both $i=0$ and $i=1$, i.e., $C(p_X,p_E,0{,}0,\gamma_X,\gamma_E)=V(p_X,p_E,1{,}0,\gamma_X,\gamma_E)$. The indirect utility function is

$$V(p_X,p_E,i,\Psi,\gamma_X,\gamma_E,W)=\frac{W}{C(p_X,p_E,i,\Psi,\gamma_X,\gamma_E)}. \quad (26)$$

### *B.3.2. Incorporating a power interruption and analyzing household responses*

#### *Disequilibrium effect of a power interruption*

For the next several subsections, we set $\gamma_X=\gamma_E=1$. Suppose that $U_{Base}$ is the initial utility level, and that the household is subject to a discrete power supply shock $\Psi_1>0$. As with firms, we begin by assuming that this initially results in a disequilibrium prior to the household responding, adjusting, or re-optimizing. For notational simplicity, denote the initial optimal consumption values as $X^*_{Base}$, $E^*_{Base}$. Then utility falls to

$$U_{Shock}=\left(\beta X^{*}_{Base}{}^{\frac{\tau-1}{\tau}}+(1-\beta)\left((1-\Psi_1)E^*_{Base}\right)^{\frac{\tau-1}{\tau}}\right)^{\frac{\tau}{\tau-1}}<U_{Base}. \quad (27)$$

#### *Inherent resilience adjustment – re-optimization and welfare changes*

To gauge the cost of this change, we need to monetize the difference $U_{Base}-U_{Shock}$. In standard welfare analysis, this type of calculation is done using the indirect utility and expenditure functions to determine the compensation required to restore the household to its initial utility level following, for example, a policy-induced price change in one commodity. However, that technique entails the comparison of two *optimum* – utility-maximizing – solutions, before and after the change, and here we want to compare a baseline optimum with a disequilibrium state.

We, therefore, ask a slightly different question: What is the problem for which optimal utility is $U_{Base}$, but the optimal value of electricity is $(1-\Psi_1)E^*$, the post-shock level? Note that this is not the same as the problem of re-optimizing following the power shock, in which the budget constraint changes (as we describe below). Instead, we imagine an "auxiliary" problem in which electricity services to households are reduced, but household electricity expenditures are not, and $X$ increases to compensate for the utility loss. This requires increasing the budget.

Note that this situation differs from standard welfare analysis in that prices do not change from the baseline to the post power-interruption state. Thus, conceptually, the compensating and equivalent variation metrics do not apply as such. Instead, we simply compare budgets between baseline and post-interruption, keeping the budget constraint in its initial form.

Let $W_{Base}$ be the baseline budget level. In the baseline,

$$U_{Base} = V(p_X, p_E, i, 0,1, W_{Base}) = \frac{W_{Base}}{C(p_X, p_E, i, 0,1)}. \tag{28}$$

Then the income for which optimal utility $U_{Shock}$ is defined by

$$\begin{aligned} &U_{Shock} = V(p_X, p_E, i, 0,1, W_{Shock}) = \frac{W_{Shock}}{C(p_X, p_E, i, 0,1)}, \\ &\textit{so that} \\ &W_{Shock} = U_{Shock} C(p_X, p_E, i, 0,1). \end{aligned} \tag{29}$$

Thus,

$$\begin{aligned} W_{Base} - W_{Shock} &= U_{Base} C(p_X, p_E, i, 0,1) - U_{Shock} C(p_X, p_E, i, 0,1) \\ &= (U_{Base} - U_{Shock}) C(p_X, p_E, i, 0,1). \end{aligned} \tag{30}$$

Equation (30) estimates the initial welfare cost of the interruption in terms of the baseline expenditure function.

We next consider the household's re-optimization in response to the shock. As in the case of firms, the difference between this and the disequilibrium case reflects the value of inherent resilience. What changes from the previous case is that because utility customers are not charged for electricity that is not delivered during an interruption, in the case of households the budget constraint changes form. Instead of paying $p_E E$, they now pay only for $(1 - \Psi_1)E$ so that their expenditure on electricity falls to $p_E(1 - \Psi_1)E$. Thus, the effect on utility is the "net" of the decrease caused by the drop in electricity, and the change resulting from the additional portion of the budget that can be reallocated to increasing the consumption of $X$.

We first consider the case in which the household re-optimizes without explicitly taking account of the initial level of electricity consumption $E^*$, i.e., it solves the problem

$$\begin{aligned} &\max_{X,E} \left(\beta X^{\frac{\tau-1}{\tau}} + (1-\beta)\big((1-\Psi_1)E\big)^{\frac{\tau-1}{\tau}}\right)^{\frac{\tau}{\tau-1}} \\ &\textit{subject to} \\ &p_X X + p_E(1-\Psi_1)E \leq W_{Base}. \end{aligned} \tag{31}$$

The optimal value of electricity for this problem is

$$E^*(1,\Psi,1,W_{Base}) = \frac{(1-\beta)^\tau(1-\Psi_1)^{\tau-1}{p_E}^{-\tau}W_{Base}}{\beta^\tau {p_X}^{1-\tau}+(1-\beta)^\tau(1-\Psi_1)^\tau {p_E}^{1-\tau}}. \quad (32)$$

We want to compare this value with the pre-shock optimum $E^*_{Base}$. It is straightforward to show that

$$\frac{E^*(1,\Psi,1,W_{Base})}{E^*(0,0,1,W_{Base})} = \frac{\beta^\tau {p_X}^{1-\tau}+(1-\beta)^\tau {p_E}^{1-\tau}}{(1-\Psi_1)^{1-\tau}(\beta^\tau {p_X}^{1-\tau}+(1-\beta)^\tau(1-\Psi_1)^\tau {p_E}^{1-\tau})} > 1, \quad (33)$$

where the last inequality follows from the fact that

$$\begin{gathered}\beta^\tau {p_X}^{1-\tau} + (1-\beta)^\tau(1-\Psi_1)^\tau {p_E}^{1-\tau} < \beta^\tau {p_X}^{1-\tau} + (1-\beta)^\tau {p_E}^{1-\tau} \\ and \\ (1-\Psi_1)^{1-\tau}(\beta^\tau {p_X}^{1-\tau} + (1-\beta)^\tau(1-\Psi_1)^\tau {p_E}^{1-\tau}) < \beta^\tau {p_X}^{1-\tau} + (1-\beta)^\tau(1-\Psi_1)^\tau {p_E}^{1-\tau},\end{gathered} \quad (34)$$

because $(1-\Psi_1) < 1$.That is, electricity consumption has *increased* from its baseline level. But this is inconsistent with the assumption that electricity is now rationed by the shock. We have not said anything about the restoration of the power supply.

However, these results enable us to identify the problem for which the optimal value of electricity is $(1-\Psi_1)E^*$, the post-interruption level. We do this by again finding the budget $W_{New}$ for which this holds. By (31), this is determined by

$$\begin{gathered}(1-\Psi_1)E^* = E^*(1,\Psi,1,W_{New}) = \frac{(1-\beta)^\tau\gamma^{\tau-1}(1-\Psi_1)^{\tau-1}{p_E}^{-\tau}W_{New}}{\beta^\tau {p_X}^{1-\tau}+(1-\beta)^\tau(1-\Psi_1)^\tau {p_E}^{1-\tau}}, \\ or \\ W_{New} = \frac{C(p_X,p_E,1,\Psi_1,1)^{1-\tau}}{(1-\beta)^\tau\gamma^{\tau-1}(1-\Psi_1)^{\tau-1}{p_E}^{-\tau}}(1-\Psi_1)E^*.\end{gathered} \quad (35)$$

Equation (35) estimates the welfare cost of the interruption given the household's inherent resilience in terms of the expenditure function evaluated at the post-shock level of electricity consumption. It could be compared to Equation (30) to gauge the value of inherent resilience. As we pointed out in the introduction to this appendix, however, it might be inferred that the metrics (expenditure functions) in the two cases are different.

### B.3.3. Adaptive responses

#### Representing adaptive behavior through the productivity parameter

It can be shown that the derivative of the general indirect utility function with respect to $\gamma_E$ is

$$\begin{aligned}&\frac{\partial}{\partial\gamma_E}V(p_X,p_E,1,\Psi,\gamma_X,\gamma_E,W) \\ &= -WC(p_X,p_E,1,\Psi,\gamma_X,\gamma_E)^{\tau-2}(\tau-1)(1-\beta)^\tau(1-\Psi)^\tau{\gamma_E}^{\tau-2}{p_E}^{1-\tau}\end{aligned} \quad (36)$$

which is positive if $\tau < 1$.The elasticity is

$$\begin{aligned}&\left(\frac{\partial}{\partial\gamma_E}V(p_X,p_E,1,\Psi,\gamma_X,\gamma_E,W)\right)\frac{\gamma_E}{V(p_X,p_E,1,\Psi,\gamma_X,\gamma_E,W)} \\ &= -WC(p_X,p_E,1,\Psi,\gamma_X,\gamma_E)^{\tau-1}(\tau-1)(1-\beta)^\tau(1-\Psi)^\tau{\gamma_E}^{\tau-1}{p_E}^{1-\tau}\end{aligned} \quad (37)$$

which is again positive if $\tau < 1$. As with production, evaluating this quantity at the re-optimized solution incorporating the power interruption would gauge the degree to which an increase in energy productivity could reduce the utility impacts of the interruption. And as with the case of the firm, we could also calculate the total differential $\frac{\partial^2 V}{\partial \gamma_E \partial \Psi} \Psi \Delta \gamma_E$ at the initial baseline.

### *Representing adaptive behavior through the substitution elasticity*

As with the production function, the derivative of the indirect utility function is a complex expression. It can be shown that the elasticity of indirect utility with respect to the substitution elasticity is

$$\left(\frac{\partial}{\partial \tau} V(p_X, p_E, 1, \Psi, \gamma_E, W)\right) \frac{\tau}{V(p_X, p_E, 1, \Psi, \gamma_E, W)} = \frac{-\tau}{(1-\tau)} \left( \frac{1}{(1-\tau)} \ln C^{1-\tau} + \frac{\left(\beta^\tau {p_X}^{1-\tau} \ln\left(\frac{\beta}{p_X}\right) + (1-\beta)^\tau (1-\Psi)^\tau {\gamma_E}^{\tau-1} {p_E}^{1-\tau} \ln\left(\frac{(1-\beta)(1-\Psi)\gamma_E}{p_E}\right)\right)}{C^{1-\tau}} \right). \quad (38)$$

As with the representative firm, this expression would be evaluated at the solution to the re-optimized problem, to measure the degree to which increased flexibility might reduce the initial loss of utility from the power shock. Alternatively, starting from the pre-shock baseline, the differential $\frac{\partial^2 V}{\partial \sigma \partial \Psi} \Psi \Delta \sigma$ would capture the joint effects of the shock and the increase in flexibility that could partially offset its impacts.

## *B.4. Incorporating general equilibrium effects*

In the Introduction, we stated that the difference between partial and general equilibrium effects of a power interruption has to do with what aspects of economic agents' economic environment change from the baseline, and why. In the previous section, prices were fixed, and the only exogenous change was the electricity shock; changes in a firm's production level and a household's utility resulted from their responses to the shock. By contrast, in a general equilibrium setting, prices, demand for the firm's product, and the household's budget or income level may all change.

Analyzing these effects is more complicated, but the framework we have described can, in principle, be used for that purpose. We will not go into detail, but, in essence, this entails adding cases to address these additional changes and proceeding analogously to the partial equilibrium analysis. For the household, for example, the key information would be contained in the gradient of the indirect utility function with respect to all the parameters:

$$\nabla V(p_X, p_E, 1, \Psi, \gamma_X, \gamma_E, W) = \begin{bmatrix} \partial V/\partial p_X \\ \partial V/\partial p_E \\ \partial V/\partial \Psi \\ \partial V/\partial \gamma_X \\ \partial V/\partial \gamma_E \\ \partial V/\partial W \end{bmatrix}. \tag{39}$$

The gradient of the production function would provide the information for the firm. In the case of either the productivity or elasticity parameters, calculations analogous to those presented above would incorporate changes in prices, exogenous demand for the firm's output, and the budget constraint for the household.

Sue Wing (2020) suggests a more general way of considering general equilibrium effects in the context of CGE simulations specifically. For both firms and households, a CGE model can be imagined to compute a parametric family of equilibrium as a function of the shock parameter, encompassing solutions to the optimization problems of firms and households. For firms, these solutions would take the form

$$\begin{aligned} &\min_{X(\Phi),E(\Phi)} p_X(\Phi)X(\Phi) + p_E(\Phi)E(\Phi) \\ &subject\ to \\ &Y(\Phi) = F(X(\Phi),(1-\Phi)E) = \left(\alpha\big(\gamma_X X(\Phi)\big)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\gamma_E(1-\Phi)E)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \end{aligned} \tag{40}$$

The full general equilibrium impact of the power interruption on the firm is then the derivative

$$\begin{aligned} \frac{dY(\Phi)}{d\Phi} &= \frac{\partial F(X(\Phi),(1-\Phi)E)}{\partial X(\Phi)}\frac{dX(\Phi)}{d\Phi} + \frac{\partial F(X(\Phi),(1-\Phi)E)}{\partial (1-\Phi)E}\frac{d(1-\Phi)E}{d\Phi} \\ &= \frac{\partial F(X(\Phi),(1-\Phi)E)}{\partial X(\Phi)}\frac{dX(\Phi)}{d\Phi} - \frac{\partial F(X(\Phi),(1-\Phi)E)}{\partial (1-\Phi)E}E, \end{aligned} \tag{41}$$

where the second equation in (41) follows from the fact that $\frac{d(1-\Phi)E}{d\Phi} = -E$. Equation (41) captures the full direct and indirect impacts of a power shock as its effects propagate through the simulated economy. As a thought experiment, solutions in this form could then be differentiated with respect to the parameters to measure the effects of adaptive responses taking these effects into account.

### *B.5. Calibration with survey data*

We focus here on calibration with respect to the re-optimized post-shock disequilibrium using the elasticities calculated above. This allows us to deal only with one-parameter-at-a-time adjustments. The multi-parameter calibration using the baseline solutions and/or including general equilibrium effects is technically similar but more complicated.

This requires relevant survey responses in terms of percentages. For example, to adjust the productivity parameter for the composite *X*, a firm might be asked what percentage of its output loss from the initial power shock was recovered using inventories of *X* (as in Dormady et al., 2019b, 2020). If we denote the numerical response as "Reduced % output loss using inventory," then, applying the expression for the elasticity of output with respect to the productivity parameter $\gamma_X$, the calibration calculation would be

Choose $\gamma_X$ so that

$$Reduced\ \%\ output\ loss\ using\ inventory = \frac{\partial F(X,E)}{\partial \gamma_X}\frac{\gamma_X}{F(X,E)} = \frac{\alpha(\gamma_X X)^{\frac{\sigma-1}{\sigma}}}{F(X,E)^{\frac{\sigma-1}{\sigma}}}. \quad (42)$$

As in Rose and Liao (2005), this equation would be solved numerically. Analogously, representing indirect utility simply as *V*, the calculation for the household energy productivity parameter (representing backup generation) given the corresponding survey response would be

Choose $\gamma_E$ so that

$$Reduced\ \%\ utility\ loss\ from\ using\ back-up = \frac{\partial V}{\partial \gamma_E} \quad (43)$$

$$= -WC\left(p_X, p_E, 1, \Psi, \gamma_{X,}\gamma_E\right)^{\tau-1}(\tau-1)(1-\beta)^{\tau}(1-\Psi)^{\tau}{\gamma_E}^{\tau-1}{p_E}^{1-\tau}.$$

The substitution elasticities would be calibrated analogously.

Table C.5- 1 summarizes an "experimental design" for this calibration approach. Note that the general equilibrium examples pertain to representative agent models rather than to the hypothetical CGE-based method mentioned in Section 3 of the body of this paper.

To interpret the table, it is important to take account of potential differences as well as similarities in sectoral and temporal disaggregation in CGEs compared with surveys. In the U.S., many CGEs are calibrated to IMPLAN I-O data mentioned in the main text of this report. IMPLAN sectoring is available up to more than five-hundred industries and can be downscaled to the zip code level.[17] However, these levels of detail are uncommon in energy-related CGE models. For example, Sue Wing's and Rose's California CGE model contains 46 sectors and 18 regions, with the county-level resolution in the San Francisco Bay Area (Sue Wing and Rose 2020a). While utility service territories do not necessarily exactly coincide with one or more counties, a CGE model can be structured to at least approximately correspond to them geographically and possibly provide intra-service territory detail.

[17] IMPLAN's sectoring is based on the NAICS.

With regard to sectoral detail, surveys are commonly structured in terms of small business customers, large commercial and industrial customers, and residential households. It may be possible to stratify samples in terms of NAICS codes (Sullivan et al., 2018). For households, both CGE models and interruption cost surveys can include household income as a factor.

Thus, it is possible that the categorization of industries, sectors, and households in a CGE model, and their geographic distributions, will at least approximately coincide with those in an interruption cost survey. This depends upon both how the model is structured and calibrated and how the surveys are designed and conducted.

By contrast, temporal disaggregation – how a power interruption unfolds over time – is likely to differ significantly between CGE models and surveys. CGE models are commonly calibrated to *annual* data, e.g., the California model of Sue Wing and Rose (2020a). In this case, a power interruption is represented by a proportional decrease in annual electricity services consumption. For example, a one-day interruption would be a 0.27% reduction, and a one-week interruption a 2% reduction in the region's annual electricity supply capacity. This stands in contrast to the detail on past or hypothetical interruptions that is included in surveys. This does not necessarily imply inaccuracy *per se* in a model but does indicate that accuracy depends on the metric used to estimate it. A practical criterion would be the degree to which disaggregated interruption cost effects estimated in a survey are consistent with the annual aggregate effects in a CGE. That is, whether the granularity in a survey "averages up" to the CGE annual aggregation.

For these reasons, the degree of correspondence between the categories and metrics in Table C.5-1 and those in the example survey questions in Appendix D is contingent on details of CGE structure and calibration and survey design, including stratification. In addition to those just discussed, these details include the specification of model and survey metrics, including units of measurement. Among other things, the model metrics in the table could be estimated in dollars, percentages, or both, as in the survey questions. But in either case, care would need to be taken that the variables in the metrics and those in the survey are concordant. For example, the average firm's "revenue" would need to be matched to an economic output variable in the CGE model (which is, in turn, defined in IMPLAN). Similarly, household "welfare" is not directly measured in a survey but can be approximated in terms of income. These and related issues and details would need to be addressed in implementing the hybrid approach for particular utilities and regional economies.

**Table C.5-1. Experimental design, assumptions, results, and metrics for survey-based calibration of behavioral models of households and firms**

| Assumptions and results | Input assumptions | Utility and Output assumptions | Cost/impact type | Model metrics for calibration |
|---|---|---|---|---|
| ***I. Disequilibrium*** | No changes other than electricity supply shock | Output and utility drop from baseline level | Direct | Welfare for households; Reduction in output, revenue loss relative to baseline for firms |
| ***II. Partial equilibrium*** | Prices fixed at pre-outage levels; electricity fixed at post-outage initial level | Households' utility and firms' production level only changed by power interruption and firm's own decisions | Direct | See below |
| *II.a Re-optimized, default parameters* | Composite input is optimally adjusted | Utility and production at post-shock level | Direct | Welfare loss for households; reduction in expenditures relative to disequilibrium case for firms |
| *II.b Change in productivity parameter* | Productivity parameter only is changed (composite fixed at Case II.a level) | Utility and production increase relative to case II.a. | Direct | Increase in welfare for households; output and revenue relative to case II.a (reduced impact of outage) for firms |
| *II.c Change in elasticity* | Elasticity changed; composite may change | Possible production increases relative to previous cases | Direct | Welfare and output increase and expenditure decrease relative to case II.a (reduced impact of outage) |
| ***III. General equilibrium (for individual representative household and firm/ industry)*** | All may change | May change in all cases | Direct and indirect | See below |
| *III.a General disequilibrium* | Electricity shock and possible changes to composite and to all prices | Possible change in Y due to changes in household income and inter-industry effects | Direct and indirect | Changes in welfare, output, revenue, and expenditures relative to baseline |
| *III.b Re-optimized, default parameters* | Electricity held at post-shock level; composite | May change (increase or decrease) from Case III.a | Direct and indirect | Changes in welfare, output, revenue, and expenditures relative |

| | | | | |
|---|---|---|---|---|
| | and prices may both change | | | to Case III.a (reduced impact of outage) |
| *III.c Change in productivity parameter* | Electricity at post-shock level; composite at re-optimized value | Utility and production increase | Direct and indirect | Changes in welfare and output relative to case III.b |
| *III.d Change in elasticity* | Elasticity changed; composite may change | Possible utility and production increase relative to previous cases | Direct and indirect | Possible welfare and output increase and cost and expenditure decrease relative to case III.b (reduced impact of outage) |

# Appendix C. Survey Questions to Inform the Parameterization of Regional Economic Models

## *C.1. Survey questions designed for firms*

(Questions about key suppliers and primary customers in the introductory stage before introducing power interruption scenarios)

Please indicate where your key suppliers are located.

◯ Only within *(study region)*
◯ Only outside of *(study region)*
◯ Both within and outside of *(study region)*

*[If the respondent answers "only outside of (study region)" or "both within and outside of (study region)," ask the following question]*

If your key suppliers are affected by a power interruption, would there be cascading effects on your organization? Please describe:

| |
|---|
| Please enter your answer here. Use as much space as you need: |

Please indicate where your primary customers are located.

◯ Only within *(study region)*
◯ Only outside of *(study region)*
◯ Both within and outside of *(study region)*

*[Follow-up question for all respondents]*

Would your customers be able to purchase goods or services from your organization during a power interruption?

◯ Yes ◯ No

(Question about the potential impacts of supplier disruption for each scenario)
Would the power interruption affect your key supplier?

◯ Yes ◯ No

*[If the respondent answers "yes," ask the following question]*
Please estimate the expected impacts on your operations due to the supply chain disruption.
________ % operation disruption due to the supplier disruption for the next ________ hours

(Gradual adaptive resilience question for each scenario- Customer demands).
Would the power interruption affect the demand for goods or services your business provides?

◯ There will be an increase in demand
◯ There will be a decrease in demand
◯ There will be no change in demand

*[If the respondent answers "there will be an increase in demand," ask the following question]*
Please estimate the expected demand increases during the interruption (in terms of revenue).
________ % demand increases

*[If the respondent answers "there will be a decrease in demand," ask the following question]*
Please estimate the expected demand losses during the interruption (in terms of revenue).
________ % demand losses

(Question before asking any type of resilience questions)

Assume that there are no strategies that you could adopt to adapt to the power interruption, including using the backup generator that you have, using inventories of final products to buffer against disruptions, or making up lost production or services after the power interruption. In that case, how much revenue would your organization lose due to the power interruption?

$ ___________ lost revenue from the power interruption

(Inherent/Immediate adaptive resilience question).
What strategies might your organization immediately adopt to adjust to the (duration) power interruption? Please select all that applies.

☐ Resume operations that require no electricity
☐ Resume (partial) operations by relying on backup power
☐ Replace inputs in short supply with other inputs that use no electricity
☐ Shut down all operations because there is no available power
☐ Use its inventories of raw materials or final products to buffer against disruptions
☐ Other

*[If the respondent selects "reduce non-essential use of electricity or switch to less electricity-intensive production process," "resume operations that require no electricity," "resume (partial) operations by relying on backup power," or "use inventories to buffer against disruptions," ask the following questions for each of the option]*

Approximately what percent of the normal operations could you sustain for how long?

________ % of the normal operation for ________ hours/days

What inputs do you need to implement the strategy? And what would it cost?

Capital/Money: $______________________________________________

Materials: ______________________________________________

Machinery/equipment, office/buildings: ______________________________

Labor hours: ______________________________________________

What portion of the lost revenue can be restored by implementing the strategy(ies)?

________ % of the expected lost revenue

*[If the respondent answers "other," ask the following questions]*
Please describe what would happen to your business, including what strategies you would implement?

| |
|---|
| Please enter your answer here. Use as much space as you need: |

Approximately what percent of the operations could you sustain for how long?

________ % of the normal operation for ________ hours/days

What inputs do you need to implement the strategy? And what would it cost?

Capital/Money: $______________________________________________

Materials: ______________________________________________

Machinery/equipment, office/buildings: ______________________________

Labor hours: ______________________________________________

What portion of the lost revenue can be restored by implementing the strategy(ies)?

________ % of the expected lost revenue

(Gradual Adaptive Resilience Question).

Because the power interruption is expected to take a longer time to restore power, there are several additional strategies that your business could adopt and further reduce the impacts. Please select all that applies to your organization:

☐ Replace inputs in short supply with other inputs that use no electricity
☐ Purchase raw materials from other suppliers who are not affected by the interruption
☐ Transfer operations and/or employees to other locations
☐ Physically relocate equipment and/or infrastructure temporarily or permanently
☐ Other
☐ None of the above

*[If the respondent selects "replace inputs in short with other inputs that use no electricity," "purchase raw materials from other suppliers who are not affected by the interruption," "transfer operations and/or employees to other locations," or "physically relocate equipment and/or infrastructure," ask the following questions for each of the option]*

Approximately what percent of the normal operations can you sustain for how long?

________ % of the normal operation for ________ hours/days

What inputs do you need to implement the strategy? And what would it cost?

Capital/Money: $________________________________________________

Materials: ________________________________________________

Machinery/equipment, office/buildings: ________________________________________________

Labor hours: ________________________________________________

What portion of the lost revenue can be restored by implementing the strategy(ies)?

________ % of the expected lost revenue

*[If the respondent answers "other," ask the following questions]*

Please describe what would happen to your business. What kinds of strategies would you take?

| Please enter your answer here. Use as much space as you need: |
| --- |

Approximately what percent of the normal operations can you sustain for how long?

________ % of the normal operation for ________ hours/days

What inputs do you need to implement the strategy? And what would it cost?

Capital/Money: $________________________________________________

Materials: ________________________________________________

Machinery/equipment, office/buildings: ________________________________________________

Labor hours: ________________________________________________

What portion of the lost revenue can be restored by implementing the strategy(ies)?

________ % of the expected lost revenue

## *C.2. Survey questions designed for households*

(Questions about residential customers' adaptive behavior)
Power interruptions of a larger geographic extent and longer duration would cause you, your family, and everyone else in the affected areas many problems and have high costs. Considering what was described, please select all the strategies that you would implement to adapt to the (duration) power interruption. You should assume that you cannot purchase a backup generator and additional fuel from stores if you do not have stored some already.

☐ Stay home and do activities that do not require electricity
☐ Run your own backup generator using the fuel you have stored and sustain critical operations
☐ Use a propane/gas/wood-fired heater/stove or outdoor grill for cooking or heating
☐ Rely on non-perishable food and bottled water that you have stored
☐ Temporarily move to other places with backup power, including other homes or emergency shelters
☐ Other

*[If respondent selects "do activities that do not require electricity," "run backup generator," or "use stove, heater or grill," ask the following question]*
What fraction of normal activities could you sustain? For how long?

________ % of normal activities for________ days

*[If respondent selects "Other," ask the following question]*
Please describe what strategies you will implement. What fraction of normal activities could you sustain? For how long?

| |
|---|
| Please enter your answer here. Use as much space as you need: |

(Questions about residential customers' potential income losses).
If the power goes out for two days, will your employer pay you?
◯ I am not currently employed
◯ My work would not be affected by this power interruption
◯ I could not go to work but would not lose any pay
◯ I could not go to work but could make up the time later and get paid
◯ I could not go to work and would not get paid

*[If the respondent answers "I could not go to work and would not get paid," ask the following question]*
How much wages would you expect to lose during the power interruption?
I would lose ___________ days of payment

If the power goes out for two days, will your household members' employers pay them? Please select all that applies.
☐ I live alone, or I am the only person earning for my household
☐ Their work would not be affected by this power interruption
☐ They could not go to work but would not lose any pay
☐ They could not go to work but could make up the time later and get paid
☐ They could not go to work and would not get paid

*[If the respondent answers "They could not go to work and would not get paid," ask the following question]*
How much wages would you expect for them to lose during the power interruption?
They would lose ___________ days of payment

### *C.3. Survey questions designed for ancillary information*

(Question about previous WLD power interruption experience).
Has your organization ever experienced an outage lasting longer than 24 hours at this location?

◯ Yes ◯ No

*[If the respondent answers "yes," ask the following questions]*
How long did the interruption last? When did it occur? What caused the power interruption?

| |
|---|
| Please enter your answer here. Use as much space as you need: |

What did your organization do to manage the impacts of the power outage? Select all that apply.

- ☐ Closed the facility until power was restored
- ☐ Sent employees home
- ☐ Moved production to facilities not affected by the outage
- ☐ Run a backup power generator
- ☐ Turned off or disconnected equipment
- ☐ Took actions to preserve perishable inventory
- ☐ Had employees work from homes
- ☐ Other

*[If respondent selects "Other," ask the following question]*
Please describe.

| |
|---|
| Please enter your answer here. Use as much space as you need: |

What was the cost of implementing the tactics? What were the benefits to your organization in terms of the prevention of business interruption (lost revenues or profits)?

| |
|---|
| Please enter your answer here. Use as much space as you need: |

(Questions about future WLD power interruptions).

What, if any, consequences would your organization experience if you lost power for two to 14 days?

If power were disrupted for two days:

| |
|---|
| Please enter your answer here. Use as much space as you need: |

If power were disrupted for one week:

| |
|---|
| Please enter your answer here. Use as much space as you need: |

If power were disrupted for longer than one week:

| |
|---|
| Please enter your answer here. Use as much space as you need: |

(Question about plans for mitigating the impacts of WLD power interruptions)

Does your organization have a plan for what to do during a long duration power interruption (i.e., an interruption lasting from several days to several weeks)?

◯ Yes ◯ No

*[If the respondent answers "yes," ask the following question]*

Please describe the plan in a brief sentence or two:

| |
|---|
| Please enter your answer here. Use as much space as you need: |

Did you make any changes in your facility or operating procedures as a result of lessons learned from this outage?

◯ Yes ◯ No ◯ Don't know

*[If the respondent answers "yes," ask the following question]*

Please describe those changes in a brief sentence or two:

| |
|---|
| Please enter your answer here. Use as much space as you need: |

(Question related to electricity customers' backup generation and other inherent resilience tactics).
Does your organization have some form of emergency backup electric power (for example, a generator powered by natural gas, diesel, or gasoline?

◯ Yes ◯ No ◯ Don't know

*[If the respondent answers "yes," ask the following questions]*

What is the fuel source for the generation equipment?

◯ Diesel or gasoline
◯ Natural or propane gas
◯ Other: _______________________________________________________

How long can the backup generation equipment operate with the fuel available on site?

_____________ hours

Does your organization perform any processes using electricity that can utilize an alternative fuel source during an outage (for example, using natural gas instead of electricity for a manufacturing process)?

◯ Yes ◯ No ◯ Don't know

*[If the respondent answers "yes," ask the following questions]*

What percent of your daily electricity consumption can you replace with another fuel?

_____________ % of the daily electricity consumption

Apart from emergency backup generation, does your firm generate any of its own electricity (for example, a solar power system or gas turbine supplying power to your facility)?

◯ Yes ◯ No ◯ Don't know

*[If the respondent answers "yes," ask the following questions]*

What percent of your daily electricity consumption is supplied by your own generation equipment?

_____________ % of the daily electricity consumption

What percentage of your organization can function without electricity from the utility?

_____________ % of the normal operation