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Regional Economic Modeling of Electricity Supply Disruptions: A Review and Recommendations for Research

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Abstract

Economic simulation models of regional economies have been applied in a number of studies to analyze the costs of electric power disruptions. Such modeling complements traditional survey methods in this context, particularly in the estimation of indirect costs of disruptions, which are those resulting from interruptions of economic production that propagate across firms and industries via market interactions. This paper surveys the literature on this modeling. It begins with a description of the structure and characteristics of the computational economic models that have been applied to this purpose. Background on key aspects of power-disruption modeling is then presented, including definitions of economic costs, the concepts of direct and indirect disruption costs, and the idea of "resilience" to disruptions—broadly, the ability of economic agents to take actions that mitigate their losses when electricity supply is interrupted. The paper continues with a review of three representative studies on regional economic modeling of power losses. It then provides a critical discussion of these studies, highlighting key methodological issues in quantifying resilience and representing it in economic models. Recommendations are made for research, and the paper concludes with a summary. Key findings include:

- Regional economic modeling is a viable methodology for estimating large-scale costs of power disruptions, especially indirect costs, and is capable of representing resilience—adaptive behavior by firms facing power disruptions—which may substantially reduce these costs;
- However, further development of the models is needed for this application, especially to improve the representation of resilience;
- New theoretical and empirical research would be required to undertake such improvements, and is contingent on improved data, especially related to adaptive behavior;

Integrating survey data related to power disruptions with national economic data on industrial firms would facilitate model improvements as well as enabling empirical (non-simulation model based) economic modeling of electricity use and the costs of disruptions that would be valuable in its own right.

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Table of Contents

List of Tables

1. Introduction

The economic consequences of electric power disruptions are the subject of an extensive literature dating back to the 1970s. This work primarily comprises survey-based studies of hypothetical localized disruptions, in which individual firms or households are queried as to their potential losses from electricity service interruptions of given durations, generally from a few minutes or less to up to one business day (Sullivan et al. 2009).[1] With increasing attention to the reliability and physical security of the U. S. electric power grid, however, there is emerging interest among regulators and industry experts in the potential economic costs of power disruptions on larger geographic and economic scales, and of longer durations. There is a small but growing literature on this issue, based on the use of economic simulation models representing large metropolitan areas, counties, or entire states in the United States.

These analyses are instances of what is referred to as "regional" economic modeling, and as explained below the models themselves can be informally described as of the "economy-wide" type. This paper reviews the literature on regional economic modeling of power disruptions. It first describes the structure and characteristics of the computational economic models that have been applied to this purpose, the analytical approaches, and several examples. Several conclusions are then drawn from this review regarding the both the advantages and the limitations of this type of modeling. Key research needs for advancing this area are identified, and several recommendations are made for research directions.

The paper is organized as follows. In the next section, different types of economy-wide models are described. Background on key aspects of power-disruption modeling is then presented, including definitions of economic costs, the concepts of "direct" and "indirect" disruptions costs, and the idea of "resilience" to disruptions—broadly, the ability of economic agents to take actions that mitigate their losses when electricity supply is interrupted. The subsequent section reviews three representative studies on regional modeling of power losses. The paper then turns to a critical discussion of these studies, and of key methodological issues in quantifying resilience and representing it in economic models. It goes on to discuss research and recommended directions, and ends with a summary and concluding remarks.

2. Types of Economy-wide Models

While large-scale computational economic modeling of power disruptions has sometimes been referred to as "macroeconomic," there are in fact several distinct types of economy-scale mathematical and computational models that have been applied to study these phenomena. Here, "economy-wide" need not mean at the level of an entire country; in the present context the focus is on regional economies in the United States, including (as in the examples discussed below) state-level and metropolitan area-level. To elaborate and provide background for discussing specific examples, we begin by reviewing terminology and substantive aspects of the relevant modeling methodologies. Note that each type is well-established and has a long history in other applications.

First, "Input-Output (I-O)" models represent all inter-industry relationships or flows in an economy, i.e., how the outputs of industries are used as inputs to others, and the overall outputs of consumer goods (or

[1] Billinton et al. (1993) review methodologies and examples of studies through the early 1990s.

“final demand”) produced by all industries, as systems of linear equations—the system of industry transactions is represented in matrix form.[2] The key technical feature of I-O models is the assumption of fixed coefficients or proportions determining input-output relations between industries. That is, the amount of input *X* that is required to produce a unit of output *Y* by a given industry does not change according to scale, or through substitution with different inputs depending upon relative prices changes, or as a result of, for example, technological change. Essentially for this reason, the basic I-O accounting framework does not represent the actions that firms might take in order to adapt to the loss of electricity.

A second class of models is the “computable general equilibrium (CGE)” type, which represent in simplified but explicit form all supplies and demands in an economy and both their direct and indirect market interactions.[3] Supply and demand are determined by the economic (optimizing) choices of consumers and firms. CGE models are therefore based on *microeconomic* principles; they are complete numerical representations of economies in the form of systems of non-linear algebraic equations or related mathematical structures.[4] By contrast to I-O models, the input-output relations among industries are nonlinear and to a degree flexible, a function of technology assumptions, prices, and other factors.

Third, “macro-econometric” models are systems of statistical forecasting equations, with parameters statistically estimated on historical times series data. These have most commonly been used to represent national economies and to study inflation and other monetary phenomena as well as aggregate (un)employment. However, they have also been used to analyze regional-level economies. Unlike most other computational economic models (including CGEs), they do not explicitly represent the decision-making behavior of consumers or firms, nor the equilibration of supply and demand in markets. In forecasting applications, they typically project over time horizons of several calendar quarters (although much longer time horizons are also represented in some applications). Although fundamentally designed for forecasting, macro-econometric models can also be used for scenario analysis by positing specific hypothetical future trends in particular factors, or changing values of key inputs to reflect scenario assumptions.[5]

To encompass each of these modeling types, the term “economy-wide” is preferable to “macroeconomic,” and to re-iterate, modeled economies can be at various scales including regional.

Each of the three model types has been applied to the large-scale analysis of power disruptions. The following section provides background on these applications, and Section 4 summarizes three representative studies of this type.

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[2] Input-output analysis was developed by the economist Wassily Leontief, starting in the 1930s. It subsequently became widely used as modern computing facilitated the development and analysis of large-scale models. Leontief received the 1973 Nobel Prize in Economics for this work.

[3] CGE models are based upon the mathematical theory of general equilibrium developed by the economists Kenneth Arrow and Gerard Debreu in the early 1950s, which is the most comprehensive framework for standard, or “neo-classical” representation of an economy. Arrow and Debreu received the Nobel Prize in Economics in 1972 and 1983, respectively, for this work. CGE models were first developed in the 1960s and 1970s, and build on and extend the I-O approach; like the latter, they were enabled by the advent of modern computing.

[4] Sue Wing (2009) provides a conceptual and technical overview of CGE modeling and its use in energy policy analysis.

[5] Macro-economic forecasting models have their origins in the 1940s and 1950s, and combined insights of Keynesian economics with statistical modeling and methods. The economist Lawrence Klein was a leader in their development, for which he received the Nobel Prize in 1980.

3. Aspects of Power Disruption Modeling

3.1 Metrics of Economic Losses

The idealized concept for assessing economic costs of electricity supply disruptions is the "marginal value of reliability," the value assigned by a customer to an incremental "quantity" of reliable service, i.e., of avoided electricity supply interruptions. In practice, economic analysis of power interruptions is based on the principle that this marginal value is equal to the value of lost electricity service, and the latter is in turn estimated in terms of reduced economic activity—such as foregone industry output—due to interruption of electricity service.

A standard applied metric for estimating this quantity is the "value of lost load (VOLL)," defined as the costs that a consumer or firm would incur from a disruption as a function of its duration.[6] In survey research, these losses are estimated by firms themselves given hypothetical disruption scenarios. The VOLL has also been estimated by using aggregate data on industry production (Leahy and Tol 2011).[7] VOLL is typically represented in terms of the "customer damage function (CDF)," which gives the costs resulting from a power disruption- induced reduction or cessation of production, measured in terms of the value of lost output in dollars, normalized by magnitude of the power interruption—e.g., in kWh or kW (Ghajar and Billinton 2006).

In I-O and CGE modeling of power disruptions, losses are instead usually gauged in terms of percentages of baseline output valued in dollars, at both the industry and economy-wide levels. Thus, the two metrics are closely related, but not equivalent. Macro-econometric models also estimate percentage reductions in overall economic output, but primarily represent impacts in terms of macroeconomic variables such as employment and personal income.

3.2 Direct and Indirect Costs of Disruptions

The distinction between direct and indirect losses from and costs of power disruptions is fundamental in the survey literature, although the definitions of these terms varies somewhat. As characterized by Billinton et al. (1993), for example, "direct costs are those arising from the electrical interruption and related to such impacts as lost industrial production…", while "Indirect costs are related to impacts arising from a response to the interruption, such as crime during a blackout (short term) and business relocation (long term)."

[6] Reflecting the economic modeling work that is the subject of this review, this paper focuses on firms and industries. For households—i.e., residential electricity customers—several measures of losses have been analyzed in survey-based literature. Most attention has been given to so-called "willingness-to-pay (WTP)," defined as the monetary amount that a household would pay to avoid interruption of service of a given duration. Doane et al. (1988) is an early example of such work; a more recent example is Sullivan et al. (2009). Academic research on residential customers' valuation of service interruptions continues but is primarily conducted outside the United States; e.g., Carlsson and Martinsson (2008), focuses on Swedish households. It should be noted that the underlying theoretical and empirical economic basis for WTP studies in general (not just on electricity) has been the subject of some controversy—the issues are discussed in Hanemann (1999) and in Horowitz and McConnell (2002).

[7] Another approach to estimating direct costs is to analyze firms' investments in back-up power generation, e.g. Matsukawa (1994).

To understand how direct and indirect costs are represented in economy-wide models, note first that in each model type what is represented are not individual firms but rather sectors or industries (or "representative firms"), at some level of disaggregation. Faced with a loss of electricity, an industry will curtail its output by some amount for some duration—the associated economic losses from this are essentially its direct costs.

However, every industry also uses the outputs of other industries (i.e., in addition to that of the electricity "industry") as inputs. So a disruption will also affect the availability of these other inputs. Generally speaking, the indirect costs are those resulting from these inter-industry output-to-input interruptions and how they determine the propagation of the disruption effects across an economy.

The details of how these are represented vary by modeling type. In I-O models, all inter-industry flows are as noted above assumed to be in fixed proportions—i.e., firms/industries do not have the capacity to substitute among inputs. In CGE models, they d—the transformation of inputs to outputs is represented by "production functions," which—up to a point—allow trade-offs to be made among inputs, so that less of one can be offset by more of another. (Such functions are described in Sub-section 4.2 below.) In both cases, however, the underlying idea of the mechanism of indirect power disruption costs is essentially the same—it is the inter-linked (through markets) nature of an economy.

In macro-econometric models, the fundamental structure is different. Some but not all examples of this type of model (in general) include inter-industry transactions as described above. The example discussed in Sub-section 4.3, below, does not.

3.3 Resilience

A key topic in this application of economy-wide models is the "resilience" of economies to power disruption—generally speaking, the capacity of consumers, firms, and markets to temporarily adjust, adapt, or otherwise compensate for the loss of electricity in ways that mitigate economic impacts. The details of how "resilience" is defined and represented in models have important implications for assessing and comparing their power interruption applications.

The resilience concept has a long history in literatures including those dealing with disaster planning and recovery and related topics, including but not limited to electric power. Its meaning varies across disciplines, but very generally has to do with the capacity of "systems"—ecological, technological, economic—to respond to harmful or damaging events in such a way as to mitigate their effects, continue functioning, and recover. The concept has drawn critical scrutiny. For example, Klein et al. (2003) point out that

> "Some analysts define resilience as a system attribute, whilst others use it as an umbrella concept for a range of system attributes deemed desirable. These umbrella concepts have not been made operational to support planning or management."

More recently, Cutter et al. (2010) observed that

> "…concerns from the research community focus on disagreements as to the definition of resilience, whether resilience is an outcome or a process, what type of resilience is being addressed (economic systems, infrastructure systems, ecological systems, or community

> systems), and which policy realm (counterterrorism; climate change; emergency management; long-term disaster recovery; environmental restoration) it should target."

In the context of the electric power system, a pertinent example is a recent report on "grid-resilience" with respect to weather-induced supply disruptions; this report does not actually define "resilience," but describes actions that would increase it in the electricity system (USEOP 2013b). These actions are primarily technology oriented, including strengthening of transmission lines and distribution sub-stations and deployment of advanced controls. A subsequent report on "energy resilience metrics" conducted for the U. S. Department of Energy adopts the definition of Presidential Policy Directive 21 (PPD-21, USEOP 2013a):

> "…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" (Watson et al. 2014).

In the context of regional modeling of power disruptions and in the examples we discuss below, resilience is explicitly or implicitly an economic concept, characterized in the terms of micro-economics specifically, particular to this discipline's theories of behavior and market structure. This framing can encompass technological elements, but is more general. At the same time, while described and mathematically modeled in terms of technical economic theory, the concept of resilience here is grounded in a simple practical tenet: Faced with a loss of electricity, firms, households, and other decision-makers will do what they can to adjust, adapt, and otherwise cope. The significance of this fundamentally behavioral perspective is its implication that economic losses from power disruptions are likely to be less than would be anticipated or estimated based on a purely technical or technological perspective.

Rose (2007) describes economic resilience in the following terms:

> "…static *economic resilience* [is] the ability of an entity or system to maintain function (e.g., continue producing) when shocked (emphasis in original)… It is thus aligned with the fundamental economic problem—efficient allocation of resources, which is exacerbated in the contest of disasters…A more general definition that incorporates dynamic considerations is the speed at which an entity or system recovers from a severe shock to achieve a desired state" (p. 384).

"Achieving a desired state" is a very general criterion. With respect to dynamic economic resilience in the present context, Rose's meaning encompasses the repair and/or replacement of capital stock following a "shock" —e.g., an earthquake, or terrorist attack—that resulted in damage to or destruction of machinery, buildings, etc., and these actions would define the recovery process. The desired state might be considered the pre-shock level of production and output. Whether this would be attainable, however, would be highly dependent on the nature and severity of the shock.

In the next section we give the characterizations of "resilience" reported in the cited studies themselves, and in the subsequent section provide further discussion.

4. Regional Economic Modeling of Power Disruptions: Three Examples

It is worth noting that the vast proportion of survey and other non-modeling studies have been hypothetical or *ex ante*. A handful of case studies exist, but this approach is of course constrained by the relatively limited number of disruption events—particularly of longer durations. Of the following regional modeling examples, two are hypothetical and one is an *ex post* case study.

4.1 An I-O Analysis

Rose et al. (1997) use a 21-sector I-O model representing Shelby County, Tennessee to analyze the consequences of electricity supply disruption caused by a hypothetical earthquake in the New Madrid Seismic Zone near Memphis. As is common in I-O modeling in the United States, their model is based on "IMPLAN," a commercially-available source of input-output transactions and related information.[8]

The analysis incorporates engineering information on the regional electric power system, and previously-developed probability damage models of the network reliability and electricity supply consequences of potential earthquakes in this fault system. In addition, previous research on earthquake effects is used to sub-divide the region into "impact zones" according to both the likely time until electricity restoration and the economic consequences. The effects of the disruption are assumed to last up to fifteen weeks. Industry-specific loss factors are based on output reductions that are proportional to the industry's loss of electricity, and are estimated by combining this engineering information with baseline economic data, also incorporating "resiliency factors" that offset the production output loss resulting from a power disruption. The researchers do not define resiliency *per se* except to say that these factors "…reflect [industries'] electricity usage and adaptability characteristics." For example, "…a resiliency factor of 0.1 [would mean] that a complete loss of electricity would lead to 90 percent loss of production." The numerical values of these factors are "adapted from the results of a survey of business vulnerability due to lifeline disruptions in Shelby County." This survey is documented in Tierney and Nigg (1997), and was an *ex post* survey of businesses following a flood event that had disrupted electricity and other services, as asked business to rate the importance of different "lifeline" services—electricity and natural gas, water, and telephone—to their operations, the extent to which these services were disrupted by the flood, and, in the case that they temporarily ceased operations, which of the disruptions was the primary reason.

Rose et al. define "direct" effects as "…output losses attributable to electricity disruption at the production site" (measured at the industry level). The I-O model is first used to estimate direct losses for each industry resulting from the disruption of electricity, as a percentage of gross economic output. Rose et al. find that while all industries incur significant initial losses, these are considerably reduced within two weeks following the earthquake. The total direct reduction in gross output for all industries over the fifteen-week time frame is 2.3% of annual baseline output.[9]

The researchers define "indirect" losses in this modeling framework as decreases in outputs of industries resulting from "bottlenecks": the loss of necessary production inputs from other industries due to the

[8] See http://www.implan.com.

[9] All of the results in the paper are also reported in terms of net output, or final demand. The quantitative magnitudes are comparable between the two metrics; for example, direct final demand losses are 1.9% of the annual baseline (compared to 2.3% losses in gross output).

latter's direct losses from the electricity disruption.[10] A second model simulation is conducted to estimate these indirect effects. Rose et al. find that these indirect, bottleneck effects cause overall fifteen-week gross output losses of 8.6% of the annual baseline, nearly four times larger than the direct losses.

In these simulations, as noted above, output loss magnitudes are based on fixed, industry-specific factors. In a second phase of their study, Rose et al. use a linear programming (LP) model to instead optimally ration scarce electricity—as supply is restored to the region following the earthquake—in order to optimize regional economic output. Put differently, electricity is provided to industries according to the incremental value of their production output. This is done in two ways. First, the power restoration pattern assumed in the above computations is maintained, but the allocation of restored power to industries is calculated using the LP to maximize gross output. Second, both the restoration pattern and the allocation of restored power are optimized according to this criterion. With the first optimization, the overall fifteen-week reduction in gross output relative the annual baseline falls to 0.62%, and with the second to 0.58%, compared to the 2.3% direct and 8.6% indirect losses in the previous cases.

4.2 A CGE Analysis

Rose et al. (2005) develop and apply a 33-sector CGE model to retrospectively analyze the effects of four rolling blackouts in Los Angeles County, California, in 2001, which occurred during California statewide electricity shortages on two days in March and two days in May of that year. IMPLAN data (see above) are used to construct so-called "social accounting matrices," which underlie and serve to calibrate the model. For this study, the modelers obtained geographically-disaggregate employment data from local authorities, and electricity data from Southern California Edison (SCE), the Los Angeles regional investor-owned utility. They combined these information sources in a preliminary analysis spatially linking the power disruption impacts to sub-regional employment and economic activity. Note that in contrast to the I-O study and the macro-econometric study described below, this was an *ex post* analysis of an actual event, and it is also the case that electricity customers had advance notice of the blackouts.[11]

Direct or "partial equilibrium" losses are defined as the value of industries' output reductions due specifically to the curtailment of electricity as an input to production. Indirect or "general equilibrium" losses are in part as in the previous I-O example—reductions in output due to curtailment of non-electricity inputs, from other industries. In the CGE framework, however, they also include output losses resulting from decreased consumer spending following wage losses as a result of a disruption-induced unemployment, decreased investment, and economic losses due to cost and price increases caused by blackout-induced scarcities.

Rose et al. define "resilience" as "coping or adaptation tactics" undertaken by firms following a power disruption, and modify their CGE model in several ways to represent it. By way of background: In a CGE model, firms' responses to changes in the magnitude of an input to (or "factor of") production—such as a reduction in electricity—are determined in part by "substitution elasticity" parameters that determine the

[10] More precisely, the I-O fixed coefficient structure implies that the output of the industry with the greatest loss becomes the "constraining factor" for other industries (that require it as an input of production), and this defines the bottleneck.
[11] Rose et al. cite an estimate of statewide advance warning times for businesses of 2.5 hours during the 2001 events, while also noting that warnings for businesses in the SCE service territory were "considerably longer"—i.e., further in advance—than this average.

possibilities for trading off among these factors in producing output. A simple example is as follows: Let Y_t be the output of a representative firm—i.e., an industry—at time *t*, and assume that producing Y_t requires the inputs capital K_t and energy E_t. The process of transforming inputs to output is represented by a "production function" $Y_t = F\left(K_t, E_t, t\right)$, where the appearance of time as an input indicates that the process may change over time. In CGE models, the most common functional form used to numerically represent this abstract model is the so-called "constant elasticity of substitution (C.E.S)," and this is the form used by Rose et al. For our simple example, this can be written as

$$Y_t = A\left(a_t K_t^{-\rho} + b_t E_t^{-\rho}\right)^{-\frac{1}{\rho}}, \tag{0}$$

where $\rho > 1$. It can be shown (from the underlying mathematical definition) that the elasticity of substitution σ between capital and energy is $\sigma = 1/(1+\rho)$.

This structure of the model in Equation (1), and in particular the elasticity, capture the fact that firms can trade-off—i.e., substitute between—factors of production. In standard theory, such actions are typically responses to changes in the relative prices of these inputs. The productivity parameters a_t and b_t represent—in a very approximate fashion—technological progress. A well-known example of this type is labor productivity. Historically, national economic output per unit of labor has steadily increased over the past century. Many CGE models represent the economy over time horizons of years or decades, and in these exogenously-set parameters enable the models to reproduce this trend into the future. A similar pattern has been observed for the aggregate, long-run relationship between economic output and energy input, and analogously, exogenous energy-productivity parameters are used to represent this phenomenon in CGE models, such as b_t in Equation (1). Specifically, under the assumption that b_t increases over time, output can also increase over time *without increasing the energy input and can also remain the same over time with a decrease in the energy input.*

In their more complex version—i.e., the mathematical representation of production embodied in the CGE model—Rose et al. adjust the analogues to ρ and b_t, above, in several ways.[12] First, because substitution elasticities in models of this type are intended to represent long-run phenomena, they first lower several elasticities to account for the fact that in the immediate aftermath of an unexpected electricity disruption, firms' ability to substitute would be limited. The adjusted parameters are those representing the capacity to substitute other fuels for electricity, and to increase the substitutability of other inputs for energy.[13] They then raise them slightly to account for, as they put it, "…ingenuity during the crisis."

[12] "More complex" refers in particular to the explicit representation of different types of energy—electricity, natural gas, petroleum—and to the use of the so-called "nested C.E.S." functional form, a hierarchical version of the C.E.S. that incorporates greater detail on production relationships.
[13] Rose et al. also identify back-up generation as an adaptive response. Because a paucity of data precluded direct representation of this in the model, they approximated it via the substitution elasticity parameter adjustments.

The energy-productivity parameters are also adjusted to capture adaptive behaviors by firms in response to the blackout—in this case, changing their use of electricity and other fuels in order to continue production, or resume it as quickly as possible. Specifically, they are raised from the baseline values to represent what Rose et al. call "conservation"—essentially, firms' "making do" with less electricity, other fuels, and other inputs, but without needing to reduce output as a consequence.

Rose et al. first simulate the economic effects of the blackout without resilience mechanisms, i.e., with no adaptive responses on the part of firms, yielding an estimate of direct, partial equilibrium losses of 7.1% of the baseline economic output. They then conduct a complete general equilibrium simulation of both direct and indirect effects, incorporating adaptive responses. In this analysis, the direct losses are reduced to 0.74%, an order of magnitude reduction. The net indirect, general equilibrium losses are 0.55% where "net" means above and beyond the direct losses, so that the combined losses are 1.29%.

4.3 A Macro-Econometric Analysis

The third example is of a structural macro-econometric model of the New Jersey economy, used to simulate a hypothetical power outage due to terrorism in the summer of 2005 (Greenberg et al. 2007). The event is assumed to occur in the service territory of Public Service Electric & Gas (PSE&G), which contains 55% of residential and 60% of the non-residential utility customers in the state, and about 80% of its population, and accounts for about 85% of its employment base. However, the study analyzes the economic effects of the outage across the entire state.

Key model variables are employment by industry, personal income to residents of the state, gross state product, and total tax revenues. In this study, employment figures were reported for non-agricultural industries in total and for four "electricity-sensitive" industries. An I-O model was also used in the study, to estimate the electricity usage by industries.

Greenberg et al. note that "Resilience is an important concept in this research," and define it as follows:

> "Resilience is the adaptations within the economy that speed recovery from a shock and avoid some losses. Defined in this way, resilience is people, governments, and organizations responding by conserving, substituting, and rescheduling their activities. In other words, they would use less electricity, use non-electric forms of energy, and not perform tasks that would have used a good deal of electric power. Resilience is aided by mitigation that lessens the impact of the shock when it occurs… [for example, the use of back-up generators]."

However, they acknowledge both that the models they use are not designed to capture these effects, and that there is an almost complete lack of data to quantify them. Thus, with one apparent exception—the response of the medical-care industry to the power loss (see Section 5.3 below) —Greenberg et al. did not explicitly represent resilience in their models or analysis.

Greenberg et al. consider three basic scenarios. A "middle" scenario assumes that 90% of power to the PSE&G service area is lost for two days, with 25% restored at the end of the second day, 50% restored at the end of one week, and all electricity restored by the end of two weeks. A "worse" scenario posits greater initial loss and slower restoration (full resumption of service in two months), while in a "less" scenario the initial loss is lower and full restoration occurs by the end of two weeks. The total electricity losses in these three scenarios as percentages of summer quarter baseline consumption in PSE&G are 5.5%, 16.4%, and 3.5%, respectively.

Each of these three cases is in turn simulated under two different assumptions regarding employment: One, that jobs lost due to the outage are restored to the state's economy by the end of 2005; two, that only half of jobs lost are restored. In the middle scenario with restoration, for example, there are net losses for 2005 with respect to each of the metrics noted above: Total non-agricultural and energy-sensitive industry employment, personal income, gross state product, and total tax revenues. In 2006, however, non-agricultural employment, and each of the non-employment variables, are *higher* than in the baseline, and by 2010 all variables exceed their baseline levels. For example, the changes in gross state product relative to baseline in 2005, 2006, and 2010 are -1.2%, +2.1%, and +0.3%%, respectively. With half-restoration of employment in the middle scenario, the changes in gross state product relative to baseline in 2005, 2006, and 2010 are -1.6%, -3.3%, and -1.8%, respectively.

Greenberg et al. explain that higher-than-baseline economic outcomes in the middle scenario with full restoration of employment (and in several other scenarios reported in the paper) are due to the macro-econometric model acting to restore economic stocks lost due to the outage, so that there is a temporary greater-than-normal level of activity in its aftermath. In the middle scenario with half restoration of employment, this rebound effect does not occur, and there are net economic losses in 2005 and 2006 that persist to 2010.

4.4 Summary; Remarks on Other Work

Key results of these studies are summarized in Table 1.

There are a number of other examples of I-O analysis of power disruptions in the literature, but these generally do not address the resilience issue as such; the one described here is representative of the basic methodology, in addition to being distinguished by incorporating resilience estimates. Rose and his collaborators have published several other studies on CGE modeling of electricity disruptions. One is also focused on the Los Angeles economy, dealing with a hypothetical terrorist attack (Rose et al. 2007); another, akin to the I-O study described above, on earthquake impacts in greater Memphis, Tennessee (Rose and Guha 2004; see also Guha 2005). Including the one described here, these are not merely representative but actually constitute most of the literature of this type, i.e., CGE modeling of power disruptions. Finally, while there is a modest literature on macroeconomic modeling of entire countries' responses to natural disasters of various sorts, it has not included U. S. regional-scale analysis such as Greenberg et al. conducted.[14]

[14] A study of the effects of Hurricane Sandy on the economy of the State of New Jersey used the same macro-econometric model and included recovery expenditures on electric and gas utilities among the firms/industries receiving them, but did not focus on electricity *per se* (Mantell et al. 2013).

Table 1. Three economy-wide regional economic model power disruption studies: Summary

Study	*Topic*	*Model type*	*Results*
Rose et al. 1997	Hypothetical earthquake-induced power disruption in metropolitan Memphis, TN	Input-Output, with linear programming adjunct	Over 15-weeks: Direct losses 2.3% of baseline gross regional economic output; indirect losses 8.6%. Reduced to 0.58% with optimal restoration and allocation of power.
Rose et al. 2005	Retrospective study of 2001 blackouts in Los Angeles County, CA	CGE	Direct losses, without adaptive (resilience) responses: 7.1% of baseline regional output; direct & indirect losses, with adaptive responses: 1.29%.
Greenberg et al. 2007	Hypothetical terrorist-induced power disruption in New Jersey	Macro-econometric	"Middle" scenario—5.5% reduction in baseline electricity use, 50% restoration in one week, 100% in two weeks, one-half restoration of employment: 1.6% reduction in annual gross state product relative to baseline first year following disruption; 3.3% reduction in second year; 1.8% reduction in fifth year.

5. Discussion

5.1 General Observations on the Studies

These examples demonstrate the utility of regional economic modeling for the analysis of large-scale, long duration power disruptions. There is to-date a relatively small number of such examples relative to the large number of more traditional, survey-based studies. However, the three cases show the feasibility of quantitatively estimating the economic costs of such events in a structured, comprehensive manner, and indicate that in principle this modeling methodology substantially enlarges the possibilities for regulators and the electric power industry to understand and plan for these disruptions.

In general and in this application, each model type has both advantages and limitations. I-O models are conceptually and computationally relatively more tractable, and pose fewer data demands, while not being well-suited for analyzing resilience. CGE models are more demanding especially with regard to data requirements in addition to the necessary underlying economic transaction data akin to the input-output type;[15] the additional data include, in particular, values for exogenous parameters of the type described above, substitution elasticities and productivity trends. However, CGE models also have the capacity to incorporate resilience and other dynamic effects. Macro-econometric models are very firmly grounded in empirical evidence, which can be considered a strength, while also implying that their use for scenario analysis strongly assumes that the relationships reflected in historical data will continue to hold in the future. In addition, their focus on employment impacts may be a desirable feature for some policy-makers. However, they are "reduced form": Actual behavior on the part of firms is not represented, even in an approximate way. For this reason, their capacity to address the details of resilience is fundamentally limited relative to that of CGE models.

The relative magnitudes of indirect losses compared to direct, as estimated with the I-O and CGE models, and the extent to which resilience or adaptive behavior can reduce the overall economic losses of large-scale electricity disruptions, as estimated especially with the CGE model, are the key findings in the analyses discussed above. In terms of the remarks in Section 3, above, this highlights that in the context of disruptions to the electric power system, resilience is not just a physical and engineering phenomenon, but also a function of how consumers and firms respond to events such as supply interruptions. Under the theoretical and quantitative assumptions in the CGE-type model especially, adaptive behavior can reduce the effects and costs of disruptions by substantial amounts relative to what would be estimated using purely technical and/or engineering methods. While the specific numerical implications of resilience in the Rose et al. I-O model are not reported, the supplemental analysis incorporating optimal allocation of scarce electricity during the recovery period in effect represents a form of adaptive behavior. The macro-econometric methodology *per se* does not incorporate resilience or adaptive behavior.

Beyond the scope and scale of power disruption analysis enabled by regional modeling, the capacity to gauge indirect effects and the value of resilience are the most important advantages of the methodology over survey-based methods. A well-known tenet in numerical energy modeling is that models' value is in providing "insight, not numbers" (Huntington et al. 1982; Peace and Weyant 2008), and this is well-illustrated here: Notwithstanding the structural and data differences among the models, the importance of indirect effects and resilience is a robust finding, at least with respect to the I-O and CGE studies. In

[15] These underlying data sets are the social accounting matrices mentioned in Section 4.2.

addition, the macro-econometric estimation of employment impacts is a useful functionality that is limited at best in the survey-based approach. This is because comprehensive assessment of such impacts is necessarily a problem in large-scale analysis across multiple industries, taking into account the baseline employment and other economic aspects of these industries. These capabilities are not within the scope of survey analysis.

5.2 Issues in Quantifying and Modeling Resilience

It is important, however, to emphasize that these findings are contingent upon the details of how modelers address resilience. Notwithstanding the capabilities demonstrated, the studies reveal that the definition, quantification, and representation of resilience in regional economic models is an area that remains in development. That consumers and firms will try to adapt and adjust is presumably uncontroversial. What are uncertain, however, are the details of how they will do so, how successful they will be, how the outcomes of their actions can be measured and quantified, and how such empirical information can be represented mathematically for incorporation into computational models. These complications imply that, at the models' current stage of development, there are significant limitations in our ability to use them not just to analyze the effects of disruptions, but also to evaluate the potential effects of policies and/or R&D to mitigate their economic costs by enhancing or increasing resilience.

The most important issue for improving the models' treatment of resilience is that, as the modelers themselves emphasize, there are very limited data on the actual responses of firms to power disruptions of the type and detail needed for empirically-grounded representation in economy-wide modeling. Greenberg et al. discuss this problem at length. As mentioned above, the single instance of their explicitly representing resilience in their modeling appears to be the health-care industry:

> "The literature indicated that medical care facilities have their own back-up power source. Using that information, we cut power loss to the health care sector of the model by only 50% rather than completely. But we had no access to similar information for many other industries" (p. 731).

Rose et al. repeatedly note the presence and implications of data limitations. As previously noted, in their 1997 input-output modeling of earthquake-induced power losses, Rose et al. cite a previous survey as the basis for their "resilience factors." They do not, however, provide details on how the survey information was used to specify numerical values for these factors.

In their CGE study of the Los Angeles power disruptions, Rose et al. (2007) cite five previous studies as sources for quantitative information on adaptive responses by businesses to loss of service, that is, resilience. One was an *ex post* survey of businesses following the Northridge earthquake of 1994 (Dahlhamer and Tierney 1996). Second was an *ex post* input-output study by the lead author of the Northridge earthquake, which used results from the same survey (Rose and Lim 2002). The rest were CGE studies by the lead author of hypothetical earthquakes, in Portland, Oregon, and in Memphis, Tennessee. In this input-output study, resilience is incorporated by reductions-in-output losses due to three factors: The "importance" of electricity in production, the ability to postpone production, and the ability to shift electricity consumption within a 24-hour period. However, no details are provided on how the numerical values for these factors were chosen.

A second major issue is the adjustment process Rose et al. apply to substitution elasticities and productivity parameters in their CGE modeling to incorporate the adaptive behavior (resilience). In principle, this is a reasonable and practical approach to representing such behavior in a CGE model. However, the researchers provide little discussion of or justification for the numerical values of these adjustments—for the elasticities, a 90% reduction from long-run values, and then a 10% increase to reflect short-term adaptive behavior; the basic issue here is unavailability of data upon which to base these changes (see Section 6, below).

Notwithstanding this quantification problem, all else being equal, changing the substitution elasticities to reflect limitations on the very short-run—hours or days—capacity of firms to respond to a disruption is in principle conceptually reasonable within the CGE framework. However, the rationale for increasing energy productivity parameters to represent "conservation," as Rose et al. describe it, as an adaptive behavior is not entirely persuasive. In the standard lexicon of energy analysis, this term refers to using less energy—that is, reducing fuel consumption—and, all else being equal, is understood to entail reduction in the output of the productive process for which energy is an input. By contrast, "efficiency" refers to the substitution of capital for energy, in the form of more energy-efficiency machinery or other equipment. As such, this is not a productivity improvement in the sense represented by the model parameters in question, but rather a substitution phenomenon. In cases in which a firm had been previously under-investing in energy efficiency in this sense, in the framework of microeconomic production theory (with exogenous technical change) the investment can be interpreted as a combination of substitution and productivity increase. However, these investments require time to plan and implement, and would be highly unlikely to occur in the immediate aftermath of a disruption.

Taken literally, what this model change implies is that in the face of a sudden disruption in electricity supply, firms will more-or-less spontaneously manage to maintain, if not the same level of output as pre-disruption, then a significant fraction of that output, at no cost. Rose et al. (2007) acknowledge that conservation is a "limited option because of the all-or-nothing nature of the situation," but do not go on to provide a convincing rationale for why conservation is nonetheless an appropriate concept in this context.

5.3 Scope and Scale in Modeling Power Disruptions

In considering these and possibly other avenues for developing regional economic modeling of electricity disruptions, it is critical to recognize and take account of the context and specific causes of such events, and the implications of these for the credibility and accuracy of cost estimation. The modeling literature has not adequately addressed this issue. In particular, the particular circumstances and nature of a power disruption could be expected to affect the degree of adaptive response—i.e., "resilience behavior" —that could be expected. Disruptions caused by technical failures in the power system for example, are likely to result in firms' responding quite differently than they might to either earthquakes or terrorist attacks. This is in part, but not entirely, due to whether the event affects electricity only, or if not, the nature of the effects on other factors. For example, a terrorist attack might cause a degree of *social* disruption that would affect individuals' and firms' capacity to respond to the *power* disruption. An earthquake might disrupt not just electricity, but other services such as water, as well as possibily causing some breakdown in, e.g., regional transportation infrastructure and systems. If so, then adaptively responding to electricity service loss specifically could be only one of multiple demands on individuals' and firms' time and attention. For these reasons, even with the further development and enhancements recommended here, the appropriate scope of regional economic modeling of power disruptions must be kept in mind: It cannot be expected to be a methodology that is fully robust for analyzing disruptions regardless of their causes and severity. Put differently, the “narrower” the event—i.e., the more it only involves electricity specifically—the more applicable the economic modeling will be, and the more useful its use in policy and regulation.

At the same time, this modeling methodology is in general likely to be most appropriate for disruptions of relatively long duration—such as those analyzed in the I-O and macro-econometric examples described above (Sue Wing 2015). There is thus a certain tension in the sense that such longer events may be least likely to solely involve power supply disruptions only.

6. Research Needs and Directions

As noted above, the economic modelers emphasize the lack of empirical data that could be used to improve the models' representations of electric power disruptions' economic impacts. These data limitations apply especially to the modeling of adaptive behavior and resilience, for example, the prevalence of back-up generation equipment. Accordingly, a high priority for advancing regional economic modeling of electricity supply disruptions is a systematic increase in the quantity and quality of this type of empirical data. Developing such data resources, however, should be closely integrated with empirical economic research to support their application to modeling. An example is the need to better understand the exact timing—on an hour-to-hour, day-to-day, and week-to-week—of firms' response to power disruptions. Rose et al. note that

> "…we are not aware of any studies that have estimated elasticities for [the] kind of 'very short run' that we consider…only empirical estimation of very short-run elasticities would enable us to assess the implications of our approach to the accuracy of the results" (Rose et al. 2005, footnote 11, p. 197).

To address this and related issues, both data *and* its application to the estimation of key parameters are required, and this example is indicative of the need for a "dual" data/analysis strategy to support improvement of economy-wide modeling of power disruptions. In this section we elaborate on this theme and discuss details. We begin by providing further background on CGE models.

6.1 CGE Modeling

The discussion in the previous section confirmed the usefulness of CGE models, in particular, for analyzing electricity disruptions, while also reviewing limitations of existing examples of this application of the models, several model features that need further development, and associated data issues. In considering the possibility of model enhancements for power disruption analysis, it is important to understand certain contextual aspects of CGE modeling and methodology.

It was noted in Section 5 that CGE models are relatively demanding in terms of data requirements. It is important to point out that these requirements arise not just in configuring such models for power disruption analysis specifically, but must be fulfilled in order to construct the models in the first place, as it were—e.g., to assign values to substitution elasticities and productivity trends—prior to using them for policy analysis of any kind. Thus, enhancements of the type discussed in this paper are fundamentally incremental.

The challenges of parameterizing CGE models in general—i.e., not just in energy applications—have long been noted in the modeling literature. In principle, model parameters can be statistically estimated. But the practical difficulties of doing so—including obtaining appropriate data—have resulted in the common practice of instead "calibrating" the models: assigning numerical values to parameters non-statistically using other information, such as the results of studies conducted for other purposes. The shortcomings of calibration are discussed, for example, in Dawkins et al. (2001), who among other points emphasize that this practice complicates the testing and verification of underlying model validity.[16]

In the present context, it is the models' representation of production that is of particular interest—specifically, the assignment of specific forms to, and parameterizations of, production functions, as discussed above in Section 4.2. The goal of improving the empirical foundations of the economic policy modeling—especially related to energy and carbon dioxide emissions abatement—has stimulated a small but growing literature on econometric (statistical) estimation of these functions and their parameters (e.g., van der Werf 2008; Dissou et al. 2012; Koesler and Schymura 2012; Costantini and Paglialunga 2014). Nonetheless, systematically incorporating the results of this type of work into CGE models for the most part remains to be accomplished.

This is one reason that validation and uncertainty quantification of CGE models have been identified by some researchers as generally lacking but vitally important. Beckman et al. (2011), for example, demonstrate a technique (based on stochastic simulation analysis) for validating a CGE model—in this case energy-oriented—and test how incorporating empirical estimates of substitution elasticities improves model performance. Similar work has been conducted for CGE models focused on agricultural market and policy analysis (Valenzuela et al. 2007) and on international trade (Hertel et al. 2007).

Any program of research on or development of CGE modeling for power disruption studies should include this type of analysis. On general principles, strong empirical grounding, uncertainty quantification, and validity assessment are fundamental criteria for computational modeling in many disciplines, not just in economics and,CGE-based. But in electricity disruption analysis (as in many other applications), it is also important to consider the possibility that underlying but unquantified model uncertainty might in fact exceed the magnitudes of the effects of interest—i.e., the economic costs of disruptions. This reflects the methodological tenet noted above, that computational models—in this case, economic—should be used for generating insights on phenomena of interest, including policy interventions, rather than for precise numerical predictions or other outputs. A necessary condition for following this tenet in practice is that such insights be robust to model uncertainties, and the type of CGE analysis cited in the previous paragraph can help ensure this in power disruption (as in other) applications.

With this background, this paper's discussion of CGE modeling of disruptions clearly implies the need for a) More data to quantify resilience and adaptive behavior, b) Improved estimates of key substitution elasticities—for which such data are necessary, and c) Theoretical research on better representing resilience and adaptive behavior in the CGE framework specifically—as discussed, a focus of such research would be the use of productivity parameters and the assertion of "conservation" to represent firms' loss-mitigating responses to electricity shortages, and whether and how these could be better grounded or otherwise improved upon.

Another important topic related to CGE modeling of power disruptions is the use of reduced form and other relatively simple models to complement full-complexity economic simulation models (Greenberg 2015). For example, Chen et al. (2015) created a reduced form of a CGE model by conducting numerous simulations of the latter under different input parameter assumptions, and then estimating a linear

[16] Dawkins et al. use the synonymous term "applied general equilibrium," and focus on trade policy applications. But their critique fully applies to energy (CGE) models as well; this point is discussed in Sanstad (2015).

statistical model on the resulting "synthetic" data. This simpler model is implemented in spreadsheet form and can be used by non-experts much more easily than the full-complexity CGE. A more basic approach, for studying short-duration disruptions, would be to construct a simple statistical model using county-level employment and wage data combined with utility data on the event itself (Sue Wing, 2015). The use of such simpler modeling approaches should be considered in conjunction with the use of CGE modeling when the latter is being considered in power disruption applications.

The next sub-section proposes a direction for empirical research that could provide a basis for work on CGE models along the lines suggested above. The subsequent sub-section discusses other aspects of CGE and other forms of simulation for electricity disruption analysis.

6.2 Empirical Economic Modeling of Electricity Use and Power Disruptions

6.2.1 Studies in Other Countries

It was noted in Section 4 that most survey-based studies of power disruptions have been of the *ex ante* type—that is, customers are asked about their potential responses to hypothetical supply interruptions of different levels of severity and duration. Two of the three economic modeling studies reviewed above were also of this type. Generally speaking, the emphasis on hypothetical events is also reflected in the literature on power disruptions in other developed countries, e.g., a very recent study on commercial customers in Finland (Kufeoglu and Lehtonen 2015).

By contrast, several recent studies analyze the costs of actual power disruptions in developing countries using econometric (statistical) methods. For example, Fisher-Vanden et al. (2015) analyze the effects of electricity shortages on manufacturing productivity in the period 1990-2004 using an econometric model of production applied to data on a large (23,000) sample of Chinese energy-intensive firms. Their model distinguishes among reduced productivity, on the one hand, and the adaptive responses of self-generation, input substitution in the form of outsourcing—obtaining more inputs from other firms—and increasing energy efficiency, on the other. They find that, in general, firms responded to shortages by substituting materials for energy rather than self-generating or increasing efficiency.

Oseni and Pollitt (2015) study the effectiveness of self-generation in reducing losses due to electricity disruptions among 4,400 first in eight African and two South Asian countries in 2007; their analysis encompasses manufacturing as well as service industries. They find that while self-generation does reduce these losses, the relative differences in unavoided losses between self-generating and non-self-generating firms depend upon their underlying vulnerabilities to disruptions and the degree to which self-generation can replace lost electricity supply.

A third example is Allcott et al. (2015), who analyze the economic impacts of electricity shortages on productivity in Indian manufacturing, including the mitigating effects of back-up generation.

6.2.2 Micro-Level Economic Studies of U. S. Firms

These examples demonstrate the value of empirical economic analysis of electricity supply disruptions when sufficient data on both firms *and* disruptions are available. But they also highlight a hurdle facing potential research of this type in the United States: Although the United States is fortunate to have an electricity supply that is in general highly reliable, this fact does limit, in a relative sense, the amount of data on actual disruptions available for statistical or econometric analysis.

Nevertheless, such data do exist for the United States and have supported reliability analysis (Eto et al. 2012), and avenues for the improvement of data of this type have been identified. Fisher et al. (2012) discuss the availability, quality, and suitability of data for analyzing the reliability of the U. S. bulk electric power system, and suggest steps to improve the completeness and accuracy of such data. To support development of the economic analysis of power disruptions, improving this type of data resource should be coordinated with designing and implementing new empirical economic studies that build upon and extend previous econometric research on the energy use of commercial and industrial firms in the United States.

This previous research has applied econometric methods to create empirical models of the use of energy, particularly electricity, by U. S. firms and industries. Here "empirical" means statistical, in contrast to simulation and/or equilibrium models such as I-O or CGE, and in addition means micro- rather than macro-economic, so that the models in question are also distinct from the macro-econometric models described previously. This literature has not focused on power disruptions, but rather has analyzed the fundamental determinants of energy use and their inter-relationships, including the roles of prices and technologies, as well as influence of industry type and spatial location.

Most such research has focused on the U. S. manufacturing sector and has been based upon plant level surveys conducted by the U. S. Census Bureau—in particular, the Census of Manufactures (CM) and the Annual Survey of Manufactures (ASM) —and by the U. S. Department of Energy—the Manufacturing Energy Consumption Survey (MECS). These have in several instances been combined with other datasets to analyze specific topics.

An early example is Doms (1993), who used the MECS to analyze the influence of technology-choice on energy use in manufacturing plants and empirically estimated the degree of substitutability among energy sources, including between electric and non-electric energy.[17] Linn (2008) combined the CM, ASM, MECS, and several other sources to analyze the links among energy prices, energy demands, and technology adoption in U. S. industry. Davis et al. (2008) use a data set that combines the ASM with Department of Energy data to study electricity productivity in the U. S. manufacturing sector, and find a high degree of heterogeneity in the efficiency of electricity use across plants, even within industries. Davis et al. (2013) use the same dataset to analyze, at the micro-level, electricity purchase prices and consumption quantities in the same sector. They find considerable variation in prices, resulting from differences in both location and the size of firms. Boyd and Curtis (2014) combined Census of Manufactures data with a management practices survey of U. S. firms to study the implications of such practices for the degree of efficiency in the firms' use of energy.

To further the development of the economic analysis of power disruptions, a new program of research could be undertaken that would integrate empirical modeling based on these plant-level economic and energy databases, with new surveys aimed at gathering information related to disruption occurrences and characteristics, resilience, and adaptive behavior, as discussed in this paper. As indicated by the previous research just described, such research could also provide a solid quantitative knowledge base on

[17] Although not at the national scale, an even earlier example of micro-econometric analysis of energy use by firms is Train (1988), who studied energy conservation by both commercial and industrial firms in the service territory of a Southern California utility.

“baseline” electricity use and economics, which would serve as a platform for both historical and scenario studies of the economics of disruptions.

This proposed program of empirical economic work would have a two-fold outcome: First, it would develop and apply “stand-alone” *micro*-econometric modeling tools that could be used to analyze both historical electricity disruption effects, and scenarios of such events in the future. All else being equal, such modeling would be primarily applicable to analyzing direct costs of disruptions, and in this respect would therefore not be a substitute for I-O or CGE modeling. However, it could provide substantially more accurate direct cost estimates than those currently available with the models. Second, it would support the research tasks on CGE modeling proposed above in sub-section 6.1, particularly the estimation of elasticities and other parameters determining adaptive responses in model simulations. In this way, the empirical economic modeling would also facilitate improved indirect cost estimation using the economy-wide models.[18]

As noted above, successful pursuit of this research direction would require further development of existing data resources relevant to disruptions—not just their frequency, severity, and spatial distribution, but also the status of firms potential for resilience and adaptive behavior. For example, Philips et al. (2015) surveyed the prevalence of back-up generation associated with critical U. S. infrastructure; going forward, such survey-based data collection could be combined and/or integrated with the plant-level datasets noted above.

It should be emphasized this proposed research would focus at least initially on the U. S. manufacturing sector. The reason is that there is unfortunately not a companion survey to the MECS that could be readily adapted to studying commercial firms in an analogous fashion. Unlike the MECS, the Department of Energy’s Commercial Buildings Energy Consumption Survey (CBECS) is not organized around the sectoral classification system underlying the National Income and Product Accounts (NIPA) maintained by the U. S. Department of Commerce’s Bureau of Economic Analysis.[19] It therefore cannot be readily integrated with the Census Bureau’s micro-level data on service and other non-manufacturing industries which, like the manufacturing databases, are organized around NIPA categories. The Energy Information Administration, which conducts the energy surveys, has created what it calls a “rough crosswalk” between CBECS and NAICS, but it is not clear how useful this would be in linking its survey with the economic surveys. This question should be investigated and an assessment made of the possibilities for conducting micro-econometric research on electricity use and the effects of power disruptions in the commercial sector.

[18] Although this paper is not focusing on further development of macro-econometric models for power outage analysis, it is worth pointing out that better empirical data on firms’ responses to outages, the micro-level details of production and energy use, and the prevalence of back-up generation, could also support improvement of these models for this purpose. As noted in this paper, while these models have specific limitations for electricity disruption analysis, they can nevertheless be a useful tool for this application subject to these limitations, and as highlighted by Greenberg et al. (2007), their applicability could be enhanced with improved data.

[19] Currently in use is the North American Industry Classification System (NAICS); historically, the Standard Industrial Classification (SIC) system was used.

6.3 A Risk-Analysis Perspective

Analyzing the effects of large-scale, long-duration power outages is *prima facie* a problem of uncertainty and risk analysis.[20] Of the three types of economy-wide models discussed in this paper, only the macro-econometric type, by virtue of being a statistical model, is designed to quantitatively incorporate uncertainty, in this case in the form of confidence intervals for estimated parameters, for example. I-O models and CGE models are intrinsically deterministic, and not designed to directly support risk or uncertainty analysis.[21]

It would nevertheless be possible in principle to use such models in a larger framework for some form of large-scale (regional), prospective economic risk analysis of power outages. The basic definition of "risk" combines the probability of an event with the consequences should it occur. The analyses discussed in this paper provide point estimates, in effect, of the economic consequences of power outages. The first step for using such results in risk analysis would be estimating the probabilities that the triggering events would occur. For weather-related events, this is possible up to a point. Assuming the analysis would be of hypothetical future events, it would require regional-scale projections of climate. The science of such projections is steadily advancing and at its current stage can support some degree of probabilistic forecasting, although it remains conditional on intrinsic climate model uncertainty, among other factors. Earthquake prediction is less developed, although it might be possible to specify probabilities of events in particular regions over relatively long time scales, if not their exact magnitudes. For events such as terrorist attacks, there are no credible means of probabilistic forecasting (i.e., of the likelihood of particular attacks in a specific place and time); in this case, a deterministic scenario analysis approach is warranted.

A risk-analysis perspective on grid reliability is the core recommendation of Watson et al. (2014), and they provide an example that is relevant to the present discussion. As noted above, it pertains to a disruption of the electric power system, due to a hurricane, and uses a security-constrained unit commitment model with economic dispatch. The researchers "arbitrarily define system damage" in terms of probability distributions of equipment failures in the modeled generation fleet and transmission network, respectively. They solve the model in a Monte Carlo procedure, first to gauge the economic costs of the disruptions, and a second time with the alternative optimization criterion of "maximizing resilience." They report that the results of this resilience optimization show that "…it is possible to significantly reduce the consequences of" the hypothetical disruption event. This example is partially related to the analysis noted above by Rose et al. (1997), in which a linear programming model is used to determine allocation of scarce power following a disruption using a criterion of "economic importance."

A formal risk analysis using this methodology would involve the minimization of *expected* cost—that is, stochastic optimization within the model itself, with respect to the uncertainty represented by the

[20] Castillo (2014) provides a survey of the literature on risk analysis and risk management related to power outages and power restoration.
[21] There is another class of general equilibrium models, so-called "dynamic stochastic," that also have numerical implementations, and explicitly incorporate uncertainty. Rickman (2010) discusses these in a regional modeling context. These models, however, are considerably smaller—i.e., less detailed—than deterministic CGE models, owing in particular to computational tractability limits; they represent an economy in very aggregate terms, and do not include the industry-level detail included in each type of model discussed in this paper. For this reason, they are not well-suited to the kind of economic analysis of power disruptions that is the subject of this paper.

parameters. While useful, a Monte Carlo analysis over uncertain parameters is conceptually and practically different. The researchers also point out that "…actual damage realization profiles will need significant domain expertise and stakeholder involvement in order to be accurately specified." Thus, as with further work on economy-wide models for power outage analysis, a considerable new effort of data development would be needed to pursue this type of risk modeling.

Nevertheless, this power-system modeling example suggests the possibility of combining such analysis with CGE modeling. In the first instance, a deterministic approach would be warranted. Going forward, however, the possibility of applying risk analysis modeling techniques, such as those reported by Watson et al., to CGE modeling and to integrated CGE-system modeling should be investigated. In this connection, while the data requirements for CGE modeling differ in general from those for electric power system modeling, the data assessment of the type recommended above should be undertaken at least in consultation with the "experts and stakeholders…" referred to by Watson et al., as quoted above. In fact, it would be ideal to conduct an integrated assessment of the two categories of data needs.

6.4 Hybrid Modeling

As noted previously, if better data on the adoption of back-up generation by firms were gathered, incorporating it into a CGE framework would be a high priority for improving CGE modeling of power disruptions. One approach to doing this would be the strategy of so-called "hybrid" energy modeling, which is the integration of explicit technology detail into economic equilibrium models, and which has been the subject of a number of studies in energy modeling.[22] The purpose of this approach is to combine the capabilities of economic modeling with those of technology analysis to enable integrated modeling of economic and technical systems. Applying this methodology to the incorporation of back-up generation into CGE models could substantially improve these models' ability to analyze how this option can facilitate adaptive behavior—i.e., resilience—in response to power disruptions.

In the future, a more ambitious potential application of this form of hybrid modeling would be the linking of CGE and power-system models to analyze the economic consequences of power disruptions in an integrated manner. For example, Watson et al. (2014) use a mixed-integer optimization unit commitment model to analyze the effects of a hurricane-induced disruption to an electric power system; this type of model could conceivably serve as the system component within a hybrid framework.

[22] A 2006 Special Issue of *The Energy Journal* was devoted to this topic (Hourcade et al. 2006). Sue Wing (2006) and Sue Wing (2008) are noteworthy examples of this type of work, in particular, integrating technical information on the electric power system into CGE models.

7. Summary, Recommendations, and Concluding Remarks

This paper described several types of economy-wide models and summarized key aspects of their application to regional economic analysis of electricity supply disruptions. Three representative examples of such analysis were reviewed, and several main conclusions reached:

1. Regional economic modeling—particularly of the computable general equilibrium or "CGE" type—is a promising methodology for addressing the potential costs of electricity supply disruptions. The models can systematically analyze regional-scale effects including both indirect as well as direct costs of disruptions, in a manner that is outside the scope of survey methods;
2. The CGE models especially are capable of representing resilience and adaptive behavior within industries and firms that can mitigate the economic losses caused by disruptions;
3. A robust finding of the studies reviewed is that resilience and adaptive behavior can in principle substantially reduce these losses;
4. At the same time, there are limitations in this work to-date, and key elements of the models need to be developed and improved if this type of modeling is going to be pursued in the future. Empirical and theoretical research is needed to improve the representation of resilience and adaptive behavior in the CGE framework specifically, including better estimation of substitution elasticities and, possibly, productivity parameters;
5. Even with such improvements, the models' credible range of application to power-disruption analysis is circumscribed in terms of the scope and severity of events that can be plausibly modeled—the models will be best-suited in the case of events involving electricity only (rather than, e.g., water supply and other service disruptions as well). At the same time, CGE models especially will be most appropriate for analyzing longer-duration events, and these may be relatively less likely to be limited to electricity. Resolving this trade-off will need to be addressed in practice;
6. Recent work on econometric and statistical modeling of the economics of power disruptions in developing countries exemplifies the usefulness of empirical economic modeling (as opposed to simulation model analysis) in this context.

A multi-pronged program of research is recommended:

A. The quantity and quality of data available to support quantitative economic analysis of power disruptions should be increased. A core activity would be the linking of previously-identified steps towards improving U. S. reliability data (including through the collection of data on back-up generation), with a new effort to adapt plant-level economic survey data collected by the federal government, which has been used to study the economics of energy use at the micro-scale in U. S. manufacturing;

B. Integrated reliability and economic data should be used to conduct new empirical (econometric and statistical modeling) research on electricity use and the potential effects of disruptions in the U. S. manufacturing sector. This research would build upon previous work on the economics of energy use (though not of power disruptions) in U. S. industry based on plant-level surveys, and yield empirical (non-simulation model-based) estimates of previous and potential future disruption costs;

a. The possibility of creating analogous data resources for, and conducting empirical economic modeling of, electricity use and power disruption costs in U. S. commercial industries should be investigated;

C. This integrated data could also be used for research to improve the treatment of resilience and adaptive behavior in CGE models for power disruption analysis;
D. Further application of CGE models to this purpose should include validation analysis and uncertainty quantification as well as the consideration and possible development of simpler reduced-form models;
E. In the future, linking power system- and CGE models for quantitative risk analysis of power outages and supply disruption costs should be considered;
F. So-called "hybrid" economic-technology modeling techniques should be considered for integrating improved back-up generation data into CGE models.

With grid reliability and resilience increasingly a focus of policy and regulation, developing and applying quantitative methodologies and tools for analyzing the economic consequences of electric power disruptions is an important research and development frontier. Regional economic modeling has shown promise in this context, but a substantial, multi-pronged research program is needed to fulfill this promise. It is hoped that this paper will be useful for decision-makers considering the support of work in this area.

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