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Measuring the Value of Electric System Resiliency: A Review of Outage Cost Surveys and Natural Disaster Impact Study Methods

3002009670

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Technical Update, August 2017

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Cornell University, Dyson School of Applied Economics and Management

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ACKNOWLEDGMENTS

The following organization, under contract to the Electric Power Research Institute (EPRI), prepared this report:

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This report describes research sponsored by EPRI.

This publication is a corporate document that should be cited in the literature in the following manner:

Measuring the Value of Electric System Resiliency: A Review of Outage Cost Surveys and Natural Disaster Impact Study Methods. EPRI, Palo Alto, CA: 2017. 3002009670.

ABSTRACT

In response to heightened public interest due to recent electric outages lasting several days and affecting large geographic areas and populations, the Electric Power Research Institute (EPRI) embarked on research to determine how the adverse effects of such events can be minimized. EPRI seeks to develop a framework for evaluating the physical and financial consequences of extended outages to determine how customers value resiliency generally, and to monetize the resiliency value of micro-grid applications specifically.

A review of the literature on how the electric and other service industries, insurers, and emergency services agencies monetize service resiliency provides the means for comparing alternative ways to estimate the value of electric service resiliency. The review revealed how conventional valuation methods (the cost of an outage) can be adapted to fit the different circumstances of resiliency. Specifically, on characterizing the outcomes of high-consequence, low-probability events, such as damage from serious riverine flooding, coastal flooding and wind damage accompanying hurricanes, ice storms, and malevolent attacks.

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

The report also examines macroeconomic impact modeling as a means for estimating the direct (corresponding to outage cost) and indirect costs (additional, cascading costs that result) of electric service interruptions from extreme events. This approach has appeal because it is consistent with the nature of severe events, the impacts are extensive and of long duration, and effect not just those directly impacted. But, those results come at the expense of extensive modeling requirements that are very region specific. The considerable developmental research required regardless of the approach undertaken is conducive to industry-wide collaboration.

Keywords
Resiliency
Discrete choice experiments (DCE)
Critical infrastructure

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1 INTRODUCTION

In response to recent catastrophic natural disasters such as "Superstorm Sandy" and the heightened terrorist and other man-made threats to our energy infrastructure, President Obama underscored the urgent need to strengthen and broaden our efforts to improve the resilience of our critical infrastructure through Presidential Policy Directive 21 (PPD-21) *Critical Infrastructure Security and Resilience* (Watson, *et al*. 2014). Others have also recognized the need for increased resilience at an even a broader scale—at the community, state, and national levels.

At the request of the Federal government, including eight Federal agencies and one community resilience group affiliated with a National Laboratory, The National Research Council launched a study to address the broad issue of increasing the Nation's resilience to disasters (the National Academies, 2012). In addition to this call for expanded efforts to increase resilience on a broad scale, there have been several more focused efforts to develop risk-based frameworks to facilitate the measurement of increased energy resilience. Electricity sector resiliency emphasis is on the development of analytic methodologies to inform policy decisions regarding electric system infrastructure planning, investment, and operations.[1]

In response to this heightened public interest, due to the recent electric outages lasting several days and affecting large geographic areas and populations, EPRI has embarked on efforts to determine how the adverse effects of such events can be minimized. Researchers in EPRI's Energy and Environmental Analysis Group are assessing the policy and research landscape from the perspective of climate change (Diaz, 2016). Their counterparts in EPRI's Power Delivery and Utilization Division are developing ways to harden the electric system to withstand better these events.

Part of this latter research is to examine local and customized ways to stay electrified when the electric system is forced out of service. Micro-grids, as they are called, are collections of customers that arrange to be isolated for the gird through an interconnected, self-sustaining electric system a grid that can provide some or all constituents' power requirements when the grid is out of service (e.g. Paaso and Pierce, 2015). While there are other benefits to such an arrangement, for example taking advantage of constituents' ability to generate power for renewables cheaper that what grid supply costs, the resiliency (and reliability) benefits are likely the largest source of benefit, C can they be monetized sufficiently to justify the expenditure?

To accomplish these objectives, EPRI seeks to develop a framework for evaluating the physical and financial consequences of extended outages to determine how customers value resiliency generally, and to monetize the resiliency value attributable to micro-grid applications. This framework must be risk based and be consistent with a generally applicable definition of

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

resilience. The framework should include several metrics and "…procedures for analyzing, quantifying, and planning for resilience of energy infrastructure systems" (Watson, *et al*. 2014, p. 11). It is within this framework that one can measure the effectiveness and performance of investments designed to improve infrastructure resilience. It also indicates how the benefits of such investments in resilient electric infrastructure can be compared with its costs.[2]

There are a number of physical components needed in any evaluation of a micro-grid, or other investments in resilient infrastructure, that define the source of the benefits and costs. In this study, we examine one of the major benefits of such investments: the "…increased supply security and resiliency against the more adverse power outage conditions" (SOW, p. 2). To monetize this important benefit of resiliency, one must establish the value to customers of a more resilient electric system. After all, they are the beneficiaries, and they likely will pay for measures undertaken to improve resiliency.

Conventional studies of the value of electric service have sought to assign monetary values to reliability, where reliability is defined for relatively localized and short power outages that by practice specifically exclude extreme events, ranging from momentary outages to those lasting a few hours.[3] To value resiliency over extended spatial and temporal dimensions, we must first identify the costs customers might incur during such outages and understand how customers and businesses might adjust and accommodate to extended outages lasting several days, or even longer. Conventional outage cost valuation methods seldom make such distinctions. It is important for determining utility resiliency investments because there are preventive and remedial actions customers can take themselves to realize private benefits (limit the adverse outcomes of an extended grid outages).

These are alternatives to investment to hardening to the local or regional grid realize which produces widely shared public benefits, which renders them a public good whose cost is socialized. To justify such an expenditure, policy makers must be able to show that the benefit exceed the costs, to monetize reliance. This report seeks to contribute to such deliberations by examining methods for monetizing electric grid expenditure that improve resiliency, and may collaterally improve reliability. [4]

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[2] Watson, *et al*. (2014) develop one such framework; they provide "…use cases regarding electricity, petroleum, and natural gas to provide tangible examples of how these resilience metrics can be put into practical use" (p. 11).

[3] Utilities' track reliability as event that are 5 minutes or longer but are not associated with what is considered a major event, which is defined differently across the country based on exposure.

[4] At the time of publication of this report, a study was released with a strikingly similar intent, employing a comparative modeling framework, as is done here, and reaching many of the same conclusions (Stanstad, A. February 2016. Regional Economic Modeling of Electric Supply Disruptions: A Review and Recommendations for Research. Lawrence Berkeley National Lab. Unfortunately, the opportunity to collaborate did not arise, but that two studies independently undertake concur to such a degree seem to validate the findings as relevant.

2
SCOPE AND FOCUS OF THE STUDY

The purpose of this study is to: "Identify a method or methods for quantifying and monetizing how customers and businesses value electric service resiliency" (SOW, p. 2). We begin with a review of the literature on how the electric service industry, as well as other utility service industries (water, natural gas, etc.), federal, state and private insurances, and emergency services agencies (fire and ambulance service, hospitals, etc.), monetize service resiliency. Through this review, we seek to identify which, if any, of these methods can be adapted to the electricity sector, or explain why methods must be developed specifically to fit the circumstance of electricity supply resiliency, outages that last for extended periods and effect large areas.

We do this analysis within the context of a conceptual framework for developing metrics of resilience for electricity in other energy sectors (e.g. Watson *et al*., 2014). Consistent with this framework, Watson, *et al*. (2014) adopt the following working definition of resiliency:

> "…the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents." (PPD-21, 2013).[5]

Watson, *et al*. (2014, p. 33) go on to define a resilience metric framework as the probability of consequence X given threat Y. The framework does not specify the specific threat or consequence, and therefore, it can be applied broadly. For immediate purposes, however, these authors focus on high-consequence, low-probability events, such as damage from serious riverine flooding, coastal flooding and wind damage accompanying hurricanes, ice storms, and malevolent attacks. They suggest that resilience metrics should: 1) be useful; 2) provide a mechanism for comparison; 3) be useable in operations and planning contexts; exhibit extensibility; 4) be quantitative; and 5) reflect uncertainty. The Seven Steps of their Resilience Analysis Process (RAP) are to:

1. Define Resilience Goals;
2. Define System and Resilience Metrics;

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[5] In a recent study by the National Academy of Sciences (The National Academies Committee on Increasing National Resilience to Hazards and Disasters; Committee on Science, Engineering, and Public Policy, 2012), the authors begin their summary remarks by emphasizing that:

- No person or place is immune from disasters or disaster-related losses. Infectious disease outbreaks, acts of terrorism, social unrest, or financial disasters in addition to natural hazards can all lead to large-scale consequences for the nation and its communities. Communities and the nation thus face difficult fiscal, social, cultural, and environmental choices about the best ways to ensure basic security and quality of life against hazards, deliberate attacks, and disasters (p. 1).

And they go on to argue that:

- One way to reduce the impacts of disasters on the nation and its communities is to invest in enhancing resilience. Resilience is *the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events.* Enhanced resilience allows better anticipation of disasters and better planning to reduce disaster losses—rather than waiting for an event to occur and paying for it afterward (p. 1).

3. Characterize Threats;
4. Determine Level of Disruption;
5. Define and Apply System Models;
6. Calculate Consequences; and
7. Evaluate Resilience Improvements.

This seems a logical place to begin an investigation of resiliency consequences because the costs and benefits of resilient investments in the electric system are certainly important and quantifiable metrics in such a framework. The importance of establishing the value of electric service resiliency is underscored further in EPRI's 2016 white paper, "Electric Power System Resiliency: Challenges and Opportunities".[6] These values are needed to guide utility expenditures on grid hardening and to justify the micro-grid investments from a public service perspective, as well as inform private investment decisions by businesses and residents to protect themselves against the consequences of a severe electric outage.

A review of methods reveals that the vast majority of the available body of studies to quantify outage cost focused on estimating the value of electricity service reliability employing a microeconomic approach. Outage costs are based on costs for outages, elicited directly from customers, of different character (estimated or realized) or that are based on estimates of willingness to pay/accept outages, also elicited directly from customers. The customers that provide data are generally representative of the service territory the sponsoring utility serves. The distinction of importance is that primary data gathered from customers provide the foundation for modeling the value of service, and hence outage cost.

In the body of available applications, reliability relates to those service interruptions, with which most customer have experienced, are momentary or are for just a few hours. That approach lends credibility to monetary estimates of the cost incurred during such an event and makes willingness to pay estimates by residential customers a candidate measure of outage cost. There is no experience (we discovered) using the microeconomic approach to measure the costs resiliency of the electric power system to high-impact, low-probability events associated with extreme weather events, natural disasters. Implementing an outage cost study just after a widespread outage might shed light on the value of electric service, or simply reflect pent up frustration from going without electricity, not what they would be willing to pay to avoid such an outcome in the future.[7]

The costs of electric service interruptions have been estimated through macroeconomic impact modeling of extreme events such as earthquakes, floods, and total blackouts that might be attributed to massive system failure or terrorist activity. Here, a model of the economy of interest (which might comport with a utility's service territory) is constructed to reflect equilibrium conditions (business as usual). It then is shocked by imposing physical, market, and consumer

[6] EPRI. 2016. "Electric Power System Resiliency: Challenges and Opportunities." Palo Alto, CA. http://www.epri.com/Pages/Power-System-Transformation-White-Papers.aspx.

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

disruptions that could be attributed to a catastrophic event. The difference in the level of economic output (gross product, wages, and profits) before and during the event defines the extent of the outage cost imposed, and presumptively what society would pay to avoid that outcome. The attraction of this approach is that costs are viewed in terms of their collective level, and therefore may be less prone to bias in values elicited from a few individuals.

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

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

Most outage cost studies have employed the microeconomic method. They were designed to estimate the value of electric service reliability based on survey data collected from random samples of business owners and residential customers. Typically, business owners are asked to provide estimates of the direct costs of an outage, defined as the value of lost production plus other outage related costs, less any outage related savings. Through a series of contingent valuation questions, residential customers review estimates of their willingness to pay/accept for electricity outages.[8] In these studies, separate outage cost estimates for both business owners and residential customers are derived from statistical analysis of these survey data. These estimates may differ by business type and by residential customer demographics.

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

[8] WTP and WTA accept are alternative way to measure utility derive from different assumption about underlying nature of demand, and hence seldom produce the same nominal result.

elicited reflect what they would do if confronted with such events, and they had the opportunity to avoid their adverse impacts (WTP)?

To assess the usefulness of these methods in estimating the value of electricity outages for extreme events, in particular to establish the resiliency value of a micro-grid, several important questions must be asked and answered:

- Are these methods more appropriate for estimating values for outages due to an isolated failure in the electrical system or a targeted terrorist attack, than an outage accompanying a catastrophic natural disaster?
- In response to survey questions, can business owners and residential customers account for the consequences of more widespread damage if the outage is due to a natural disaster?
- Can these methods be used to value outage costs when the outages last several days or even weeks?
- Are the results from individual studies (e.g., for a single utility) applicable to different regions or micro-grids simply by summing the individual values based on differences in the characteristics of the mix of business and differences in the population demographics?
- Do these values underestimate the true outages costs of a natural disaster when other key serve lifelines into and out of a micro-grid have also suffered damage, or input and output supply chains have been interrupted?

To compare outage cost (microeconomic), macroeconomic, and insurance data methods for monetizing damages, we begin by defining a customer damage function (CDFs) that serves to convert outage cost data into a consolidated estimate of damage for specified set of circumstances. They can be categorized as follows:

- Microeconomic methods
  - Surveys of businesses
  - Surveys of residential customers
  - Discrete Choice Experiments (DCE
- Macroeconomic methods
  - Estimation of change in economic activity following specific events
  - Change in insurance premiums

These are described in detail, comparing and contrasting methods, outputs and performance (valuation) metrics. We review survey methods used to generate the outage data based on eliciting consumers' estimates of willingness to pay/accept. We contrast that approach with generating data for the CDFs using discrete choice experiments.[9] Both are employed to elicit

[9] Outage costs have also been estimated through indirect methods, for example, substituting other known, or in some cases estimated, indices for the value of electricity. Simple proxies such as electric utility rates have been used in the past to represent the value of service reliability, and so have estimates of foregone leisure time based on wage rates, under the assumption that customers make optimal tradeoff decisions between leisure and labor activities. While these methods are easy to apply, they are not generally applicable in a broad set of circumstances.

Also, after-the-fact assessments of actual outage events have provided estimates of the value of electricity supply, such as the survey conducted to assess the direct and indirect economic costs of the Great New York Blackout of data directly from customers to estimate the damage function's parameters, a bottom-up approach, and what distinguishes them?

We then proceed to examine natural hazards assessment methods employing structural characterizations of the economy, a top-down approach where damage is derived from a structural representation of the economy and how it is affected by a catastrophe. Finally, we look at the application of insurance premiums to estimate resiliency value. We close by comparing and contrasting these approaches against what the utility sector requires to estimate the value of improved resiliency.

1997. Customers were asked about their experiences to obtain direct accounts of losses attributed to the blackout, and thus to estimates of the value of reliability based upon actual customer experience. These are perhaps the most situationally realistic outage cost data available. But such events are rare, and the expense of generating data sets of sufficient size for such analyses may be prohibitive ("Outage Costs Research Paper," May 2015 unpublished draft anon). While this review does not focus on these methods, there may be instances where these methods complement other approaches to estimating outage costs.

3
MICROECONOMIC, SURVEY-BASED OUTAGE COST STUDIES

Survey-based methods are the most popular and widely used way to estimate customers' electricity outage costs. Their prominence derives in part from their building up electric service valuation (or its antithesis, outage-induced damage cost) from what customers express as the cost they would incur under stipulated conditions. Before discussing the various statistical methods available to elicit individual's customer outage costs, it is useful to derive the concept of a comprehensive customer damage function.

Deriving Customer Damage Functions

One would expect that estimates of outage costs would differ depending the character of service interruptions; frequency (how often), amount of advance notice provided, and its duration (how long it lasts). For residential customers, outage cost is expected to differ by customer characteristic and demographics. An outage at a residential premises where nobody is at home has less impact than one where several people are at home during the outage. If one of those at home depends on electricity for a critical heath service, then the outage cost may be even higher.

Outage costs may differ across commercial and industrial customers, depending on the type of business they conduct, the physical plant they operate from, how it operates, the corporate structure they operate under, and are there other facilities that can serve demand during an outage? The last factor may be important as it determines of output is lost or just more expensive to maintain.

Therefore, to use these data for utility investment decision making and to understand regulatory policy implications, and importantly to compare the (mean) cost of an outage across customer classes, outage cost is normalized (to \$/kW or \$/kWh) and aggregated by customer type into a customer damage function (CDF). The normalization is typically based on annual electricity usage or peak demand of the population studied.

The Value of Energy Supplied

Let us denote the expected frequency (f_i), magnitude, (m_i) and duration (d_i) of outage event i, for $i = 1 \ldots I$. Then we can denote the estimated outage cost of an outage event of duration d_i (for a given f_i and m_i) for customer j by $c_j(d_i)$, for $j = 1 \ldots J$. By aggregating, (averaging) these individual outage cost estimates we can derive an appropriate system level CDF (based on a normalization by kW or kWh) as:

$$C(d_i) = \left[\sum_{j=1}^{J} c_j(d_i)\right]/J \qquad \textbf{Eq. 3-1}$$

The estimate of total cost for a given contingency can be calculated as:

$$COST_i = m_i f_i C(d_i) \qquad \textbf{Eq. 3-2}$$

We can then develop $COST_i$ estimates over all expected duration events (I) as expected cost as follows:[10]

$$ECOST = = \sum_{i=1}^{I} COST_i = \sum_{i=1}^{I} m_i f_i C(d_i) = \left\{\sum_{i=1}^{I} m_i f_i \left[\sum_{j=1}^{J} c_j(d_i)\right]/J\right\} \qquad \textbf{Eq. 3-3}$$

where,$0 \leq f_i \leq 1;\ \sum_{i=1}^{I} f_i = 1$.

To use this function to estimate outage costs the functional parameters must be quantified.

The Value of Un-Served Energy

The value of electricity can also be expressed as the value of energy not supplied (unserved) due to an interruption in service. There are two separate representations of this method for placing a value on unserved energy, and both can be calculated from the CDFs derived above.

The first representation is the Interrupted Energy Assessment Rate (IAER), defined as:

$$IEAR = \frac{\sum_{i=1}^{I} m_i f_i C(d_i)}{m_i f_i d_i} \qquad \textbf{Eq. 3-4}$$

The second representation is the Value of Lost Load (VoLL), defined as;

$$VoLL = \frac{C(d_i)}{d_i \times LF_i}, \qquad \textbf{Eq. 3-5}$$

Where: LF_i is defined as the load factor for customer group i, and all other variables are as defined above.

As specified here, it is important to be reminded that both IEAR, and VoLL are based on the costs related to the duration of a service interruption, as indicted by customers, and not on the amount of energy that went unserved. The two quantities may not be directly related, so IEAR and VoLL are at best proxies for the value customers place on supply.

The Outage-Cost Survey Methodology for CDF Estimation

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

To be one of the essential, quantifiable metrics needed to operationalize a resilience metric framework such as the one outlined above by Watson, *et al*. (2014, p. 33), resiliency outage costs must also be applicable to outages of substantial duration, several days or weeks. If survey methods, can be designed to value outages of these durations, the CDFs would be important components of the final two steps of the framework's seven step Resilience Analysis Process

[10] For simplicity, we have assumed that outage estimates for customers depend only on magnitude, frequency, and duration. However, costs may also vary due to business type (e.g. SIC, business size, etc.) consumer demographics, time of day, time of year, etc. These additional factors could be easily incorporated into the definitions in equations (1) through (3) simply by adding additional subscripts to the variables. As is seen below, the survey instruments designed to elicit customer outage costs often collect the data to allow for outage costs to differ according to these additional characteristics as well.

(RAP), calculating consequences and evaluating resilience improvements. To the extent that particular resilient investment in the electric system reduces the expected frequency, magnitude and/or duration of outages, or the numbers of customers affected by the outages, the information embodied in appropriately constructed outage cost estimate would constitute much of the benefit side of such investments.

The issue is: can customers associate an outage cost, either by assigning a WTP to avoid it or constructing a monetary damage cost estimate from their reckoning of the business and operation impacts, if they never have encountered such an event? Can they place themselves is such a hypothetical situation and provide cost data that are reliable?

The purpose of outage cost surveys is to elicit from customers data to quantify this important metric. As defined above, this means obtaining estimates of the outage costs for outage events of expected frequency (f_i), magnitude, (m_i) and duration d_i that is representative of customers j, denoted by $c_j(d_i)$, for $j = 1\ldots J$. To do this, surveys typically are administered by some means to a random sample of commercial, industrial, and residential customers, where the sample is representative of the different types of commercial and industrial customers, and demographics of residential customers. Convention is to sort customers by these very general distinctions and not impose other differentiating segments, although some studies of commercial and industrial customers distinguish customer by their economic activity (for example by NAICS category). The result is the estimates of outage cost come with a very high variance, indicating structural differences that are not account for.

According to the 2003 study by Gyuk, *et al*. (2003), there were numerous efforts dating back at least to the 1980s to "…quantify the value of [electric system] reliability as a basis for both public policy and private investment and operating decisions regarding generation, transmission, distribution and retail offerings" (p. 3). As outlined above, the value of service reliability in these studies has been equated to the economic loss customers would incur if a specified outage event were to occur, as described by the Customer Damage Function (CDF). From an empirical perspective, the CDF might be written in its most general form as (Gyuk, *et al*., 2003, p. 1):

$$Loss = f[outage\ attributes, customer\ characteistics, geographical\ attributes] \quad \textbf{Eq. 3-6}$$

That is, Direct Cost = Value of Lost Production + Outage Related Costs – Outage Related Savings). See Table 3-1.

Table 3-1
Example of Direct Outage Cost Measurement for Non-Residential Customers

At a most general level the direct cost of an outage is given by:

Direct Cost = Value of Lost Production + Outage Related Costs – Outage Related Savings

The *Value of Lost Production* is the revenue the business would have generated in the absence of the outage minus the revenue it generated given the outage. It is their net loss in the economic value of production after their ability to make up for lost production has been taken into account. It includes the entire cost of making or selling the product as well as any profit that could have been made on the production.

Outage Related Costs are additional production costs directly incurred because of the outage. These costs include:

- Labor costs to make up any lost production;
- Labor costs to restart the production process;
- Material costs to restart the production process;
- Costs resulting from damage to input feed stocks;
- Costs of re-processing materials (if any); and
- Cost to operate backup generation equipment.

Outage Related Savings are production cost savings resulting from the outage. When production or sales cannot take place, there are economic savings resulting from the fact that inputs to the production or sales process cannot be used. For example, during the time electric power is interrupted, the enterprise cannot consume electricity and thus will experience a savings on their electric bill. In many cases, savings resulting from outages are small and do not significantly affect outage cost calculations. However, for manufacturing enterprises where energy and feedstock costs account for a significant fraction of production cost, these savings may be quite significant and must be measured and subtracted from the other cost components to ensure outage costs are not double counted. These savings include:

- Savings from unpaid wages during the outage;
- Savings from the cost of raw materials not used;
- Savings from the cost of fuel not used; and
- Scrap value of any damaged materials.

In measuring outage costs, only the incremental losses resulting from unreliability are included in the calculations. Incremental losses include only those costs described above and beyond the normal costs of production. If the customer is able to make up some percentage of their production loss at a later date (e.g., by running the production facility during times when it would normally be idle), the outage cost does not include the full value of the production loss. Rather, it is calculated as the value of production not made up plus the cost of additional labor and materials required to make up the share of production eventually recovered.

Source: Sullivan, *et al*. (2012) p. 16.

For most studies, the data needed to estimate these CDFs have been generated through survey-based methods in which a random sample of customers are asked to provide estimates of their costs for a number of different outage situations. While some characteristics of study design are dictated by circumstances particular to the study population, the nature of the electric utility, and the study's specific objectives, many of the previous studies, to the extent possible have "…employed a common survey methodology, including sample designs, measurement protocols, survey instruments and operating procedures" (Sullivan, *et al*., 2012, p, 15). Much of this methodology is found in the *Outage Cost Estimation Guidebook* (Sullivan and Keane, 1995).

To illustrate the methods, we discuss the study design by (Sullivan, *et al*., 2012, p, 15-18) in their recent value of service study for PG&E. In the surveys, non-residential customers were asked to estimate the direct costs they would experience during a service outage (e.g. Direct Cost = Value of Lost Production + Outage Related Costs – Outage Related Savings). Cost estimates for residential customers are based on willingness to pay questions (how much would you be willing to pay to avoid an outage) because they do not experience many instances where directly measurable costs become apparent or their elements can be individually monetized. To measure the differential (marginal) effects of outages, key characteristics of the outage, such as magnitude, duration (5 minutes, and 1, 4, 8, and 24 hours), time of day/year, etc., are varied systematically in the survey instrument. Businesses are asked questions about type of business, size, electricity usage, labor use, etc. Residential customers are asked about energy usage, and household demographics, etc. Both are conditioning (distinguishing) variables in the CDF

Over the years, there have been important improvements in survey design and in sampling methods. There have been substantial improvements in the statistical and econometric methods applied to the data in order to quantify the relationships between the level of customer losses and customer characteristics. Sullivan, *et al*., (2012, p, 15-18), for example, argue that they introduce some significant methodological improvements into their 2012 study of value of service for PG&E. As explained in Table 3-2, they introduce a dynamic survey instrument design and an optimal sample design.

Also in Table 3-2, there is a discussion of the efforts to improve customer damage functions based on a two-part econometric regression model using outage cost survey data. In the first part, a Probit model is estimated to determine the probability that a given outage cost is greater than zero. This is seen as necessary because survey response include extreme value response, cost associated with specify defined outage of zero (costless) or a very large number. Survey responses available are generally relatively small (a few hundred), so extreme values can substantially influence the results. In the absence of a way to ascertain if these are real or protest responses, the first (data censoring) analysis attenuates the effect to the extreme value responses.[11]

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[11] Protest or strategic bids reflect the respondent's effort to influence the outcome. If a survey respondent thought that the data gathered would justify an investment to reduce outages that are costly to it, it might provide a very large number as it outage cost estimate, either as A WTP or direct cost value. Surveys report values from respondents in the millions, even for residential customers. Conversely, a zero bid might be offered because the respondent suffers little from outages and fears that investments will be made that proportionally benefits others and it pays for in higher rates. . But, zeros and very large dollar amounts can be legitimate bids, so how do we decide which to keep and which to toss out as strategic? The first stage conditioning estimation does accomplish that, data

The second part of the estimation employs a generalized linear regression model (GLM) that estimates outage cost, the value assigned to its frequency, magnitude and duration, given that it is greater than zero. A much more detailed discussion of why this particular regression specification was chosen, rather than the Heckman two-step model, for example, is found in (Sullivan, *et al*., 2009, pp. 15-23).

Table 3-2
Example of Improvements in Sampling and Estimated Consumer Damage Functions

Sampling	Damage Function Estimation
Dynamic survey instrument design: Each respondent was randomly assigned to one of 24 different outage onset times (for 24 hours of the day) and reported costs for a weekend scenario with a randomly assigned outage duration. This design helped to understand how outage costs differ across times of the day and week, for outages from 5 minutes to 24 hours. Thus, the analysis was not limited to outage scenarios for summer weekday afternoons, which were useful for generation planning, but not directly applicable to transmission and distribution planning. **Oversampling in Bay Area:** By analyzing how aggregate economic output per unit of electricity varied across PG&E's service territory outage costs are likely to be significantly higher in the Bay Area. Thus, the sample design had specific quotas for the numbers of Bay Area and non-Bay Area customers and included an oversampling of non-residential customers in the Bay Area. **Optimized sample design:** The sample design took advantage of information from the 2005 PG&E VOS study to optimally define the number of usage strata and boundaries for the usage strata. Thus, the sample stratification minimized the variance in the estimated outage cost, which maximized the precision of the 2012 estimates.	**Improved customer damage functions:** Customer damage functions are statistical models that predict how outage costs vary across customers, outage duration and other outage characteristics. In a 2005 study, a Tobit regression model was used to estimate the customer damage functions. However, the 2009 meta-analysis for LBNL showed that a two-part econometric model is more appropriate for modeling outage cost data. In this study, Sullivan et al. applied the two-part econometric model to this dynamic survey data to develop estimates for how outage costs vary by time of day and week for each customer class. **Customized cost per unserved kWh estimates:** To develop the cost per unserved kWh estimates, it is necessary to produce a load ratio that estimates the relative amount of unserved electricity for each outage scenario and respondent. Previous studies simply applied the load factor (ratio of average kW to peak kW) for each customer class because the outage scenarios were primarily focused on peaking periods. In this study, the estimates of the costs per unserved kWh were customized to each scenario (based on outage timing) and each respondent (based on rate profile).

Source: Sullivan, *et al*. (2012) p. 16.

are just censored to attenuate the tails of the distribution, which is a compromise that raises other concerns about undervaluing legitimate distribution tail values.

Efforts to Expand the Applicability of Existing CDF Outage Cost Studies

Despite differences in study objectives and the methods of analysis, the body of outage cost studies has several things in common. They are expensive (hundreds of thousands of dollars) and limited in their geographic scope (e.g. to the sponsoring utility's service territory). Furthermore, at the time many of these studies were undertaken, the mid to late 1990s, utilities believed these studies might be used by others to gain competitive advantage or by adversaries in regulatory proceedings.[12]They were understandably reluctant to release more than summary reports from such studies. It was not until about 2003 that detailed results from these studies were released into the public domain, and even then only under stringent guidelines (Sullivan, *et al*., 2009).

The release of these data led to an initial meta-analysis, a statistical approach that combines the data and results from multiple studies to increase their statistical power (over individual studies), improve estimates of the relative size of the effects (outage attributes) of interest, resolve uncertainty when reports disagree, and make it possible to generalize results to a broader population.[13] This study was made possible, in large measure, because the data from the studies were collected using a common methodology (Gyuk, *et al*. 2003).[14] These initial studies represented 13 years of experience and included data based on a variety of outage scenarios for large C&I customers, small and medium C&I customers, and residential customers. The data covered parts of United States, but notably includes no utilities in the Northeast or north-central Midwest.

A second meta-analysis was conducted in 2009 that provided additional estimates of the value of service reliability for electricity customers across the United States (Sullivan, *et al*., 2009). The study included data from 28 value of service reliability studies undertaken by 10 U.S. electric utilities conducted over the period 1989 through 2005. This study was updated in 2015 (Sullivan, *et al*. 2015). To put these electricity outage costs into perspective, Table 3-3 contains a summary of the up-dated results for average customers (as defined in the database).

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[12] At the time (early to mid-1990s), outage cost studies were becoming recognized as providing valuable data for directing reliability investments (mostly generation), coincidently, the movement to introduce competition in electric retail supply picked up stream. Having VOLL estimates would provide competitors a way to gauge the ceiling on what customers would pay at retail for power.

[13] In the literature on the valuation estimates for an environmental good or services, meta-analysis is viewed as method for benefits transfer because of its "…ability to combine and summarize large amounts of information from previous studies. This strength can also lead to one of the greatest weaknesses of this method, which is the loss of important valuation details across time and space in the aggregation process." (Bergstrom and Taylor, 2006, p. 351.

[14] As stated above, the methodology is detailed in Sullivan and Keane (1995).

Table 3-3
Estimated Interruption Costs by Duration and Customer Class

	Duration					
	Momentary	30 Min.	1 Hr	4 Hrs	8 Hrs	16 Hrs
	*---------------------------------US 2013 Dollars---------------------------------					
Med. & Large C&I (>50,000 annual kWh)						
Cost per Event	12,952	15,241	17,804	39,458	84,083	165,482
Cost per Average kW	16	19	22	48	103	203
Cost per Unserved kWh	191	37	22	12	13	13
Small C&I (<50,000 annual kWh)						
Cost per Event	412	520	647	1,880	4,690	9,055
Cost per Average kW	188	237	295	857	2,138	4,128
Cost per Unserved kWh	2,255	474	295	214	267	258
Residential						
Cost per Event	4	5	5	10	17	32
Cost per Average kW	3	3	3	6	11	21
Cost per Unserved kWh	31	6	3	2	1	1
Source: Sullivan, *et al* .(2015) p. xii.						
Note: These interruptions costs are for the average-sized customers; the data are rounded to whole numbers.						

While the results from this up-dated study are important, the authors are quick to point out that their use must be made with care. As in most meta-analyses, certain critical variables in the data were so highly correlated (region and year in this case) that the separate effects could not be estimated, and data from the Northeast/mid-Atlantic region, and large cities around the Great Lakes were limited at best. These concerns, combined with the fact that some survey data were more than 15 years old, led the authors to argue for the need for a coordinated, nationwide effort to collect interruption cost estimates for all regions and utilities using consistent methods.

Finally, for purposes of our current study objectives, the authors point out that:

> "…although the revised model is able to estimate costs for interruptions lasting longer than eight hours, it is important to note that the estimates in this report are not appropriate for resiliency planning. This meta-study focuses on the direct costs that customers experience as a result of relatively short power interruptions of up to 24 hours at most. For resiliency considerations that involve planning for long duration power interruptions of 24 hours or more, the nature of costs changes and the indirect, spillover effects to the greater economy must be considered. These factors are not captured in this meta-analysis (Sullivan, *et al*. 2015, p. xiv).[15]

[15] They refer to a study by Sullivan and Schellenburg entitled "Downtown San Francisco Long Duration Outage Cost Study" of March 27, 2013, prepared for PG&E as containing study of and a literature about estimating the costs of outages lasting from 24 hours to seven weeks. This study could not be found.

Because the stock of outage cost surveys limited the focus to 12-18 hour outages and did not explore the effect of the extent (locally or regionally) of the outage, the results of the metastudies cannot be extended to value resiliency. For example, Gyuk *et al*. (2003) argue that "…costs of large-scale outage events (e.g., State- or region-wide power outages) are not well documented and are mostly based on natural disasters for which it is difficult to separate costs of electric interruptions from damages caused by other disaster features (e.g., property damage from wind or water)" (p. 3).

Additionally, in their report on a conceptual framework for developing resilience metrics, Watson, *et al*. (2014) argue that while some damage estimation capabilities exist for some structures (e.g., HAZUS), additional capabilities are required to estimate disruption levels to specific infrastructures. When a natural disaster hits a region, there is substantial uncertainty as to the extent of the damage to energy infrastructure system components. They support the development of analytical models and the collection of historical data to create capabilities that can accurately predict system conditions after a high-consequence, low-probability event occurs.

Survey-Based Discrete Choice Experiments

From the discussion above, it is clear that the results from past outage cost studies do little to inform us about the value of the resiliency of our electric system; they are silent about outages that are longer than 12 hours. It is compelling to ask: Why can't we simply initiate additional outage cost studies in which customers are surveyed and asked to place WTP pay estimates on much longer outages, either in a separate study or by extending the level of duration used in a reliability study? These studies could benefit from recent improvements in study design, and the data could be analyzed using the improved statistical methods mentioned in the last update to the 2008 meta-analysis.

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

It is important to underscore that there are two critical components of any choice modeling exercise: the choice model itself, and the survey design and data collection activities. It is convenient to begin with a discussion of a clear definition of a discrete choice experiment and the form of the statistical model used in its estimation.

Discrete Choice Experiment Defined

In a recent paper, Carson and Louviere (2011) argue that "[i]t is often difficult to determine what actually was done in work involving data collected with stated preference surveys because the terms used to describe various procedures have ambiguous and sometimes conflicting meanings" (p. 539). To clarify these issues, they set out to develop a common nomenclature for what is done in a data collection exercise to elicit stated preferences. By adopting this nomenclature, we can identify exactly what is being proposed here and place it in proper perspective with other methods.

They propose the following definition. "A discrete choice experiment (DCE) is a general preference elicitation approach that asks agents (consumers or business decision makers) to make choices(s) between two or more discrete alternatives where at least one attribute of the alternative is systematically varied across respondents in such a way that information related to preference parameters of an indirect utility function can be inferred." (Carson and Louviere, 2011, p. 543).[16] There are many elicitation frameworks encompassed within the definition, including a single binary choice, as well as a sequence or multinomial choice questions.

As mentioned above, a (DCE) is an alternative approach that offers a long-standing, well-tested theoretical basis in random utility theory (RUT). DCEs are consistent with the theory of economic demand. RUT is based on a latent construct labeled "utility, which exists in a person's mind, but which is unobservable to researchers. There are two components to latent utility, an explainable, or systematic, component, and an unexplainable, or random, component. The systematic components consist of the attributes that distinguish the differences in the choice alternatives, as well as covariates of individuals that explain differences in the choices individuals make. The random components are unobservable factors that also affect individual choices.

The DCE has a number of attractive features. Preferences can be constructed for hypothetical or generally unavailable goods and services by eliciting stated preferences (SP) from subjects; what would they chose if these choices were available? This makes DCE attractive for valuing resiliency to protect against the consequences of infrequent outages. It also can be used to decompose actual purchase decisions into its value-imparting elements.

If one has data for both Stated Preferences and Revealed Preferences (RP), and explanatory variables (the parameters to be estimated, the betas) are the same, then the SP betas will be proportional to the RP betas. This proportionality of the beta's can be tested statistically (Louviere, *et al*., 2008). The comparison between stated preferences and revealed preferences is not particularly relevant in the case where the purpose is to estimate the value of electric service interruptions with different characteristics. Interruptions are not market goods; they are infrequently encountered events that must be treated as hypotheticals.

However, (Louviere, *et al*., 2008) go on to state that by applying the same logic, one is able to combine data from DCEs that have different preference elicitation formats, range of alternatives offered to respondents, nature decision making contexts exemplified by the DCE, and samples. The key insight is that if the vectors of model preference parameters are the same for all data

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

sources but random component variances differ, vectors of estimated preference parameters should be proportional to one another.[17] The capacity to combine these data sets places a premium on how DCMs are designed by separate utilities so that down the road the data sets can be combined for purposes of meta-analyses to expand the applicability of individual DCMs.

Conjoint Analysis (CA) and Discrete Choice Experiments (DCE) are often treated as synonymous methods. Louviere, *et al*. (2008) observe that (CA) does not begin with a well-defined behavioral characterization of choices, but defines a process of sampling across alternative attributes. DCE is rooted in an established behavioral portrayal that imposes important consistency structure on the parameter estimates. This is particularly important in studies where the objective is to estimate total willingness to pay (WTP) for a good (e.g. WTP for an electric system interruption), rather than just to measure how attributes effect marginal preferences. Thus, a respondent's certainty about a decision will change when asked about larger changes than smaller ones, and a DCE can capture this important effect.[18]

The Formal RUM Model

As above, we model this choice situation as though the i^{th} customer is faced with J options, and the utility (material benefit or satisfaction) of the option j is given by:

$$U_{ij} = \beta' Z_{ij} + \varepsilon_{ij}, \qquad \textbf{Eq. 3-7}$$

where

U_{ij} = the latent, unobservable utility of customer i associates with option j;

Z_{ij} = is a vector of features (outage attributes and/or customer characteristics;

β' = vector of parameters to be estimated; and

ε_{ij} = the random component associated customer i and choice j, an error term.

If the customer chooses option j, then it is assumed that U_{ij} is the maximum of the utilities for all the J alternatives considered in the decision process. The statistical model is driven by the probability that option j is made:

$$Prob\ [U_{ij} > U_{ik}]\ for\ all\ k \neq j \qquad \textbf{Eq. 3-8}$$

This indicates the probability that the utility of option j for individual i is greater than the utility of any other option k.

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[17] Louviere, *et al*. (2008) provide references for the statistical framework needed to combine these data sets.
[18] These authors argue that: "This raises the key question of to what market context does one "normalize" the WTP estimate? One school of thought is to normalize to the RP context, but the opposite argument also can be made" (Louviere, *et al*., 2008, p. 68). Their conclusion is: "… [p]articularly in a public policy context, the less noisy SP (stated preference) context is a better reflection of what well-informed consumers would do" (Louviere, *et al*., 2008 p. 68).

The Utility Maximizing Statistical Model

Different probabilistic DCE specifications can be derived from Equation 3-7, depending on the assumptions made about the probability distribution of $\varepsilon_{i,j}$. Not all stochastic specifications for $\varepsilon_{i,j}$ are consistent with utility maximization. McFadden (1981), however, showed that under the assumption of an independent and identically distributed (i.i.d) type 1 extreme value distribution,

$$F\,(\varepsilon_{ij}) = exp\,(-e^{-\varepsilon ij}) \qquad \textbf{Eq. 3-9}$$

There is a probabilistic choice model that is consistent with utility maximization. We can express the probability of option j by individual i (Prob [Y_i = j]) as:

$$Prob\,[Y_i = j] = exp\,[\beta' Z_{ij}] \,/\, \{\textstyle\sum_j [exp\ \beta' Z_{ij}]\} \qquad \textbf{Eq. 3-10}$$

This is called the conditional logit model.

In this conditional logit model, utility (as expressed through the choice made) is assumed to depend on both characteristics of the choices and the customers who make them. It is helpful, therefore, to distinguish between the two sets of factors. $Z_{ij} = [X_j + W_i]$, where the former, X_j, are the variables that characterize program features, and the latter, W_i, are customer characteristics. The model now can be written more explicitly as:

$$Prob\,[Y_i = j] = exp\,[\beta' X_j + \alpha' W_i] \,/\, \{\textstyle\sum_j [exp\,(\beta' X_j + \alpha' W_i)]\} \qquad \textbf{Eq. 3-11}$$

In this formulation, the alternatives that are explicit to the customer fall out, and those choices reflect differences in program features. It is the customer characteristics that do not vary from choice to choice (and do not vary even across the several data observations that must be constructed for each choice set). If these factors are to be in the model, the model must be modified. An effective modification is to create a set of dummy variables for the choices and multiply each by the common W (Greene, 2008).[19]

Survey Design, Sampling, and the Data

We know from above that there are two essential elements in the study and survey design for a DCE: respondents must be asked to make a choice between two or more alternatives in a *choice set.* Furthermore, the alternatives presented in the choice situation must be constructed by means of an experimental design that varies one or more attributes within-and/or between-respondents. Otherwise, it will not be possible to estimate economic quantities tied to preference parameters.

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[19] Because all customers are given the same choice sets from which the choices are to be made, this conditional logit model also suffers from what is called the independence of irrelevant alternatives (IIA), in that the ratio of the probabilities of any two alternatives is always independent of the remaining probabilities (Allison, 1999). The IIA assumption, as it is called, can only be tested if some sample members have different choice sets Allison, 1999, pp. 167-68), so in this case too, there is no way to test for any bias.

The multinomial probit (MNP) model (Daganzo, 1979) replaces the i.i.d. assumptions of the multinomial logit model with a multivariate normality assumption. The MNP model relaxes the IIA assumptions. The shortcoming of the model is the computational demands. The relevant probabilities that enter the log likelihood function and its derivatives must be approximated by simulation.

The application of DCE to utility service choice decisions was demonstrated by a recent EPRI study.[20] The study focused on consumers' preferences for two alternatives (to conventional rates) for purchasing electricity; a time-of-use (TOU) structure and a fixed bill (pay a fixed amount for power, regardless of the amount used, for a year). A survey was constructed to elicit from respondents their preference from among TOU and fixed bill designs that differ in the levels of the attributes. Data collected from over 1,000 residences in three utility markets were used to estimate a choice (preference) function that was embedded in a market share estimation tool tailored to each utility's residential customer population using census data.

The study demonstrates that DCE survey design and implementation methods can be applied effectively to electric utilities' residential customers to characterize preferences as a function of service attributes and customer demographics. The extension to measuring outage costs is compelling; consumers attribute value to reliability or resiliency based the nature of outages, the level of attributes discussed above (magnitude, duration, notice) and their demographic characteristics. The extension to resiliency would expand the range of the attribute features (to several days or even weeks), and the extent to which a business can meet its obligations elsewhere or by using another energy source. Residential customers could also expand their adjustments to accommodate the outages, for example with an emergency generator, and there could be more complex interactions among attributes.

A DCE survey would be constructed to efficiently sample the topology of attribute levels, following established practices (Louviere et al. (2008). Instead of estimating a damage function, a choice model would be developed that links outage attribute levels and customer characteristics, to the cost associated with an outage in such a way as to revel the underlying preference for resiliency. This produces a way to associate preferences for services with different levels of resiliency directly. In this way, DEC might also be applicable for estimating outage costs for smaller commercial customers. A feasibility study of this kind is underway as an alternative to collecting outage cost data directly through expensive interviews: and it might be extendable to large customers.[21]

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

[20] A complete discussion of this research is available in EPRI (2016); a shorter version is in Neenan *et al*., 2016.

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

4
ESTIMATING RESILIENCY VALUE FROM INSURANCE DATA

A recent study on the costs of electric grid disruption was conducted from an insurance perspective. This paper explores four case studies, one of which was the 2003 northeast blackout. The analytical framework exploits insurance loss data, and scales the insured values up to total economic losses for the insured and the uninsured. Economy-wide losses are then approximated by applying per-customer insured losses to all insured households and businesses in the affected area (Mills and Jones, 2016).

In this paper, the authors compare their estimates of dollar losses per customer with those for the 16-hour interruption estimates for summer days from Sullivan, *et al*. (2015). They had no data to distinguish between small, medium, and large C&I customers, but their per-customer outage loss estimates were bracketed by those from Sullivan, *et al*. (2015). They attribute this difference, at least in part, to the larger number of policy holders in their database and perhaps to the availability of more advanced loss-prevention devices such as interruptible power supplies, backup generation, and surge protection devices.

In contrast, their estimates of per-household losses were 50-to 200-times larger than those in Sullivan, *et al*. (2015). [22] From this, Mills and Jones (2016) conclude that traditional survey methods to estimate value of service reliability seem not to fully capture the costs of grid disruptions to households.[23]

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

Insurance claims are not well –suited for estimating how customer value resiliency. They may serve a role in providing a useful perspective in verifying (for example bracketing) estimates

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

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

from other methods of the cost of catastrophic events and the derivation of measures with what customer would pay to avoid them.

5
A MACROECONOMIC APPROACH TO ESTIMATING THE VALUE OF ELECTRIC SERVICE RESILIENCY

The preceding sections reviewed efforts to estimate the costs of electric service reliability. They are based on customer damage functions and are derived from the statistical analysis of survey data collected from random samples of residential and non-residential electricity customers. We also examined the potential for estimating outage costs from data collected through a discrete choice experiment. Finally, we also reviewed a recent study that derived the value of electric service from insurance claims file.

As stressed above, estimates derived from available outage costs based on survey methods are ill suited for estimating the value of electric service resiliency. The notion of the value of electric grid resiliency implies service interruptions that are of much greater duration and extent than those analyzed in estimating the value of system reliability. Through the application of discrete choice experiments, it may be possible to a develop survey methods and statistical analysis to derive estimates of the outage costs for interruptions of longer duration based on customer-elicited data. But, would that tell the whole story of who is effected and how?

Outages of extended duration that affect large geographic areas and large populations are the likely result of high-consequence, low-probability events, such as damage from serious riverine flooding, coastal flooding and wind damage accompanying hurricanes, ice storms, malevolent attacks, and electric outages due to collateral serious failures in infrastructure. In these situations, the of costs incurred from a service interruption include direct physical damages and indirect, spillover effects to the greater economy. These costs, some of which may be averted, may not be distinguishable in a survey-based outage cost study, especially if utility service territories (the focus of most outage cost studies) and regional economics do not fully overlap.

Efforts to estimate these indirect spillover effects and to disentangle the costs due to simultaneous lifeline failures date back at least 25 years. Prior to that time, efforts to estimate losses from disasters such as floods, earthquakes, and hurricanes focused primarily on the physical damage to buildings and structures. Any attempt to measure the costs of such disasters was limited almost exclusively to the capital-related costs of repair and replacement of damaged buildings and lifeline components.

The need for more comprehensive estimates of the economic costs was highlighted in two efforts by the by the National Research Council in the late 1980s and early 1990s. The panelists and committee members underscored the need to identify and estimate the various economic impacts from a catastrophic earthquake, including:

> "…direct economic losses due to destroyed or severely damaged buildings and other structures (such as dams and lifeline systems, direct economic losses due to damaged or destroyed contents of buildings and other private property, indirect economic losses due to disruption of the private sector (that is, business interruption), loss of revenues and increases in expenses for the public sector, and losses of individual and household

income due to injury, death, or job interruption" (The National Academies National Research Council, 1992, p. 3).

To address these issues, they recognized the need for serious economic impact modeling. Efforts to identify the appropriate modeling strategies were not addressed until the mid-to late 1990s. Some were developed in detail and embodied in FEMA's HAZUS-MH software, which is a nationally applicable, standardized method to estimate potential losses from earthquakes, hurricane winds, and floods. The idea was to use the results from direct losses estimated from physical damages to buildings and other structures as input into a regional impact model to estimate the indirect economic losses.[24]

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

To describe these efforts and assess their potential for estimating the regional impact of electricity lifeline interruption and its implications for the resilience of the electric system, it is useful to begin with a brief review of the two major types of regional impact modeling.

Economic Impact Modeling

An economic impact analysis is designed to measure (estimate) the change in economic activity in a region that is caused by specific and defined exogenous changes in the economy from a baseline measure. Examples include tax breaks to encourage new business activity in the region (high-tech firms), public investment to promote efficient use of natural resources or environmental improvements (parks, energy efficiency standards and incentive), and in welfare systems (school or hospital). Cost/benefit analyses are often conducted to justify the expenditure of public funds (which may involve raising taxes).

Impact modeling can also be applied to examine the effects of exogenous shocks to the economy, such as bad harvests or other weather-related outcomes in an agricultural economy. These shocks could also be caused by natural disasters or lifeline disruptions on a broad scale. By estimating the impact of these catastrophic events on the overall economy, it may be possible to assess the benefits of measures to avert the impact of catastrophic environment events—e.g., to measure the value of electric system resiliency. The impact of these changes can be examined at any level, for a neighborhood, town, city, county, or state. The study could also focus on a particular region, country, continent, or the entire globe, provided that very large economic systems can be characterized sufficiently.

The important distinction is that outage costs studies employ bottom-up methods (cost elicited from customer classes) to estimate adverse situation costs by customer class that are aggregated to a specific geographic area (a utility's service territory). Economic impact studies are top-down derivations of how the economy in general is affected, which is not necessarily attributable to

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

electric customer classes nor exclusively served. This distinction points out an important consideration; can an electric utility make resilience investments based on general economy-wide estimates of value, in effect use electric revenues to improve the resiliency of other public and private services? If so, how would the costs be allocated to customer classes to be recovered in rates (and from whose rates)?

The Input-Output Model

Economic impact analyses often are undertaken using the Input-Output (I-O) methodology that dates back to Leontief's original work in the late 1930's and early 1940's. Since that time, it has been proven an effective way to assess the economic effects from expenditures made as part of public policy initiatives at the National, state and local levels. In contrast to more aggregate or macro-economic analyses, I-O analysis has the ability to differentiate the effects of policy initiatives by important economic activity sector.

The I-O model provides a fruitful way to depict and investigate how the underlying processes that bind an economy together are effected by a shock, a new public policy, or some other substantial change of economic circumstances. I-O is used primarily to evaluate public policies where the interests of all citizens (society) are included, in contrast to investment decisions by private firms that consider only the costs and benefits they realize.

Its strength lies in a detailed representation of: a) the production of goods and services (primary and intermediate input requirements), b) their distribution of sales by individual industries in an economy, and c) interrelationships among these industries and other economic sectors of an economy, especially consumers but including government. The methodology's analytical capacity (and hence attractiveness) lies in its ability to estimate the indirect and induced economic effects stemming from the direct policy expenditures that lead to additional purchases by final users in an economy. These distinctions are described below (The structure of the I-O model and it analytical capacity are described in Appendix D).

IO by itself may not be sufficient to estimate resiliency value, as discussed further below. But it can play an important role as an embedded element of a more generalize characterization of an economy and how it is effected by catastrophic events.

Computable General Equilibrium Model

Despite its popularity for policy impact assessments, I-O is criticized because the production technology in all sectors is assumed to be of the fix-coefficient form that exhibits constant returns to scale. In other words, outputs (goods and services) are created from inputs in fixed proportions regardless of the level of output. That may not be the case in many sectors, especially in those that are characterized by technologies with different productivities, or production and service activities are subject to economies (or diseconomies) of scale and scope. Economic impact analysis has benefited from the development of applied computable general equilibrium (CGE) analysis that allows for a more flexible characterization of productive activities.[25] [26]

In one sense, the CGE model can be viewed as an extension of Leontief's I-O model (based on fixed input-output coefficients) that allows for the substitution among factors of production and in demand (allowing for supply-constrained production), and by including more than one class of consumers. Most models allow for the substitution among primary factors of production such as labor, capital, energy, and materials inputs.[27]

By relaxing many of the more restrictive assumptions of the I-O model, CGE models have proven to be powerful analytical tools for policy evaluation at state, regional, and country levels. Advances over the past 20 years in optimization software and computer speed have created a research environment that allows for the specification of complex interregional models on a truly global scale. GTAP is an excellent example of the capacity of computable general equilibrium models available to examine issues related to international trade policy, environmental and energy issues, and poverty and migration on a global scale.[28]

While much of the economic impact analysis concerns itself with answering questions about the impact of changes in economic policies, it also has been used to examine the effects of external changes to the environment, either weather or climate induced. For example, studies have examined external shocks such as an increase in the price of imported oil, or, in an agricultural economy form shocks such as bad harvests or other weather-related outcomes.

Viewed from this perspective, a natural disaster is no more than a special class of an external shock that effects the economy. One might think that the level of disaster relief and other government aid as important policy instruments that could be analyzed to ascertain if they can

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[25] General equilibrium theory attempts to explain the behavior of supply, demand, and prices in a whole economy with several or many interacting markets, by seeking to prove that the interaction of demand and supply will result in an overall (or "general") equilibrium. General equilibrium theory contrasts to the theory of partial equilibrium, which only analyzes single markets. General equilibrium theory studies economies using the model of equilibrium pricing and seeks to determine in which circumstances the assumptions of general equilibrium will hold. The theory dates to the 1870s, particularly to the work of French economist Léon Walras in his pioneering 1874 work *Elements of Pure Economics*. Wikipedia.

[26] These general equilibrium models have allowed for the conversion of the Walrasian general equilibrium structure from an abstract notion into a realistic set of empirical models of actual economies.

[27] Intermediate inputs are still assumed to be combined in fixed proportions to product products. In so doing, it is also necessary to assume that intermediate inputs weakly separable with respect to labor, capital and the other primary factors of production.

[28] According to its website, GTAP (Global Trade Analysis Project) is a global network of researchers and policy makers conducting quantitative analysis of international policy issues. GTAP's goal is to improve the quality of quantitative analysis of global economic issues within an economy-wide framework. The standard GTAP Model is a multiregional, multisector, computable general equilibrium model, with perfect competition and constant returns to scale. Innovative aspects of this model include:

- Treatment of private household preferences using the non-homothetic CDE functional form.
- Explicit treatment of international trade & transport margins. Bilateral trade is via Armington assumptions.
- A global banking sector which intermediates between global savings and consumption.

The GTAP Model also gives users a wide range of closure options, including unemployment, tax revenue replacement and fixed trade balance closures, and a selection of partial equilibrium closures (which facilitate comparison of results to studies based on partial equilibrium assumptions).

avoid the adverse outcomes, or remediate them once realized. However, in the case of natural disasters, we must consider changes in the internal environment that are brought about by the external shock from the natural disaster. The direct damage to fixed plant and equipment in the short run is certainly a shock in the spirit of those mentioned above, but there are many other disruptions that are endogenous to the economy, called indirect impacts. The changes in regional or local trade patterns are good examples of these endogenous shocks to the economy after a natural disaster.

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

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

Within a CGE model, interactions also matter. However, unlike the I-O model, CGE models usually assume that there is input substitution in production between labor, capital and other primary factors of production, and there is substitution in demand in response to changing relative prices. It allows for flexibility and adaptability in economic activity that may mitigate some of the impacts of an adverse shock.

Finally, in the choice of a CGE model, there is the implicit notion that economic structure matters. By structure, we mean such things as the share of exports in gross domestic product (GDP), or the share of agriculture or manufacturing in total output, or the share of wages in value added. In so doing, it is necessary to reproduce, to the extent possible, the detailed structure of the economy in the model. Given the relaxation of many of the assumptions of the I-0 model, this implies that the data requirements to construct a CGE are even more extensive than in the case of an I-0 structure. The problems of obtaining the data mount rapidly as the desire to disaggregate the model into more distinct production sectors, for example to distinguish the impact of power losses by business activity or industry sector.

The Economic Data and Links to Natural Disaster Direct Damages

Constructing a CGE model to estimate the value of electric service resiliency requires assembling detailed regional economic data for the empirical characterization of the economy of interest. It is also necessary to link those models with other data detailing the direct damages from natural disasters. The IMPLAN database is ideally suited (and in fact constructed specifically) to inform the I-O models and it provides much of the data needed in constructing a CGE model for regions across the United States.

Expectations about and quantification of the structural damage or other system impacts (particularly those related to lifelines) that could affect performance of the economy are embodied in FEMA's HAZUS-MH software. For this reason, HAZUS-MH is a starting place to generate direct (physical) damage data. However, it is likely that additional data will be needed as well, especially if the electric sector is to be examined in detail, down to the radial delivery system. We begin with a brief discussion of the IMPLAN database.

IMPLAN

IMPLAN is an economic impact assessment database and software system.[29] It combines a set of extensive databases concerning economic factors and demographic statistics with a highly refined and detailed system of impact modeling software.

The database includes information for five-hundred-and-twenty-eight different industries (generally at the four or five-digit North American Industrial Classification level), and a number of other economic variables. These data, along with national input-output structural matrices, inform the interrelationships between and among these sectors through a set of inter-industry accounts. The database also contains complete Social Accounting Matrix (SAM) data.[30]

I/O data are available at the national, state, and county level. The database is extremely flexible and can be used to develop impact models for stipulated geographic areas (like utility service territories) or acknowledged economic regions throughout the country. [31] The user can also modify the data and selected algorithmic relationships within each model to more accurately account for regional economic relationships among critical sectors of the economy. For example, different output-to-income ratios can be specified for certain industries, as can different wage rates to reflect local economic practices like union-influenced wages and minimum wage policies.

The user can also alter trade-flow assumptions, including the modification of regional purchase coefficients that determine the mix of goods and services purchased locally with each dollar in each sector. This might be important for studying resiliency polices that would alter the relative distribution or nature of the goods and services a utility purchases, especially if a resiliency policy involved the creation of microgrids. As is pointed out below, these capacities are essential in making changes to the model's parameters and assumptions to account for accurately the

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[29] MIG, Inc. (formerly the Minnesota IMPLAN Group, Inc.) is the corporation that is responsible for continued development and maintenance of the software system, as well as yearly updates to the massive database.

[30] A SAM is a representation of macro-economic accounts of a socio-economic system that captures the transactions and transfers between all economic agents in the system in a manner common with other economic accounting systems. It records transactions taking place during an accounting period, usually one year. The accounts are represented as a *square matrix*; where the incomings and outgoings for each account are shown as a corresponding row and column of the matrix; characterizing interconnections between agents in an explicit way. It portrays all the economic activities of the system (consumption, production, accumulation, and distribution), although not necessarily in equivalent detail. An overriding feature of a SAM is that households and household groups are at the heart of the framework; only if there exists some detail on the distributional features of the household sector can the framework truly earn the label 'social' accounting matrix. Also, a SAM typically shows much more detail about the circular flow of income, including transactions between different institutions (including different household groups) and between production activities, and in particular recording the interactions between both these sets of agents via the factor and product markets (This is a slightly edited description of a SAM found in Round, (2009, p. 14-1).

[31] Rose, et al. (2007, p. 523) argue that "[T]he IMPLAN system consists of an extensive database of economic data, algorithms for generating regional input-output tables and social accounting matrices, and algorithms for performing impact analysis. IMPLAN is the most widely used database for generating regional I-O models and SAMs in the United States". Many other economists, regional scientists and impact modelers would agree.

short- and perhaps longer-term changes in the structure of a regional economy after a natural disaster.

HAZUS-MH

In the early 1990's, FEMA embarked on an ambitious undertaking to expand the Nation's capacity to estimate losses (damages) from major types of natural hazards, including earthquakes, floods, and severe winds. The result is the enhanced capacity for estimating losses from natural hazards as embodied in an integrated software package, HAZUS-MH, with a separate module for estimating the losses from each type of hazard. As stated in the introduction to the technical manual for the flood model:

> "…the earthquake and flood modules are now operational, and are undergoing continual improvements. The wind module is currently under development.
>
> This expanded analytical capacity will assist public officials at all levels of government in preparing estimates of losses from natural hazards, and in facilitating emergency response, planning, and hazard mitigation. One can envision numerous private-sector applications as well, particularly by the insurance and construction industries and others interested in economic development.
>
> From a natural hazards policy perspective, the capacity of HAZUS to generate consistent loss estimates for these multiple hazards is particularly significant. To achieve this consistency, HAZUS, to the extent possible, draws on shared national databases. The national inventory of housing and commercial and industrial facilities is perhaps the best example of a shared database. Because of the unique nature of each hazard, however, different attributes of the shared data are most critical in determining loss estimates from individual hazard. For example, for flood loss estimation, knowing a building's first floor elevation and specific location within a community is more critical than in estimating earthquake losses. In contrast, knowing the height of the building and certain of its structural characteristics is more critical in estimating earthquake losses" (*Multi-hazard Loss Estimation Methodology Flood Model HAZUS®-MH MR5 Technical Manual* p. 1).

The HAZUS Flood Model is an integrated system designed to identify and quantify flood risks. Its purpose is to support communities in making informed decisions regarding land use and related issues in flood prone areas. The methodology consists of two basic analytical processes, the flood hazard analysis and the flood loss estimation analysis (Scawthorn, 2006):

> "The hazard analysis portion of the model characterizes the spatial variation in flood depth and velocity in a given study area for either riverine or coastal flooding conditions. The damage and loss portion of the model estimates structural damage to buildings and infrastructure through the use of depth-damage, or vulnerability, curves. From these estimates, direct and indirect economic losses are computed and results are presented as figures, tables, and maps" (Scawthorn, 2006, p. 62).[32]

The components of the flood model in HAZUS-MU are characterized in Figure 5-1 and Figure 5-2. In the Hazard Module, the study region is defined, as is the type of flooding, and inundation boundaries established. These are applied to the study region's inventory and, in turn, the hazard

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[32] Depending on the degree of user expertise, the flood model is can be operated at two levels. Level 1 requires minimal user interface and additional data, while Level 2 requires user-supplied local data for performing more detailed analyses. This more detailed analysis is facilitated with the assistance of the Flood Information Tool (FIT).

boundary is applied to the inventory. This information feeds the damage and loss portion of the model. The resulting direct damage feeds into the indirect economic loss model, the second part of the analysis. The modules of interest are described in Appendix E. Data from this module inform the economic impact model that assesses the damages on the broader economy.

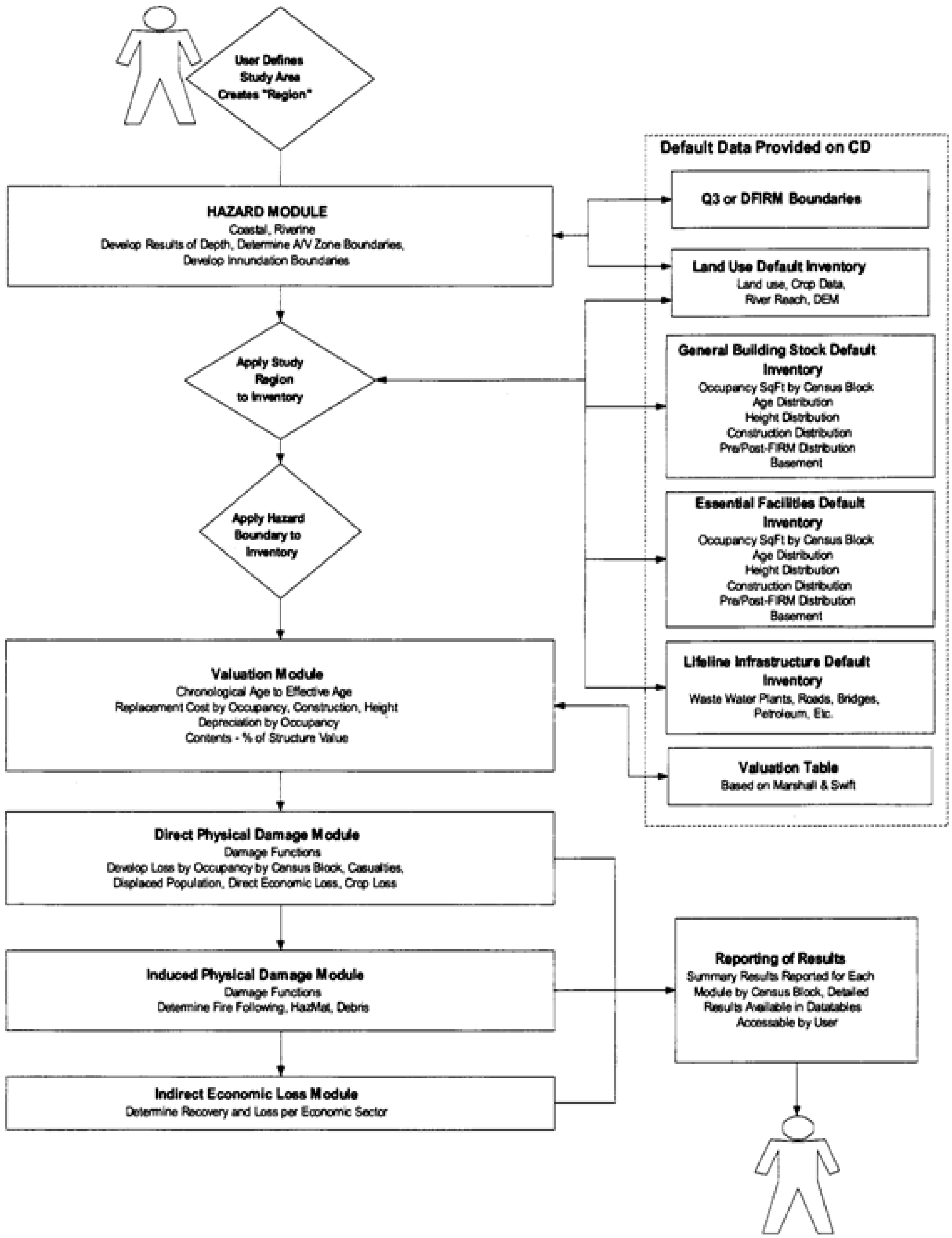

Figure 5-1
Idealized Flood Damage Estimation Model

The HAZUS Earthquake Model HAZUS Earthquake evaluates a wide range of losses resulting from scenario earthquakes to provide state, regional, and community government officials a basis for decisions concerning preparedness and disaster response planning, and to stimulate and assist planning for mitigation to reduce potential future losses (Whitman, *et al*., 1997).

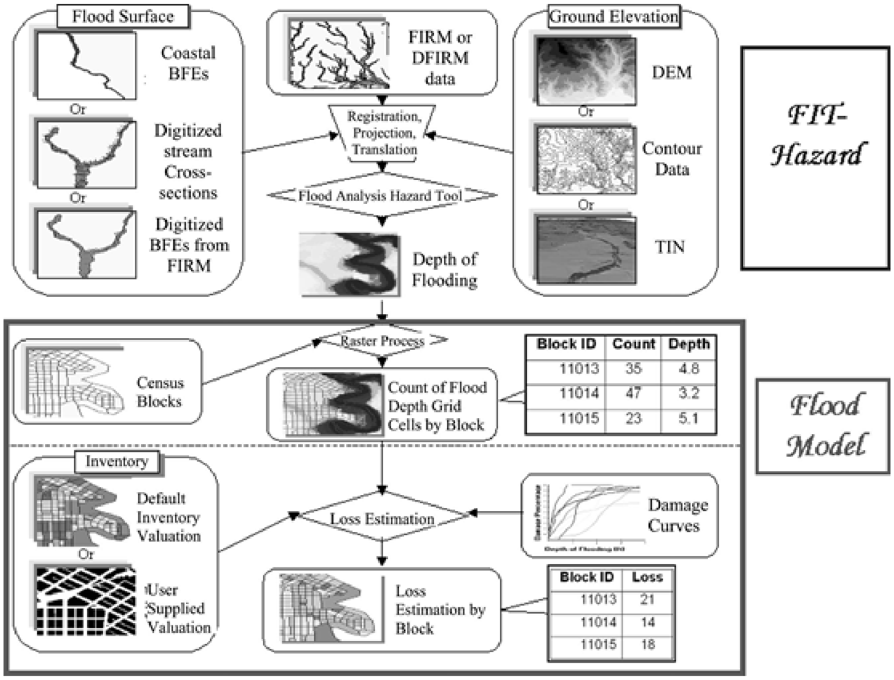

Figure 5-2
Overview of FIT and HAZUS

As with the flood model, the earthquake loss estimation methods embodied in the HAZUS Earthquake software are comprised of several separate modules, (Kircher, *et al*., 2006). There are five essential modules (Figure 5-3). The first is used to calculate the nature of the seismic hazard, including the ground shaking and site effects, ground failure, as well as tsunami and surge effects. This characterization is combined with the inventory of buildings and other structures to assess the likelihood of the various states of direct damage to buildings, lifelines, and other components of the built-up environment. There is also a module to estimates the induced damage due to inundation, fire, the release of hazardous materials, and debris.

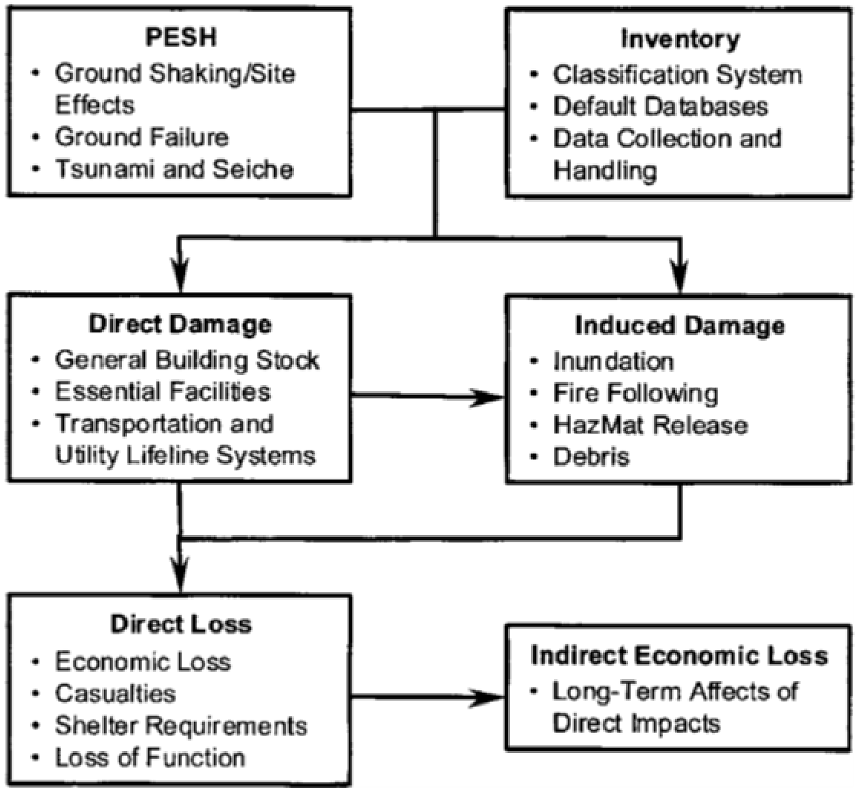

Figure 5-3
Major Components of HAZUS Earthquake.

These damage estimates are converted into direct monetary losses. The estimates of economic loss and loss of function are of most interest in the study of the cost of resiliency of the electrical system. These direct losses are in turn passed to the modules that estimates indirect economic losses.

Using Direct Damage Data from HAZUS or Elsewhere in Economic Impact Models

At the time of its development, HAZUS contained a prototype I-O impact model. This was to illustrate the kinds of data and adjustments that are required to put the data from HAZUS into a form that can be used by the impact model (See chapter 15 in *Multi-Hazard Loss Estimation Methodology Flood Model HAZUS®-MH MR5 Technical Manual* for a detailed discussion.)[33] Because the I-O model is only a prototype, the data from HAZUS that needed to pass to the impact model (be it an I-O model or a CGE model) would have to be done outside the software platform. The discussion in HAZUS, however, is extremely helpful, in explaining how the direct damage from the HAZUS modules, or from other sources, might be input into the impact model, particularly in altering input-output coefficients, regional trade flows, elasticities of substitution

[33] A similar discussion is also in chapter 16 of the *Multi-Hazard Loss Estimation Methodology Earthquake Model HAZUS®MH MR4 Technical Manual* (2003).

between different types of energy and/or primary factors of production, and other parameters of the impact models.[34]

Until recently, all applications of CGE models to natural hazards have been experiments with synthetic models (see Boisvert, 1992; Brookshire and McKee, 1992). More realistic applications have been undertaken by Rose and Guha (1999), and Rose and Liao (2002) to estimate impacts of utility lifeline disruptions in the aftermath of an earthquake. Given the capabilities of this approach, the potential for applications to other aspects of hazard loss estimation is encouraging.

Various types of disequilibria relating to imbalances in labor and capital markets, and trade also can be incorporated into CGE models (see, e.g., Rose *et al.*, 2004). Finally, adjustments in CGE models can also be made to reflect a range of resiliency options (e.g., recalibrating models to reflect emergencies rather than conditions for business as usual).

At a minimum, several refinements are needed of the standard CGE model for estimating economic losses from natural hazards, most notably to incorporate elasticities of substitution between energy sources and other primary factors. For example, to what extent can natural gas (if available) substitute for electricity (which is not available) during an event, or using available local labor to substitute for labor resources unable to get to the facility?

Applications of Impact Modeling of Natural Hazards and Terrorist Attacks

Major interest by economists in the study of the economic impact of natural disasters dates back only to the late 1970's and early 1980's, about 10 years after the passage of the National Flood Insurance Program (NFIP) in 1968. Prior to that time, the Nation relied almost exclusively on structural engineering solutions to solve flood problems.[35] Thus, it is not surprising that most of

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[34] The last section of Appendix A illustrates, by example, how the structure of an I-O model can be altered (e.g., public program spending in some cases requiring a larger proportion of some inputs to be purchased from outside the region), or lead to policy *induced* changes in consumer spending patterns (changing the propensities to consume locally by sector, or in total).

[35] The Nation's interest in the damage caused by natural hazards, particularly floods, dates back at least to the turn of the 20th century, but the Flood Control Act of 1917 was to that time the most important piece of flood control legislation prior to the Flood Control Act of 1936. However, it was limited in scope to the lower Mississippi and Sacramento Rivers (the latter being devastated by hydraulic mining). During that time, the Corps of Engineers remained committed to a "levees" only policy to prevent the disastrous effects of floods, only to have that policy tested when most of the levees were overtopped or breached in the great flood of 1927.

The serious New England floods of 1936, combined with the Great Depression, established context for the Flood Control Act of 1936. Communities and states were financially strapped, so the Federal Government authorized 250 flood control projects with work relief monies to provide jobs. The Act offered a two-pronged approach to flood loss reduction. The Department of Agriculture was to develop plans to reduce runoff, while the Corps of Engineers was to develop engineering plans for downstream projects. In reality, most of the effort was undertaken by the Corps.

In the three decades that followed, the Nation had relied almost exclusively on structural engineering solutions to solve flood problems but the overall flood damages had yet to decline. By the 1960, there were many fewer flood control projects because of difficulties justifying them on economic and environmental grounds, and new legislation limiting development in flood-prone areas.

> "With the establishment of the National Flood Insurance Program (NFIP) in 1968, the nation moved much closer to a balanced approach to flood hazards and floodplain management. Congress established the NFIP as a "quid-pro-quo" program. Through it, relief from the impacts of flood damages in the form of federally-backed flood insurance became available to participating communities contingent on flood loss reduction

the people involved with the study of natural hazards and hazards policy had engineering backgrounds. The involvement of some well-known geographers, a number of planners and some social scientists concerned with the human toll from natural disasters were notable exceptions.

Heightened interest by economists in disaster impacts coincided with an introduction of an expanded list of policy measures in the NFIP to regulate the development of hazard prone areas through land use controls, non-structural solutions for mitigating flood damages, such as elevation, anchoring structures, and flood proofing, and risk sharing through flood insurance. These policy options affected all phases of emergency management: mitigation, preparedness, response, and recovery.

There were expanded efforts to evaluate these alternative policy options from a variety of perspectives.[36] Some economists were asked to assist efforts by FEMA and others to explore methods for estimating the direct and indirect economic losses from natural hazards, including floods, earthquakes, hurricanes, etc. Some of these economists, such as Boisvert, Brookshire, Cochrane, Jones, McKee, and Rose, are authors on papers in the list of references.

Rose, beginning in these early years, commenced what became a long-term research program to estimate the direct and indirect economic impacts of natural hazards, extended to those that may be due to terrorism, or those due to major failures in components of critical lifelines. Rose and colleagues have made important conceptual contributions to the literature on economic impact modeling. Their empirical work has focused extensively on modeling the effects of disasters, be they natural, or otherwise. They are optimistic about the range of applications of other aspects of hazard loss estimation that are possible using the recent advances in CGE modeling. Electric system sustainability might be one such application. However, they are careful to point out places where the data available for the analysis is limited, and underscores the need to examine the sensitivity of important results to the data in which there is the least confidence.

A number of the Ross et al. applications of impact modeling to natural and other disasters are in the list of references. They address a broad range of topics, including:

- The Regional Economic Impact of an Earthquake: Direct and Indirect Effects of Electricity Lifeline Disruptions (1997)
- Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions (2005)

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measures embodied in state and local floodplain management regulations. Occupants of existing structures in flood prone areas would benefit from subsidized flood insurance premiums, but new floodplain occupants would have to pay actuarially-based premiums. Those already living in the floodplain likely did not understand the flood risk involved in their locational decisions, but future occupants would through information provided by the NFIP. The program would be strictly voluntary in terms of community participation and individual purchase of insurance. As history would reveal, the NFIP would ultimately have a profound impact in two important areas: first, by accelerating the identification of flood prone areas on maps, and; second, in providing incentives for state and local units of government to enact measures to regulate development in these identified areas." (Wright, p. 34).

[36] Kunreuther, for example, continues to be among the best known economists doing research on many aspects of hazard's policy and hazard's insurance (e.g. Kunreuther, et al., 2013 and Michel-Kerjan, and Kunreuther, 2011).

- Business Interruption Impacts of a Terrorist Attack on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout (2007)
- The Economic Impacts of the 2001 Terrorist Attacks on the World Trade Center: A Computable General Equilibrium Analysis (2009)
- Regional Economic Impacts of a Verdugo Earthquake Disruption of Los Angeles Water Supplies: A Computable General Equilibrium Analysis (2011)
- Estimating the Economic Consequences of a Port Shutdown: The Special Role of Resilience (2013)
- Improving Catastrophe Modeling for Business Interruption Insurance Needs (2016)

It would be daunting to discuss in detail the construction of the impact models that underpin all of these studies, and the ways in which data from many sources were combined to inform the empirical structure of the model. To gain perspective on the overall methodology, what follows is a summary of two of these studies that discusses the model structure, the data used, the types of empirical results, and compares the conclusions that can be drawn from them.

The Regional Economic Impact of an Earthquake: Direct and Indirect Effects of Electricity Lifeline Disruptions (1997)

This paper represents an early attempt to simulate estimates of the regional impact of an earthquake-induced disruption (of 15 weeks) in the electric system in the New Madrid seismic zone near Memphis, TN. Rose argues that losses from earthquakes are typically measured as physical damages that result from ground shaking. His objective was to expand the scope of the damages by estimating the collateral loss of production of goods and services by businesses cut off from electric service, and by businesses indirectly affected because their suppliers or customers were without power, the indirect effects.

The authors describe how the I-O model is modified to distinguish between direct and indirect impacts. Several simulations were conducted to estimate total production losses under a variety of conditions to examine how different policies related to the allocation of scarce electricity supplies could reduce the losses during the recovery period. These reallocations were accomplished through solutions to a multi-region linear programming model.[37]

The study was a culmination of a multidisciplinary effort. Researchers characterized the Memphis economy, and considered ways to simulate the area's electricity network and integrate these engineering results with spatial economic data to provide a baseline for electricity demand. This information was combined with survey data developed by others to quantify economic losses by sector and sub region. Direct losses due to electricity outage at production sites were based on several factors, including; electricity usage, the resiliency of productive activities, and the restoration timeframe. A resiliency factor for each industry was adapted from Tierney and Nigg (1997). A non-linear restoration curve was approximated and calibrated with restoration data from ATC-25 (Rojahn, 1991) and the Northridge Earthquake (Chang, 1996).

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[37] While the results of these linear programming results are quite interesting, they have more direct implications for response and recovery. The results are predicable, so I do not discuss them in this review.

The initial (base) simulation calculated that gross output was reduced by nearly 50% ($329 million) from baseline production during the period. They also simulated a "bottleneck" case to account for the fact that the highly concentrated petroleum refining sector was the most severely disrupted sector. The bottleneck resulted in the loss of gross output rising to over three-fourths of baseline production. The additional 25% reduction in baseline output during week zero is a true indirect effect. It is not associated with material damage to the facility, but to losses arising from interdependencies of economic activities among faculties.

Base case demand and regional gross output fell by 1.9% and 2.3% on an annual basis, respectively. Equivalent loss values for the "bottleneck" scenario were 7.0% and 9.0%. This translates into an indirect effect of 6.3%, of gross regional output on an annual basis, or $2.2 billion, nearly four times the direct effect of electricity disruption. Clearly, indirect effects need to be accounted for to portray the full implications of catastrophic events.

Business Interruption Impacts of a Terrorist Attack on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout (2007)

Rose and his collaborators estimate what is purportedly "…the largest category of economic losses from electricity outages -- business interruption rather than direct physical facility demand -- in the context of a total blackout of electricity in Los Angeles (LA) from a terrorist attack."[38] They focus on the indirect effects and how they can be attenuated by resilience, ways in which business operations can be modified during a shock. [39]

In the study, the authors are concerned with the notion of economic resilience, defined as the ability or capacity of a system to maintain function (continue production) when shocked, and more inclusively incorporate dynamic considerations--the ability and speed of a system to recover from a shock. Resiliency, as defined for the study, can be either:

> "*Inherent*—ability under normal circumstances (e.g., the ability of individuals or businesses to substitute other inputs for those curtailed by an external shock, or the ability of markets to reallocate resources in response to price signals), [or]
>
> *Adaptive*—ability in crisis situations due to ingenuity or extra effort (e.g., increasing input substitution possibilities in individual business operations, or strengthening the market by providing information to match suppliers without customers to customers without suppliers)" Rose, *et al*. (2007 p. 516).

Resilience in this case is also limited to post disaster conditions and response, distinguished from pre-disaster activities to reduce potential losses through mitigation. Efforts to harden the electric system would seem to fall into the latter category (mitigation). They deserve attention because electric utilities may be able avert some of the consequences through: system hardening investments; developing micro-grids to provide more resilient service provision for essential

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[38] In conducting the study, the authors also note that the economic impacts of power outages differ in the case of a targeted terrorist attack and natural disasters in a major way. In the latter case, damage is likely to be more widespread, so that it is more difficult for businesses to cope during the outage and when power is restored.

[39] The authors omit several considerations, such as the value of any lives lost, increased crime, psychological trauma, some infrastructure costs, and property damage. These could be large in some instances, and various cost estimating factors might be used to complement our analysis for some of these considerations (see Zimmerman *et al.*, 2005a).

services; and programs to foster the adoption of distributed generation that can operate when the grid fails (e.g., using storage).

In documenting their work, the authors focus on several resilient remediation responses to electricity disruptions. They include: conservation (utilizing less electricity per unit of output); fuel substitution (utilizing some other fuel to provide services); backup power (utilizing an alternative source of generation); production rescheduling (making up lost production at a later date); and electricity importance (utilizing the portion of a business that does not need for electricity). While it is convenient to think of these resilient responses as applicable to businesses, the authors highlight the fact that about 33% of electricity consumption in LA is by households.

For purposes of simulation, they assume that there is a total electric power outage where all transmission lines into the LA area are destroyed. As such, all sectors would be affected equally at first. As transmission lines are repaired, accumulated sectoral loss differentials arise, since only remaining portions of the county will be without power. Restoration may effect customer classes unequally, depending on how service is reinitiated.[40]

The study employed two assumptions regarding recovery that bookend the range of situations that can result. One assumes that outage will last two weeks (see Zimmerman *et al.*, 2005a) and that recovery will proceed in a linear fashion (one 15th of customers are reconnected each day of the two-week outage), defining the lower bound on impacts. In the other, the upper bound on impacts, recovery takes place at the end of the two weeks (immediately for all customers).

Implicitly, this analysis is based on the following assumptions:

- No advance warning (notice) of the terrorist attack
- No rolling blackouts to mitigate the impact of the disruption
- No splicing of power lines across with neighboring electric systems
- Linear approximation of reduction in individual service in the best case
- Inapplicability of some resilience considerations

Despite the fact that at the time this study was initiated CGE models had not been applied to terrorist attacks, the authors argue that its use was ideally suited for such a situation.[41] In

[40] If the system is rebuilt from outside in, large customers served directly off the higher voltage radials lines would be the first to be restored and residences and small business connected at the grid edge, the ends of radial lines, would be last to have power restored.

[41] See footnote 10, page 521 of Rose, *et al*. (2007) for a detailed discussion.

conducting their analysis, the authors utilize the LA CGE model.[42] The data for the LA county social accounting matrix (SAM) were derived from the IMPLAN database.[43]

Given this model design, the authors focus on the several types of general equilibrium (GE) effects.[44] The CGE model traces chain reaction effects of shock that go beyond the immediate, partial equilibrium (PE) effects. One CGE indirect effect is output losses by downstream (in the economic system) customers as the result of a disrupted firm's inability to provide them with their crucial inputs. A second CGE effect is output losses by upstream suppliers due to the cancellation of orders for inputs by disrupted firms.

A third effect is that all firms also experience losses in sales from decreased consumer spending associated with decreased wages from firms directly affected by the electricity outage, as well as all firms suffering indirect effects. Fourth, reduced investment resulting from with decreased profits of firms suffering the electricity outage negatively affects other firms. Finally, there are reductions in output in all firms from subsequent cost (and ensuing price) increases due to damaged equipment and other dislocations that lead to reduced productivity in firms directly impacted.[45]

In discussing the results, the authors compare the economic impacts when only partial equilibrium effects to those that include the larger general equilibrium effects under two different sets of assumptions: when only inherent (latent) resilience responses associated with normal input and import substitution are considered, and when both inherent and adaptive resilience actions are in play.

In summary, the total CGE effect is a reduction in economic activity of about 94% during the event, which translates into an economic loss of $21 billion. This figure compares to a base year gross output of $540 billion. Thus, the economic loss is about 4% of one year's output in LA County. In contrast, a basic I-O model would estimate only the PE effects—ignoring all

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[42] In the model, production activities at the top level allow for substitution possibilities among a capital-labor-energy-materials aggregate input. The next level reflects the choice of a material input aggregate, and a capital-energy- labor-input. Next, the capital-labor-energy combination is made up of labor and a capital-energy combination. To capture the role of electricity more explicitly, they include an energy sub-nest consisting of fuels and electricity. Fuel use is a CES function of petroleum and gas, while overall electricity use is derived as a Leontief (fixed coefficient) aggregation of private electric utilities and state/local electric utilities.

In the model, transactions between L.A. County and the two external sectors are based on the Armington function for imports and the constant elasticity of transformation function for exports.

Incomes from labor and capital employment are shared among institutions after deductions are made for taxes of all kinds and business deductions for depreciation and retained earnings.

Household production and consumption of goods and services are modeled using Cobb-Douglas expenditure functions, while government consumption is a Leontief expenditure function.

[43] Elasticities of substitution for regionally produced inputs and for imports are based on a synthesis of the literature, and other major parameters are defined during the model calibration process. Spatial data on economic activity and the electric power system are incorporated into the analysis as well.

[44] To measure these effects, various parameters must be altered and constraints on electricity availability must be adjusted. In addition, to reflect short-run conditions during the outage, elasticities of substitution between all primary input combinations are reduced by 90%.

[45] This latter category, however, is not included in our estimates below.

resilience (even inherent substitution). On this basis, the implied inherent resiliency in the economy is about 6%.

When all adaptive resilience measures, except for production rescheduling are included, total CGE output reductions fall by 59%--to 13 billion. The weakest reliance factors are conservation and adaptive electricity substitution, and, when indirect effects are considered, alternative generation has the potential to be the most effective at cushioning losses. By including opportunities to reschedule production, total CGE effects fall by an additional $10 billion—to about $3 billion.

To judge the results relative to other regional economic impact studies of power outages, the estimate of losses in the absence of resilience ($1.5 billion/day) are very similar to those reported by Lave et al. (2005) for New York City. To translate these output changes into value added terms, the losses are about $878 million/, or about $878/day, or $89/person/day. To place these in the context of reliability impacts, this translates into $.29/kWh unserved.[46]

The general take away that Rose, *et al*. (2007) put forward is "…that indirect [negative] effects in the context of general equilibrium analysis are moderate in size. The stronger factor and one that pushes in the opposite [positive] direction is resilience" (p. 513).

Summary

A CGE model makes explicit the indirect impacts of catastrophic event, which can be especially large for an extended and widespread event. Because it includes indirect costs that may be substantial the CGE method should be considered for estimating the value of investments that improve resiliency.

[46] The calculation is residential customer centric. It assumes that the average customer uses 8,000 kWh/yr., which translates to 307 kWh over the two-week period and suffers a lost equal to $89, resulting in a loss of $.29/kWh, at the lower range of VoLLs estimated for electrical outages of 12 hours.

6 SUMMARY AND CONCLUSIONS

Findings

A review of the literature on how the electric and other service industries, insurers, and emergency services agencies monetize service resiliency provides the means for comparing alternative ways to estimate the value of electric service resiliency. Resiliency refers to outages that last for extended periods and potentially affect large geographic areas. The focus of the methods reviewed was on high-consequence, low-probability events, such as damage from serious riverine flooding, coastal flooding and wind damage accompanying hurricanes, ice storms, and malevolent attacks. This comports with the interest of the electricity sector in valuing resiliency. The review revealed how alternative valuation methods (the cost of an outage) can be adapted specifically to fit the circumstances of electricity supply resiliency.

In this review, we examine two microeconomic methods to derive estimates of outage costs from customer survey data. One is based on customer damage functions (CDFs), while the other is based on discrete choice experiments (DCEs). Neither has been applied to measuring electric service resiliency. The DCE method is an especially promising approach because it associates outage cost with the specific attributes of the cause of the outage, and produces willingness to pay measures consistent with economic orthodoxy..

We also examine macroeconomic impact modeling to estimate the indirect costs of electric service interruptions from extreme events. These impact models use as input the estimates of direct physical damage to structures and lifelines from software designed specifically for use by federal, state, regional and local governments in planning for natural hazards mitigation, emergency preparedness, response and recovery. They then derive indirect effects, the losses that result for the disruption of economy transactions, which may exceed the direct losses.

A study of insurance claims demonstrates another way to estimate the cost of electric grid disruptions by extrapolating insured business loss data (insurance payouts) for extreme events to the broader population of non-residential and residential customers. This exploratory approach has appeal because it uses secondary data (premiums) that reflect customers' implied estimate of the cost of an outage. This method has several shortcomings that render then not particularly useful by itself. However, it may serve a role in verifying the resiliency values estimates produced by other methods, especially if the utility industry enlists insurers to gather and provide the requisite data on an ongoing basis.

A Categorical Comparison of Methods

Table 6-1 contains a comparison of the three approaches to valuing resiliency of the electrical system. It provides a means for comparing and contrasting the major design features of the methodologies, the effects that are measured, and example applications.

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

The review did not find any microeconomic applications that specifically measure the costs of resiliency of the electric power system, outages lasting several days or weeks, events that are likely to follow high-impact, low-probability events Hence, the large body of empirical research to estimate the value of reliability are of little use in estimating how customers value resiliency.

The microeconomic approach can be adapted to measuring the value of resiliency. One such approach t utilizes discrete choice experiments (DCE). A DCE elicits data directly from customers. Unlike the CDF approach, the objective is to characterize how the individual attributes of an outage influence the cost associated with it. Doing so attaches probability weights to the notice, duration, frequency and other physical attributes of an outage. Once fully conformed, outage costs for any set of attribute levels can be calculated. The attraction of DCE includes its theoretical underpinning in random utility theory and its general consistency with economic demand theory

Both methods consider the direct cost individual incur themselves, not the costs that their outage has on others. To address these broader issues, there have been some attempts to estimate the costs of electric service interruptions through macroeconomic impact modeling of extreme events These studies were based on simulated natural or manmade interruptions, and the results have been published in academic journals. A model of the economy of interest (which might comport with a utility's service territory) is constructed to reflect equilibrium conditions (business as usual), and then it is shocked by imposing physical, market, and consumer disruptions that could be attributed to a catastrophic event. This approach is called computable general equilibrium (CGE).

Comparing economic output (gross product, wages, and profits) before and during the event defines the extent of the outage cost imposed, and by construction represents what society would pay to avoid that outcome. The attraction of this approach is that costs are viewed in terms of their collective level, and therefore they may be less prone to bias than are values elicited from a few individuals, as in microeconomic approaches.

Methods for applying macroeconomic impact analyses are different from the statistical models used in the microeconomic approaches. The data requirements differ as well. Moreover, to model the impacts effectively, the CGE impact models must be constructed to represent a meaningful economic region. The economic regions may encompass electric customers in more than one utility's service territory, thus making it difficult to assign losses directly to electric customers by utility.

An additional shortcoming of the CGE model is that it is difficult to disaggregate the measures of the indirect market impacts (losses) so that they can be assigned to the several service lifelines (telephone and internet, electricity, water, transportation, natural gas) that could have failed during the disaster. Attempts to disentangle these effects may well be accomplished by systematically comparing the losses, simulating situations where selective lifelines are assumed not to fail. Perhaps more importantly for the electric sector, the CGE model does not distinguish impacts of value to customer classes (residential, commercial and industrial) as defined by electric rates. This may limit its application because the value of resiliency may be different across those classes, and would affect the degree and location of resiliency investments are made.

Although there are only a limited number of these simulation experiments to estimate the indirect economic damages from natural disasters, they offer promise as providing a more complete picture of the costs. They include the effects of "inherent" and "adaptive" of individuals and business firms on the magnitude of the economic losses. The simulations examined were limited to post-disaster conditions and response, distinguished from pre-disaster resilience-related activities to reduce potential losses through mitigation. Efforts to harden the electric system would seem to fall into the latter category (mitigation). That is, electric utilities may be able avert some of the consequences of natural disasters through system hardening investments, developing micro-grids to provide more resilient service provision for essential services, and programs to foster the adoption of distributed generation that can operate when the gird fails (e.g., using storage).

Based on this discussion of the differences between the approaches to outage cost estimation, it is hard to imagine that the three methods, microeconomic, macroeconomic, and insurance claims, are substitutes for one another. Rather, the methods could very well complement one another.

Next Steps

Three distinct methods are available. All require a substantial development effort to demonstrate their applicability to measuring resiliency value in ways that support utility investment decisions. Is one superior, or do all deserve development?

Application of the CDF and DCE methods requires concerted effort to develop and implement the survey methods, estimate the cost or preference function, and incorporate the results into an analysis platform that facilitates exploring the consequences of events of different nature, scale, and scope. This requires a substantial investment in developing and demonstrating research methods. But once they are refined, they would be widely applicable in two ways. First, the methods can be applied a wide range of catastrophic situations, which is important because the catastrophic events utilities face are regional in nature; for example, flooding on the coasts and tornados inland. Second, the result of studies can be extrapolated to other markets and customer circumstances because of the inclusion of demography and business characteristics as contributors to the value of resiliency. Not every utility has to undertow a detailed study to calibrate a resiliency model.

The combination of large development costs that produce results that have a high degree of industry relevancy militates for a collaborative DCE value of resiliency initiative. Spreading the cost of development and demonstration among many entities makes this a cost-effective enterprise that does not limit subsequent applications by individuals. Further benefits are realized if applications are coordinated among entities to develop a robust and hence widely applicable data repository to support value determination research. The DCE is also applicable to reliability and power quality valuation studies, so generalizing the development of the DCE methods would serve multiple interests.[47]

CGE is a more holistic approach to measuring electric service value that focus on regional economic activity rather than just electricity supply. Because it is based on the consequences of disruptions to economic activity in general, electricity sector impacts are not the whole story. Consequences extend to other essential services like water, transportation (public and private) and other energy sources (like natural gas, gasoline, propane). To what extent are the impact coincident, and as a result who is responsible for considering their prevention? A big picture portrayal of catastrophic events may provide insights into planning to provide resiliency that may make some electricity system resiliency investments more valuable and others less so because of the collateral effects. It may point out the need for collaboration among providers of essential services to consider infrastructure investments in light of the collective implications of catastrophic events. In other words, resiliency Amy be a public good whole provision is a public policy, not electricity sector, decision.

Portraying the impacts of economic disruptions comes at a price. Estimating a CGE model requires assembling detailed data on the local economy and modeling the implications that are dependent on the nature of that economy and its population. The more exacting the representation of a local economy, the less the result are applicable to other area or regions. Studies undertaken in a variety of climatic and economic situations to establish cause and effect relationship may produce generalizable results. Collaboration among utilities and others is warranted because there is considerable development work to be done to produce CGE methods whose results can be widely employed to individual markets and situations.

The electric supply and delivery system always has been vulnerable to service outages from a variety of low probability/ high impact events. The widespread dissemination of consequences of recent storms (Sandy, Louisiana Flooding), and the growing anxiety about terrorists attacks on the electric system (as yet unrealized), combined with the increasing importance of electricity as an engine of the economy, has raised concerns about today’s electric grid adequacy. Specifically, some argue it is not resilient enough. Resolving that issues requires quantifying how customer value a more resilient electric system.

There are solutions, including collective (public good) investments in hardening assets, such as: moving grid equipment under ground; and installing self-healing systems and recuperative capabilities that speed up reconnecting and energizing customers. These are expensive propositions that may deliver benefits unevenly across customers, because they value resiliency differently, but all pay for proportionally. Customers can pursue private solutions such as on-site generation coupled with storage, or by forming power supply collectives (microgrids) that can operate independently from the grid and provide almost any desired level of service interruption. These too add costs to the provision of electric service, but primarily to the microgrid participants who likely are the primary beneficiaries.

The consideration of public and private resiliency investments requires attributing monetary value to resiliency: What is the cost to achieve a higher level of insulation from the consequences

[47] EPRI has proposed the collaborative development of methods for establishing the value of power quality, and service reliability and resiliency.

of catastrophic events? Utilities and regulators are obliged to address the question of the value of resiliency to support decisions about public good investments. Policy makes are equally obliged as their actions are consequential; they provide benefit and incur costs that inure to tax payers. Those decisions have ripple effects. They will influence the degree of private investment in resiliency by those who value it more, and hence investment and production decisions by the manufactures of such equipment. There are several approaches to monetizing the value of resiliency. All require a substantial research and development effort. Fortunately, the needs of all can be achieve through collaboration.

Table 6-1
The Value of Resiliency--Comparison of Approaches

	Methodology		
	Microeconomic		**Macroeconomics**
Methodology Feature	**Customer Damage Function (CDF)**	**Discrete Choice Experiment (DCE)**	**Computable General Equilibrium Model**
Event	Event resulting full outage (typically) or a partial outage (occasionally) at single or multiple businesses or residences. Could be in context of extremely localized (a neighborhood(s)) or extremely wide spread).		Natural disaster (hurricane, flood earthquake, snowstorm) devastating a large area.
Events used in analyses	Specify alternative levels (or changes in levels) of outage attributes; primarily notice, but may include, notice, frequency, exposure).		Events are specified in terms of return frequencies (100-yr. flood, 1% yearly; 500-year earthquake, 0.25% yearly)
Valuation Concept	Associates losses (damages) with the attributes of a defined event (notice, duration, frequency) that results in loss of power.		Losses for a defined event are indirect economic losses in the economy.
Common reference terms	<u>CDF</u> Outage or damage cost, value of lost load.	<u>DCE</u> Outage or damage cost, value of lost load.	Direct physical damage, direct and indirect economic losses.
Theoretical Basis	No well-defined behavior theory of choices;	Consistent with Random Utility & demand theory	Consistent with Walrasian general equilibrium theory
Mechanism	• Residential: elicit willingness to pay from individuals. • C&I: ask businesses to estimate costs incurred.	Elicit estimates of attribute importance to outage cost: • Residential customers; • Small C&I businesses; • Perhaps large C&I businesses.	For a defined event, estimate physical damage to buildings, lifelines & other components of built environment.

Table 6-1 (continued)
The Value of Resiliency--Comparison of Approaches

	Methodology		
	Microeconomic		Macroeconomics
Methodology Feature	**Customer Damage Function (CDF)**	**Discrete Choice Experiment (DCE)**	**Computable General Equilibrium Model**
Research Methods	• Survey residential customers. • Sampling is across alternative attributes levels. • Conduct interviews with business managers /operations staff. • Estimate WTP/outage costs statistically.	• Survey residential and C&E customers. • Sample from topology of event attribute levels (a wider range of attributes level than in conventional outage cost methods) • Links outage attribute levels & customer characteristics to cost of an outage. • Estimate WTP/outage costs statistically.	• Construct a general equilibrium model of economic activity in the effected region. • Shock economy (change structure of model) to account for physical damage to buildings, lifelines & other parts of built environment. • Simulate indirect economic impact.
Outage cost estimates	For each customer class, determine number of customers affected & calculate the aggregate outage /damage costs based on average per customer outage costs.		Costs are defined as changes in economic output, value added, employment, and wages.
Direct cost			Direct Economic Costs are: • Market and/or depreciated value of damaged buildings and contents (by occupancy class) and structures; • Impacts to lifeline system functionality, component costs, & time to recover are considered.
Indirect costs	• Residential: elicited as willingness to pay values. • C&I: Survey and interviews designed to elicit incurred costs categorically.		Explicitly accounts for the direct material cost incurred by the firms effected physically and collateral costs incurred by others as result of lost business transactions
Spatial Scope	Conventionally the context is an outage by the facility/home, no specific reference to its extent, but some respondents might include some of those considerations implicitly.	Can add the extent of an outage as an attribute and measure its importance in determining outage cost.	Accounts for collateral effects upstream & downstream on firms, even those that are incurred by individuals or businesses not directly affected by the event.

Table 6-1 (continued)
The Value of Resiliency--Comparison of Approaches

	Methodology		
	Microeconomic		Macroeconomics
Methodology Feature	**Customer Damage Function (CDF)**	**Discrete Choice Experiment (DCE)**	**Computable General Equilibrium Model**
Temporal Scope	Conventionally outages of 12 hours or less have been examined.	Potential to examine long duration outages with careful survey design.	Dictated by severity of the disaster and the estimated time to recover.
Granularity by Outage Duration	As currently constructed, outage costs are for: • PQ (momentary or a few seconds to 5 minutes) • Reliability for events from 5 min. to 12 hrs.	Potential to construct a single model that include a wide range of durations (covering PQ to disasters) along with notice, frequency, scale and scale.	Duration is dictated by: • Severity of natural disaster; • The estimates of the recovery time for electric system, and/or other critical lifelines or facilities.
Customer Granularity	Conventionally distinguishes outage cost by customer class: • Residential customers by demographics; • C&I firms by 2-to 5-digit NAICS code.	Allows establishing deep interactions of customer characteristics that support segmentation of customer by their distinct demographic and premise's characteristic	Aggregate indirect market impacts (losses): • Are not easily disaggregated to be assigned directly to electric customers by service class. • May encompass electric customers in more than one Utility's service territory.
Application's	Standard in electricity sector for estimating outage costs, but administered only occasionally and by only a few utilities.		Applications of the effects of simulated natural disasters have been developed to: • Link estimates of physical damages buildings, structures, and infrastructure to regional economic impact models; • Modify structure of regional model to account for physical damage; Monetize indirect economic impacts of the disaster through counterfactual comparison of what the important economic variables would have been absent the disaster.
Examples of Studies Conducted	Over 25 studies used to construct a meta-study model of outage cost (ICE).	None found	A single simulation of the economic effects of a complete blackout in the LA area resulting in a localized, two-week outage.

Table 6-1 (continued)
The Value of Resiliency--Comparison of Approaches

	Methodology		
	Microeconomic		Macroeconomics
Methodology Feature	**Customer Damage Function (CDF)**	**Discrete Choice Experiment (DCE)**	**Computable General Equilibrium Model**
Examples of Uses of outage cost estimates by electric utilities	• Generation capacity planning may use VoLL to determine investments. • Used in some wholesale markets as an implicit measure of value. • Used by ERCOT to set the ceiling price on hourly energy, as was the case in the initial England and Wales Power Pool. • Some US utilities use VoLL to set retail hourly RTP prices to derive prices for load curtailment programs.	Same as for customer damage functions but with a greater degree of customer granularity	None was found.

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A
THE INPUT-OUTPUT METHODOLOGY

Input-output analysis, developed in the in the late 1930's and early 1940's by W. Leontief, has, since that time, proven to be an effective way to assess the economic effects from expenditures made as part of public policy initiatives at the National, state and local levels. In contrast to more aggregate or macro-economic analyses, input-output analysis has the ability to identify the differential effects of policy initiatives by important economic sector. \

The input-output model provides a fruitful way to depict and investigate the underlying processes that bind an economy together. Its strengths lie in a detailed representation of: a) the production (primary and intermediate input requirements), b) distribution (sales) of individual industries in an economy, and c) the interrelationships among these industries and other economic sectors of an economy. The methodology's analytical capacity lies in its ability to estimate the *indirect* and *induced* economic effects stemming from the *direct* policy expenditures that lead to additional purchases by final users in an economy.

These *indirect* and *induced* changes in economic activity result from what are now commonly known as "multiplier" or "ripple' effects throughout the various sectors in the economy. The expenditure of one dollar sets in motion a cascading set of impacts in the form of other expenditures; it is the cumulative impact that is of most interest. Depending on the nature of the policy expenditures, these *indirect* impacts could be in the form of additional purchases of a variety of goods and services, for example: a) raw materials and primary factors of production; b) semi-finished or intermediate goods; c) capital equipment. There are changes in output or sales, and changes in employment and income, as well as changes in payments to land, capital and other primary factors of production.

Part of these *direct* and *indirect* effects is in the form of the increased labor income generated in the economy due to the increased economic activity. To the extent that part or all of this additional income is spent within the economy, there are some additional "ripple" effects that are now commonly referred to as *induced* impacts, and they also can be estimated using the I-O methodology. The magnitudes of both the *indirect* and *induced* effects differ by economic sector.

The Structure of I-O Model of an Economy

To trace these effects by sector, one must first understand the input structure of the major sectors or industries in the economy understood. Given certain assumptions about the nature of production in the economy, the information about the purchases and sales of products among these sectors can be used define this industry input structure, and in turn, provide the analytical and empirical basis for estimating the *indirect* and *induced* impacts of policy initiatives.

Before one can understand the kinds of analysis possible with the help of an input-output model, one must understand the structure of the model and the nature of production and consumption in the economy implied by the model.[48] To engage in production, any industry must purchase inputs and sell output. Industries purchase raw materials, labor, capital equipment, and intermediate inputs from other sectors. Some of these purchases can be outside a state, region, or even the country. In turn, the industries sell products to governments, to other industries as intermediate inputs, and to consumers. Some of these sales can also be to firms or consumers outside a state, region, or even the country.

These patterns of purchases and sales are conveniently summarized in the inter-industry transactions table, essentially a double entry bookkeeping system for an economy that is defined at the major industry or sector level. Often just the process of constructing the table and the understanding of the economy obtained in doing so is worth as much as the analytical analysis that can also be performed. This is particularly true of state or regional I-O models.

The I-O Economy, Open with Respect to Household Consumption

To understand the analytical power of the I-O system, it is convenient to define the components of the model algebraically. Assume there are n sectors in the economy that produce goods for sale as intermediate inputs by other sectors or to consumers, governments, or other final users of the products. Then, let:

Y_{ij} = sales of sector i to sector j;

Y_i = gross sales of sector i

D_i = consumers' final demand for sector i's output;

G_i = combined government, investment, export, and any other exogenous final demand

In addition, for sector i's output;

W_i = total wage bill paid by sector i;

V_i = total payments to other components of value added by sector i;

E_i = total employment of sector i; and

M_i = the value of inputs purchased from outside the region by sector i.

Using these definitions, we can write for each of the n sectors in the economy:

$$Y_i = \sum_{i=1,n} [Y_{ij}] + D_i + G_i \; (i = 1,\ldots,n) \qquad \textbf{Eq. A-1}$$

Each of these equations is a single row of the inter-industry transactions table, and these rows record the inter-industry transactions for intermediate inputs among sectors. For each sector i, the value of gross output is equal to intermediate sales to other sectors plus sales to final demand. The columns of the table, on the other hand, record the purchases by any sector j from itself and all other sectors.

[48] There are many standard texts on Input-Output methods, for example, C. Yan, *Introduction to Input-Output Economics*. New York: Holt, Rhinehart and Winston, 1969, and H. Richardson, *Regional and Urban Economics*. Harmondsworth, Middlesex, UK: Penguin, 1978.

In addition to the sales and purchases of these intermediate inputs, the sectors also purchase labor (payments include wages, salaries, and proprietor's income) and other primary factors (the remaining components of value added in the sector, including returns to land and capital). These purchases are often reported in the transactions table, along with the value of imports from abroad and from other regions of the country.

Labor income is given by:

$$\sum_{i=1,n} [W_i] + W_D + W_G \qquad \textbf{Eq. A-2}$$

The payments to the other components of value added are recorded as:

$$\sum_{i=1,n} [V_i] + V_D + V_G \qquad \textbf{Eq. A-3}$$

The value of imports is given by:

$$\sum_{i=1,n} [M_i] + M_D + M_G \qquad \textbf{Eq. A-4}$$

Finally, although not found in an I-O transactions table, we can also report total employment as:

$$\sum_{i=1,n} [E_i] + E_D + E_G \qquad \textbf{Eq. A-5}$$

By assuming that: a) the production of a good requires all inputs in fixed proportions and b) production is subject to constant returns to scale, the input structure or technology for each sector can be derived *direct*ly from the data in the inter-industry transactions table. We can calculate the inputs requirements as:

$a_{ij} = Y_{ij}/Y_j$ = *purchases from sector i/dollar of sector j's output (the direct intermediate input requirements)* **Eq. A-6**

$w_i = W_i/Y_i$ = *payments to labor/dollar of sector i's output* **Eq. A-7**

$v_i = V_i/Y_i$ = *other value added/dollar of sector i's output* **Eq. A-8**

$m_i = M_i/Y_i$ = *value of imports/dollar of sector i's output* **Eq. A-9**

Finally, although it is not in the transactions table, we can define the employment requirements for output by sector as:

$e_i = E_i/Y_i$ = *employment/dollar of output of sector i* **Eq. A-10**

By rearranging Equation A-6, we can write the transactions between sector i and sector j as:

$$Y_{ij} = a_{ij} Y_j \qquad \textbf{Eq. A-11}$$

in turn, substitute Equation A-3 into Equation A-1 to obtain:

$$Y_i = \sum_{i=1,n} a_{ij} Y_j + D_i + G_i \ (i = 1,\ldots,n) \qquad \textbf{Eq. A-12}$$

Thus, we have expressed the value of a sector's output in terms of final demand, the output levels from the other sectors, and the input requirement coefficients. In matrix notation, we can write the Equations in A-12 as:

$$Y = AY + D + G \quad \textbf{Eq. A-13}$$

where Y is an (nx1) column vector of Y_i's; A is an (nxn) matrix of a_{ij}'s; and D and G are (nx1) column vectors of D_i's and G_i's, respectively. Subtracting AY from both sides, yields:

$$(I-A)Y = D + G \quad \textbf{Eq. A-14}$$

This equation highlights the fact that gross output in each sector minus intermediate demand equals final demand. Multiplying both sides of Equation A-6 by $(I-A)^{-1}$, yields:

$$Y = (I-A)^{-1} [D + G] \quad \textbf{Eq. A-15}$$

Through this set of equations, the data in the input-output table are used to characterize the technology of an economy at the sector level and express the interrelationships among sectors of the economy in terms of those input-output coefficients. In so doing, Equation A-15 can be used to calculate equilibrium output levels in an economy-- the output levels from each sector of the economy necessary to meet both intermediate demands (AY) and final demands [D + G]. It is this equation, involving the Leontief Inverse, $(I-A)^{-1}$, that underpins much of the policy impact analysis performed using an inter-industry model. Letting h_{ij} = the i,j^{th} element of $(I-A)^{-1}$, it can be shown that h_{ij} = *direct* plus *indirect* dollars of gross output of sector i needed to deliver one dollar of output of sector j to final demand. Since this particular transformation of the A matrix translates the *direct* input requirements per dollar of output into the *direct* plus *indirect* inputs per dollar of final demand, it is the effects of the "multiplier" rounds that is captured in the individual elements, h_{ij}, of the Leontief Inverse.

By defining W, V, and E as (1xn) row vectors of *direct* wage (including proprietor income), other value added and employment requirements per dollar of output i (with elements w_i, v_i, and e_i, respectively), we can also use the Leontief Inverse to calculate the *direct* plus *indirect* payments to labor, and other value added and employment, respectively, by sector to meet given levels of final demand by the equations:

$$W^{DI} = W (I-A)^{-1} [D + G] = W Y \quad \textbf{Eq. A-16}$$

$$V^{DI} = V (I-A)^{-1} [D + G] = V Y \quad \textbf{Eq. A-17}$$

$$E^{DI} = E (I-A)^{-1} [D + G] = E Y \quad \textbf{Eq. A-18}$$

The expressions on the right-hand side of the second equals sign are obtained by substituting Equation A-15 into the expressions in between the two equals signs. This exercise reinforces the fact that payments to labor, payments to other components of value added, and employment are proportional to output. It also suggests that it is computationally efficient to calculate Y in Equations A-16 through A-18 before pre-multiplying by W, V, and E.

Closing the I-O Model with Respect to Households

In the model described above, it is assumed that household final demand (D) is exogenous to the economy; as output in the economy expands or contracts, there is no change in consumption by households due to the corresponding changes in income payments to households. This is an unrealistic assumption to make when considering an economy of any size. Thus, it is important to relax this restrictive assumption; in so doing, we are able capture the additional economic effects of changes in household consumption *induced* by changes in income to households.

To close the economy with respect to households, we can essentially treat the household sector as an additional sector of the economy—sector n+1 if you will. Accordingly, the payments from the other sectors in the economy to households are already captured in total by Equation A-2 above, and on a per dollar of output basis by Equation A-7. Total final purchases by households by each sector are given by the elements of the vector D (e.g. D_i). To put these purchases on a per unit basis, one must divide consumption by sector by total payments to households that are given in Equation A-2. That is, one can define the input-output coefficients for this new n+1 sector as:

$a_{i,n+1} = D_i / Y_{n+1}$ = the input or consumption requirements from each sector by households per dollar of household income, where

$$Y_{n+1} = [\textstyle\sum_{i=1,n+1} (W_i) + W_D + W_G] \qquad \textbf{Eq. A-19}$$

To make the notation consistent, one can now redefine the *direct* labor income requirements as:

$$a_{n+1,j} = W_j / Y_j, \text{ (for } j = 1 \ldots n+1) \qquad \textbf{Eq. A-20}$$

The intuition for closing the economy in this way is straightforward. As with any other sector, the household sector produces an output, in this case, the output is labor services. As with the other sectors, the household sector purchases inputs from the other sectors, but in this case the inputs are goods for final consumption. Accordingly, the average, and in this case also the marginal, propensities to consume out of income by sector are given by the individual $a_{i,n+1}$'s, and the overall marginal propensity to consume locally (MPC) out of income is given by:

$$1 \geq MPC = \textstyle\sum_{i=1,n+1} [a_{i,n+1}] \qquad \textbf{Eq. A-21}$$

By definition the MPC is less than or equal to unity.

We can now describe the transactions in this economy that is closed with respect to households by an expression similar to Equation A-12 above:

$$Y_i = \textstyle\sum_{i=1,n+1} [a_{ij} Y_j] + G_i \ (i = 1, \ldots, n+1) \qquad \textbf{Eq. A-22}$$

There are now n+1 sectors in the economy. In matrix notation, we can write:

$$Y^* = A^*Y^* + G^* \qquad \textbf{Eq. A-23}$$

Where: Y* is an (n+1x1) column vector of Y_i^*'s; A* is an (n+1xn+1) matrix of a_{ij}'s; and G* now representing the only exogenous final demand in the economy, is an (n+1x1) column vector of G_i's.

Again, subtracting A*Y* from both sides, we obtain:

$$(I-A^*)Y^* = G^* \qquad \textbf{Eq. A-24}$$

Gross output in each of the n+1 sectors minus intermediate demand equals final demand, and the output in each sector to meet any given level of exogenous final demand is now given by:

$$Y^* = (I-A^*)^{-1} [G^*] \qquad \textbf{Eq. A-25}$$

The interpretation of the elements of $(I-A^*)^{-1}$, call them k_{ij}, is similar to that of h_{ij} from above. In this case,

k_{ij} = the direct plus indirect plus induced output of sector i, needed to deliver one dollar of output j to final demand **Eq. A-26**

The elements $k_{n+1,j}$ have a special interpretation:

$k_{n+1,j}$ = the direct plus indirect plus induced income (payments to labor plus proprietary income) per dollar of output j to final demand **Eq. A-27**

Thus, to calculate the *direct* plus *indirect* plus *induced* payments to households for any given level of exogenous final demand (the similar expression to equation, we now have:

$$W^{GI} = K_{n+1}[G^*] \qquad \textbf{Eq. A-28}$$

Where: K_{n+1} = the n+1 row of $(I-A^*)^{-1}$

Since employment and payments to other value added are still exogenous in the economy, and remain proportional to output, the *direct* plus *indirect* plus *induced* other value added and employment effects are given by:

$$V^{GI} = V^* (I-A^*)^{-1} [G^*] = V^*Y^* \qquad \textbf{Eq. A-29}$$

$$E^{GI} = E^* (I-A^*)^{-1} [G^*] = E^*Y^* \qquad \textbf{Eq. A-30}$$

where all vectors denoted by an "*" include an n+1 element.

Changing the Structure of the Economy

Finally, although policy analysis within an I-O framework is traditionally thought of in the way described above, policy programs can also alter the input structure of the economy. For example, program spending in some cases requiring a larger proportion of some inputs to be purchased from outside the region) or that lead to policy *induced* changes in consumer spending patterns (changing the propensities to consume locally by sector, or in total). In the former case, there could be a systematic reduction in some of the a_{ij} coefficients in one or more of the first n sectors. In the latter case, there could be changes (either up or down) in some of the $a_{i,n+1}$ coefficients. In either case, there would be a change to the matrix A*; let us call this new matrix of input coefficients A^P. In this case, one can calculate the *direct* plus *indirect* plus *induced* changes in household income and payments to other value added, and employment due to the combined structural changes to the economy and the changes in exogenous final demand as:

$$\Delta Y^P = (I\text{-}A^P)^{-1} [\Delta G^*] \quad \textbf{Eq. A-31}$$

$$\Delta W^{GIP} = K_{n+1}{}^P[\Delta G^*] \quad \textbf{Eq. A-32}$$

$$\Delta V^{GIP} = V^*[\Delta Y^P] \quad \textbf{Eq. A-33}$$

$$E^{GIP} = E^*[\Delta Y^P] \quad \textbf{Eq. A-34}$$

where $K_{n+1}{}^P$ is the n+1 row of $(I\text{-}A^P)^{-1}$.

Clearly, if the *direct* effects of a policy can all be reflected in changes in G*, then $A^* = A^P$, and the results are identical to those from Equations A-31 through A-34.

B

FLOOD LOSS ESTIMATION METHODOLOGY FRAMEWORK

(Material is from Scawthorn, *et al*. (2006b), and appears here is edited and somewhat abbreviated form)

The Inventory and Valuation module: Most aspects of building and other inventory are common to all three models of HAZUS, earthquake, wind, and flood. In seismic and wind loss estimation, cost of repair is the measure of economic loss, effectively equating it to the cost of new construction. Flood estimated losses are often based on depreciated value, because the National Flood Insurance Program pays claims on the basis of depreciated value.

Direct Damage module: The HAZUS Flood Model uses estimates of flood depth along with depth-damage functions (plots of floodwater depth versus percent damage, plotted for a variety of building types and occupancies) to compute the possible damage to buildings and infrastructure that may result from flooding.

Damage to General Building Stock: The method for estimating direct physical damage to the general building stock is simple, and it is computed for each occupancy class in a given census block, with default damage functions along with estimated water depths--either riverine or coastal-- to determine the percent damage.

Damage to Essential Facilities: Essential facilities provide service to the community and should be functional following a flood (hospitals, fire stations, schools). Depth-damage curves are used to estimate damage to essential facilities. The effects of flood proofing on facilities can be accounted for by modifying the depth damage functions.

Damage to Lifeline Systems: Damage to transportation and utility lifeline systems is estimated based on the vulnerabilities of components to inundation, scour/erosion, and debris impact/hydraulic loading. Fragility modeling is applied to bridges; water and wastewater system components with medium exposure; and electrical power, communications, natural gas, and petroleum lifeline systems that have vulnerabilities similar to water and wastewater systems. Impacts to system functionality, component costs, & <u>time to recover</u> are considered.

Damage to Vehicles: Flood damage to vehicles can be substantial. Damage functions were developed based on the location of critical vehicle components in passenger cars, light trucks and heavy trucks, and the depth of inundation.

Damage and Loss to Agriculture: Damage to crops depends on the timing and duration of flooding, as well as the depth of flooding. Damage functions are based on <u>calendar date and duration modifiers</u>. Losses are estimated based on the area of inundation versus total area of cropland and the subsequent reduction in output, investment, and income. The loss model is based on the Corps of Engineers AGDAM methodology and program.

Consideration of Warning in Depth-Damage Relationship: Flood forecasting is a regular occurrence today and the capability for estimating possible reduction of flood damage by taking actions after warning is provided in the Flood Model by consideration of warning time and altering depth-damage functions. The effectiveness of flood warning in reducing damage is estimated by modification of Day curves, (Harold Day 1960s), and damage reduction related to forecast lead time, defined as time required for warning dissemination and effective public response.

Direct Economic Losses: Direct economic losses include building repair and replacement costs-structural and nonstructural damage-building contents losses, building inventory losses, relocation expenses, capital related income losses, wage losses, and rental income losses. The first three categories are building-related losses. The other losses are time dependent--a function of time required for building restoration or outage time.

Indirect Economic Losses: Floods produce economic dislocations for firms not damaged. Businesses are forward linked (rely on regional customers to purchase output) or backward linked (rely on regional suppliers for inputs); they are vulnerable to interruptions, even if not damaged. Interruptions (indirect economic losses) are not confined to immediate customers or suppliers. Successive rounds of customers and suppliers are impacted. Limited physical damage ripples transmitted through the regional economy. Indirect losses depend on factors such as availability of alternative supply sources and product markets, length of production disturbance, & deferability of production.

C
EARTHQUAKE LOSS ESTIMATION METHODOLOGY FRAMEWORK

(Material is from Kircher, *et al*. (2006), and appears here is an edited, somewhat abbreviated form)

The framework of the original methodology includes the six primary components (modules) shown in Figure below. The modules are interdependent. Each component is required for comprehensive loss estimation. The degree of required sophistication can differ greatly by user and application. The modular approach permits both estimates based on simplified models and limited inventory data, as well as refined estimates based on more extensive inventory data and detailed analyses. This modular methodology allows users to limit their studies to selected losses. We start from a user-chosen earthquake, the Potential Earth Science Hazards (PESH) module estimates ground motion and ground failure (landslides, liquefaction, and surface fault rupture).

Inventory module: describes the physical infrastructure and demographics of the study region. There are groups of infrastructure such as: 1. general building stock; 2. essential and high potential loss facilities; 3. components of transportation lifeline systems; and 4. components of utility lifeline systems.

Direct Damage module: provides damage estimates in terms of probabilities of reaching or exceeding discrete states of damage for a given level of ground motion or failure. Damage estimates also include time to restore function of essential facilities and lifelines and anticipated service outages for potable water and electric power systems. This module is the heart of the methodology and for buildings is based on the same technology as that used for "performance-based" engineering of structures by *FEMA 273 (*FEMA, 1997) and *ATC-40* (SSC 1996).

Once estimates of direct damage are made, induced damage can be evaluated. Induced damage is defined as the secondary consequences of the earthquake. Induced damage includes consequences of fire following the earthquake, inundation due to dam or levee failure, hazardous materials--HazMat--release, and debris generated by collapse or demolition of damaged structures. The Induced Damage module calculates damage due to fire following and the quantity of debris generated. The module geographically locates dams and levees whose failure might cause inundation and hazardous materials sites.

The Direct Loss module: calculates direct economic and social losses. Direct economic losses include: capital-related costs of repair and replacement of damaged buildings and lifeline components; and income-related costs due to relocation, business interruption, rental loss, etc. Direct social losses are quantified in terms of casualties, displaced households, and short-term shelter needs.

The Indirect Loss Module: assesses broad and long-term implications of direct impacts, such as changes in employment and personal income. Past earthquakes have shown that these losses are primarily a function of damage to buildings. This is true for two very basic reasons: 1. buildings are the predominant kind of facility in the built environment; and 2. buildings are vulnerable to earthquake damage. Buildings provide shelter for people, whether at home or at work, house commercial and industrial operations, and serve as essential facilities, such as schools and hospitals. Accurate prediction of building damage and loss is at the heart of reliable estimates of earthquake impacts.

The Building Damage and Loss Function modules have two components: Capacity curves & Fragility curves.

The capacity curves are based on engineering parameters e.g., yield and ultimate levels of structural strength that characterize the nonlinear (pushover) structural behavior of the 36 different types of model buildings. For each building type, capacity parameters distinguish between different levels of seismic design and anticipated seismic performance. Fragility curves describe the probability of damage to a building's: structural system; nonstructural components sensitive to drift; and nonstructural components (& contents) sensitive to acceleration. Fragility curves distribute damage to physical damage states: slight, moderate, extensive, and complete.

The methodology also requires methods for: 1. building classification by model building type and occupancy; 2. building design and performance categories; 3. structural and nonstructural systems and contents; 4. Building damage states; 5. building capacity; 6. building response; and 7. building loss.

The HAZUS Earthquake methodology also includes "Special" building damage functions for those essential facilities (e.g., post- 1973 California hospitals) that are known to be of superior design and construction. For these building the parameters of the capacity and fragility curves reflect greater seismic capacity and reliability of these buildings. While essential facilities are important, they typically represent only a very small fraction of buildings.

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