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ORIGINAL PAPER

Mitigation and Resilience Tradeoffs for Electricity Outages

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Abstract
Large-scale electricity outages have the potential to result in substantial business interruption losses. These losses can be reduced through a number of tactics within the broader strategies of mitigation and resilience. This paper presents a methodology for analyzing the tradeoffs between mitigation and three categories of resilience. We derive optimality conditions for various combinations of strategies for a Cobb-Douglas damage function and then explore implications of a less restrictive Constant Elasticity of Substitution damage function. We also calibrate the model and perform Monte Carlo simulations to test the sensitivity of the results with respect to changes in major parameters. Simulation results highlight the possibility that substitution away from mitigation towards resilience may lower total expected costs from large-scale outages for a given level of risk reduction expenditure when the marginal benefit of resilience is high relative to the expected marginal benefit of mitigation.

Keywords Electricity outages · Economic losses · Reliability · Mitigation · Resilience · Risk reduction trade-offs

Introduction

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

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What is often overlooked is the behavioral response on the customer side to partial or complete electricity outages. These responses basically involve tactics to cope with electricity shortages and have been brought under the heading of resilience (Rose et al. 2007a, b; Greenberg et al. 2007). From an economic perspective, resilience pertains to actions taken to use resources as efficiently as possible to maintain production in the face of a disruption of critical inputs and to accelerate recovery (Rose 2004, 2017; Xie et al. 2018). It is actually a process where resilience capacity can be built up in advance to be implemented when needed (inherent resilience), as well as various improvisations once the disruption has begun (adaptive resilience).[1] Prime tactics in the electricity arena to minimize business interruption (BI) are: conservation, backup generators, distributed generation, relocation, and production rescheduling. Formal modeling at the microeconomic level has been done in the context of economic production theory to analyze the optimal mix of tactics, i.e., to create an overall optimal resilience strategy (Rose and Liao 2005; Dormady et al. 2018a). Analyses have been undertaken to examine the effectiveness of these tactics at the level of the individual business and the broader supply-chain implications in relation to the Northridge Earthquake power outages, post-regulation electricity shortages of the early 2000's, and simulated disasters such as a terrorist attack (Rose and Lim 2002; Rose et al. 2005; Rose et al. 2007a). Many resilience tactics have already been implemented, and insurance companies have been known to reimburse policy-holders for the purchase of back-up generators (Eto et al. 2001). More recently, progress has been made in actually measuring the cost, in addition to the effectiveness, of various resilience tactics (Dormady et al. 2018b).

A critical gap in our understanding of how to cope with electricity disruptions is the optimal mix of pre-event activities (generally categorized as mitigation) and post-event activities (resilience). As electricity reliability is usually couched in terms of mitigation, we can also refer to this as the "reliability-resilience trade-off."[2] The purpose of this paper is to develop an analytical model to examine these trade-offs under various conditions relating to characteristics of individual mitigation and resilience strategies and matters of timing. More specifically, we develop and calibrate a theoretical model in which expected BI from electricity outages can be decreased using a combination of mitigation and resilience strategies. In order to calibrate the model, we use a benefit-cost

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

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

ratio for each strategy to reflect the total expected BI loss reduction from an electricity outage as a function of spending on each. By minimizing the sum of total expected losses and expenditures on risk reduction strategies, we calculate the optimal mix of risk reduction strategies for a given level of total expenditure.

Overview of Strategies

We specify a set of risk reduction strategies and the pathway through which they reduce total losses from an outage in Table 1. We define this set to include: 1) ex-ante mitigation strategies intended to reduce the magnitude of electricity outages, 2) ex-ante customer investments in inherent resilience that reduces the need for electricity in the event of an outage, 3) ex-post customer adaptive resilience expenditures that reduce the BI from losing electricity, and 4) ex-post dynamic resilience that reduces the duration of the recovery of the utility and hence increases the speed[3] of recovery of business activity. We also note several characteristics of each strategy that may be relevant to assessing particular models of outage costs. Not all of these delineations are highlighted in the models presented in this paper but are intended to serve as guidance for which particular cases can be considered in future research.[4]

This paper presents a theoretical model in which a benevolent social planner selects an optimal portfolio of mitigation and resilience in order to minimize expected electricity outage losses. While there are important considerations related to externalities (e.g., whether consumer-level optimization decisions affect BI for other consumers), the assumption that decisions are made by a single social planner allows us to abstract from game theoretical components of the mitigation/resilience tradeoff. We explore a range of models in which mitigation and resilience can reduce BI losses. In each case, we assume that mitigation and inherent static resilience require expenditures before it is possible to know whether or not an outage will occur within a given timeframe, while adaptive static resilience and dynamic resilience are undertaken ex-post.[5] We develop this framework in both one-period and multi-period frameworks, and employ a Monte Carlo simulation centered on the uncertainty in the efficacy of mitigation and resilience.

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

[4] Note that this paper encompasses only the electricity generation and utilization stages of electricity. It omits the distribution aspect, where several tactics, including many market-oriented ones such as dispatchable ancillary services and black start services, could reduce losses. While these are beyond the scope of our paper, the modeling framework can be adapted to include various alternative mitigation and resilience tactics.

[5] While mitigation and inherent static resilience expenditures are often large investments that are paid for over many years, the decision to make these investments is made prior to the realization of whether an outage occurs so the costs can be viewed by discounting the stream of future payments to the time that the investment decision was made. Further, while utilities can recoup some of these costs through rate of return regulation we abstract away from these details because their inclusion does not alter our analysis. While there are complex situations related to electricity storage where modification in investment timing are possible during the course of an outage, these complications are beyond the scope of our paper.

Table 1 Strategies for reducing BI

	Mitigation	Dynamic Resilience	Adaptive Static Resilience	Inherent Static Resilience
Example	Smart Meters/ Regulatory Tariffs	Dispatching Replacement Equipment Quickly	Production Re-Routed to Non-Affected Areas	Purchase & then Use Backup Generator
Decision-making Entity	Utility	Utility	Customer	Customer
Affects Magnitude	X			
Affects Frequency[a]	Some[b]			
Affects Duration of Recovery		X		
Affects Speed of Recovery		X	X	X
Public Good or Private Good	Public	Public	Private	Private
Period when Expenditure Takes Place	Before Outage	After Outage Begins	After Outage Begins	Before Outage
Period when Implementation Takes Place	During Outage	After Outage Begins	After Outage Begins	After Outage Begins
Time Periods in Analysis	At least 1	At least 2	At least 1	At least 2

[a] Frequency refers to how often outages occur rather than the electrical frequency (Hertz) associated with the electricity

[b] Some types of mitigation will reduce the frequency with which outages take place, but for the purpose of the analysis presented in the paper, we abstract away from this effect

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

Background

In our model, planners seek to minimize the sum of expected losses contingent on a certain total level of expected mitigation and resilience expenditure. Damages occur only if an outage takes place, which happens with probability P. Losses are a function of mitigation and resilience expenditures as well as an underlying parameter that reflects the inherent disaster risk. We assume that planners have decided on a targeted overall expenditure level for disaster loss reduction.[6,7]

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

[7] While we focus on business interruption as measured by decrease in GDP (Sanstad 2013), there are several alternative ways to measure losses from electric power outages including Value of Lost Load (VOLL), System Average Interruption Duration Index (SAIDI), and expenditure on backup generation (See, e.g., Keogh and Cody 2013, Matsukawa and Fuji 1994; Beenstock et al. 1997). There are also distinction between "direct" and "indirect" losses, where the former term refers to losses in revenue and lost consumer output while the latter term refers to supply chain losses. Our modeling framework is sufficiently general to cover these alternative definitions of losses.

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

The planner's general problem is to minimize:

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

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

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

Below, we define the loss function in a Cobb-Douglas specification, i.e., $D(\gamma, m, r) = \gamma m^{\alpha} r^{\beta}$, where α and β are elasticity parameters reflecting the efficacy of the loss reduction strategies. γ is the level of economic losses from outages given current levels of mitigation and resilience. A larger γ parameter indicates greater disaster damages at all levels of mitigation and resilience.

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

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

Analytics of Mitigation vs. Adaptive Resilience

First, we consider the simplest case: a single period in which we analyze the trade-offs between reliability and resilience, where the probability of an outage is exogenous with respect to the mitigation to promote reliability and resilience to reduce business interruption. In essence, the model minimizes the allocation of expenditure across these two broad strategies. More specifically, this case examines the trade-off between mitigation that reduces the magnitude of the loss from the outage and adaptive resilience that reduces the ensuing BI. Adaptive resilience refers to customer actions that result from improvisation after the outage begins, with no pre-outage expenditure. Examples would include: conservation, re-routing production to branch plants that have electricity, making up lost production at a later date,[8] etc. This can be treated as a one-period model because of the anticipation of the amount of adaptive resilience, which itself takes place in only one period (in contrast to the 2-period nature of inherent resilience).

Given our Cobb-Douglas framework in which disaster damage is given by $D(\gamma, m, r) = \gamma m^\alpha r^\beta$, the planner's problem is given by the following explicit production function and expenditure constraint:

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

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

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

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

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

The invariance of each risk management alternative to the price of the other options is driven by the assumption that damages are determined according to a Cobb-Douglas function. This functional form assumes a constant elasticity of substitution (equal to unity). The functional form also calls for the share, but not the absolute level, of total expenditure for each input (strategy) to be driven by the Cobb-Douglas parameters. The optimal level of expenditure on each risk management alternative is strongly affected by the benefit-cost ratios

[8] Production rescheduling would best be modeled with 2 periods following the onset of the outage.

in relation to their marginal productivities, and the absolute levels of mitigation and resilience are determined by their costs. Similarly, the relationship between the probability of an outage and adaptive resilience is a result of the fixed expected expenditure on resilience. As the probability of an outage decreases, the amount of adaptive resilience rises in order to hold expected expenditure constant. Note, however, that this suggests lower overall losses from outages, in part, because adaptive resilience expenditures are less likely to be needed.

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

$$\frac{\partial m^*}{\partial c} = \frac{\alpha}{p_m(\alpha+\beta)} > 0$$

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

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

$$\frac{\partial r^*}{\partial c} = \frac{\alpha}{p_r P(\alpha+\beta)} > 0$$

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

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

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

As a numerical example, suppose that an entity would experience outage costs of $100 million if a disaster struck at baseline levels of mitigation and resilience. Further suppose that an electricity service disruption occurs with probability P = 0.25, and that the entity is currently spending $10 million on mitigation and $5 million on resilience. The entity wishes to increase its risk reduction expenditure by 10% to $16.5 million total.

We can parameterize the values α and β based on beliefs about the marginal effectiveness of remaining mitigation and resilience strategies. Suppose, for example, that the next best remaining mitigation tactics (given the existing level of $10 million in mitigation) provides benefits in relation to costs of 4:1, and the best remaining resilience tactics provides benefits of 5:1.[9] We would require α such that a 10% increase in mitigation expenditure (a $1 million increase) results in a reduction in disaster losses of $4 million. Similarly, we require β such that a 20% increase in resilience expenditure (a $1 million increase) results in a reduction in disaster losses of $5 million. In each case, we hold the level of the alternative risk reduction at current levels. The resulting values are $\alpha = -0.428$ and $\beta = -0.281$.

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

There is, of course, uncertainty in each of the assumptions underlying the parameterization. To investigate the sensitivity of the results to these assumptions we conducted a simple Monte Carlo analysis by assuming that each parameter is a random variable. The optimal levels of mitigation and resilience are defined deterministically as a function of the price of resilience, the price of mitigation, the probability of an outage, the budget constraint, and the Cobb-Douglas parameters. The relevant BCR and the existing levels of mitigation and resilience in turn determine the Cobb-Douglas parameters.

We took 10,000 draws of each of these variables and re-evaluated the optimal level of mitigation and resilience according to the solution derived in the analytical model. Because there is little evidence by which to determine the appropriate range and distribution for these variables, we choose a relatively wide range for our Monte Carlo draws. Moreover, because our primary motivation is in understanding the relationship between each variable and the mixture of mitigation and resilience, we are generally unconcerned with the particular values of mitigation and resilience in the parameterizations themselves. In each case, we draw from a triangular distribution. This distribution allows us to specify the minimum, maximum, and modal values from which variables are drawn, and to guarantee the non-negativity of variables. Table 2 presents the range of each randomized variable in the Monte Carlo analysis.

In Fig. 1, we show the correlation between mitigation and adaptive resilience in turn with: 1) the BCR of adaptive resilience, 2) the BCR of mitigation, 3) the probability of an outage, and 4) the risk reduction expenditure target. The primary discernible patterns are the relationships between adaptive resilience and the probability of an outage, and between mitigation and

[9] The mitigation BCR stems from Rose et al. (2007a, b), and the resilience BCR from Dormady et al (2018a). We note a major distinction between the benefits of investment in mitigation and dynamic resilience versus benefits of investment in inherent and adaptive static resilience. The former has public good attributes, in that reducing the magnitude or duration of the outage benefits all customers. However, the latter is a private good, in that it only directly benefits the firm undertaking the investment. Our BCRs factor this into their numerical values (see Rose 2017). Note also that distinctions made above pertain to partial equilibrium analyses; general equilibrium analysis, which would include supply-chain effects, include spillover effects that cannot be captured by either the utility or individual firms (see also Sue Wing and Rose 2018).

the BCR of mitigation. The former occurs because the Cobb-Douglas specification implies the share of expected expenditure allocated to adaptive resilience remains constant regardless of how frequently adaptive resilience actually takes place. The BCR of mitigation has a relatively strong impact because the BCR of mitigation tends to be relatively low, resulting in a larger alpha parameter.

Refinements of the Base Case Model

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

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

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

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

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

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

In Table 3 we present a set of cases that provide a robust understanding of the various risk management options and how they would be incorporated into a model of optimal risk strategies.

Table 2 Variable Ranges in Monte Carlo Analysis

	Minimum	Mode	Maximum
BCR Mitigation	3	4	5
BCR Inherent Resilience	8	10	12
BCR Dynamic Resilience	6	8	10
BCR Adaptive Resilience	7	9	11
Mitigation Price	5	10	15
Resilience Price	5	10	15
Probability of Outage	0.01	0.25	0.5
Damages from Outage	50	100	150
Damages in Second Period (Dynamic Resilience Case Only)	5	10	15
Expenditure Target	10	15	20

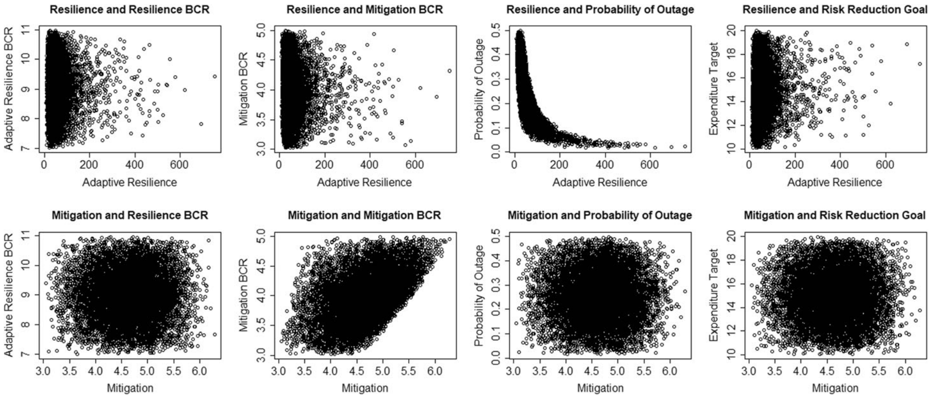

Fig. 1 Sensitivity of Mitigation and Adaptive Resilience to Parameter Assumptions

Case II. Include Inherent Resilience

Some resilience strategies require ex-ante expenditures. For example, while portable generators can reduce the amount of time that a business goes without power during an outage, the generator, and often the fuel, must be purchased beforehand. Such strategies are referred to as inherent resilience (Rose 2004, 2017).

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

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

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

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

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

Inherent resilience in this case is similar in nature to mitigation - it occurs with certainty and yields benefits according to its underlying parameter. The major difference, of course, as noted earlier in the paper, is that mitigation is undertaken by the electric utility, and most resilience is undertaken by its customers.

By substituting these values into the budget constraint, we find:

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

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

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

Table 3 Modifications to Base Case Model for Each Strategy

	Mitigation	Dynamic Resilience	Adaptive Resilience	Inherent Resilience
I. Base Case	X		X	
II. Include Inherent Resilience	X		X	X
III. Include Dynamic Resilience	X	X	X	

The key results are largely unaffected by the introduction of inherent resilience. The optimal allocation of each risk management option increases as its associated parameter falls (becomes more negative) and decreases as the parameters for the other risk management options fall. Because inherent resilience expenditures in this model formulation occur with certainty (rather than occurring only if an outage takes place, as is the case with adaptive resilience), the optimal allocation of spending on mitigation and inherent resilience is essentially identically motivated though the actual levels depend on BCR levels. Indeed, inherent resilience functions look much like mitigation. The major difference is that mitigation reduces losses for all customers, but inherent resilience reduces losses just for the customers that implement it.

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

Case III. Include Dynamic Resilience

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

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

$$\min_{m,r_a,r_d} \; P\,\gamma m^{\alpha} r_a^{\beta} + I(r_d = 0)^* D_2 + P\,p_r r_a + P^* I(r_d = 1)^* p_d + p_m m$$

$$s.t. \quad P p_r\, r + P p_d{}^* I(r_d = 1) + p_m m = c$$

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

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

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

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

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

$$r_d^* = 0$$

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

The optimal risk reduction levels are:

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

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

$$r_d^* = 1$$

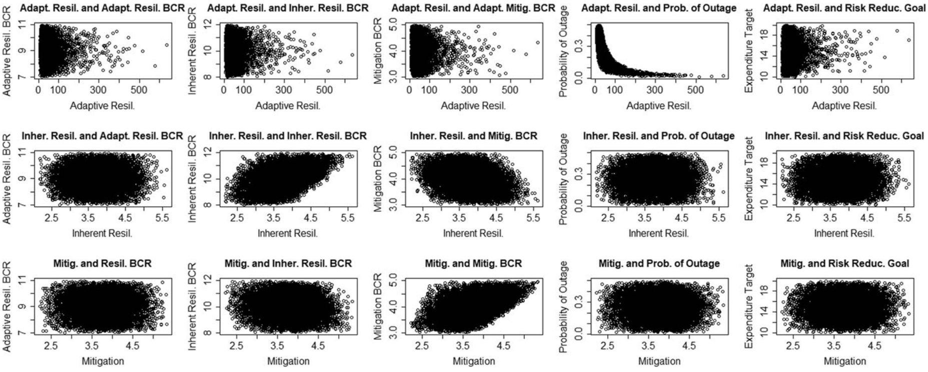

Fig. 2 Sensitivity of Mitigation, Inherent Resilience, and Adaptive Resilience to Parameter Assumptions

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

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

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

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

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

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

We again present a Monte Carlo analysis in Fig. 3. Dynamic resilience introduces additional complexity into the model. It should only take place when its cost is relatively low or when the losses from the outage in subsequent periods are relatively high. If dynamic resilience is justified, the total amount of mitigation and adaptive resilience declines because funding must be allocated to pay for the dynamic resilience. This

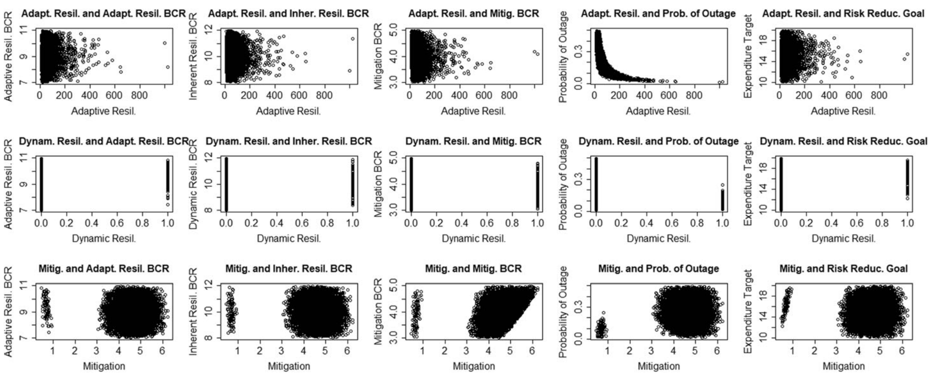

Fig. 3 Sensitivity of Mitigation, Adaptive Resilience, and Dynamic Resilience to Parameter Assumptions

complicates the formulation of the optimal level of mitigation and adaptive resilience by inducing relationships between these risk management strategies that do not exist in the simple Cobb-Douglas formulation. For example, mitigation expenditure is not correlated with the cost of adaptive resilience in the base case, but they are related when dynamic resilience is introduced because the cost of adaptive resilience influences the attractiveness of dynamic resilience.

Case IV: Alternative Damage Function

The results so far have assumed that damages follow a Cobb-Douglas functional form. While the Cobb-Douglas specification simplifies the cost-minimization problem it also places specific constraints on the relationship between mitigation and resilience. For example, the Cobb-Douglas form implies that the quantity of mitigation is invariant to the price of resilience and vice versa. In order to explore these relationships, we consider a generalization of the Cobb-Douglas functional form: Constant Elasticity of Substitution (CES). The CES is more general in that it does not require fixed expenditure shares for each of the risk reduction strategies.

In the CES specification the social planner's optimization problem is:

$$\min_{m,r} \; P^*\gamma(\alpha m^\rho + \beta r^\rho)^{\frac{1}{\rho}} + Pp_r r + p_m m$$

$$s.t. \quad Pp_r\, r + p_m m = c$$

The new parameter, ρ, relates to the elasticity of substitution between mitigation and resilience. Specifically $\frac{1}{1-\rho}$ is the elasticity of substitution between mitigation and resilience. When ρ is equal to 1, mitigation and resilience are perfect substitutes and as ρ approaches zero, the damage function approaches the Cobb-Douglas specification.

The solution to this problem is:

$$m^* = \frac{c\left(\frac{p_m}{\alpha}\right)^{\frac{1}{\rho-1}}}{p_m\left(\frac{p_m}{\alpha}\right)^{\frac{1}{\rho-1}} + Pp_r\left(\frac{p_r}{\beta}\right)^{\frac{1}{\rho-1}}}$$

$$r^* = \frac{c\left(\frac{Pp_r}{\alpha}\right)^{\frac{1}{\rho-1}}}{p_m\left(\frac{p_m}{\alpha}\right)^{\frac{1}{\rho-1}} + Pp_r\left(\frac{p_r}{\beta}\right)^{\frac{1}{\rho-1}}}$$

In contrast to the Cobb-Douglas solutions, the optimal level of mitigation depends on the price of resilience, and the optimal level of resilience depends on the price of

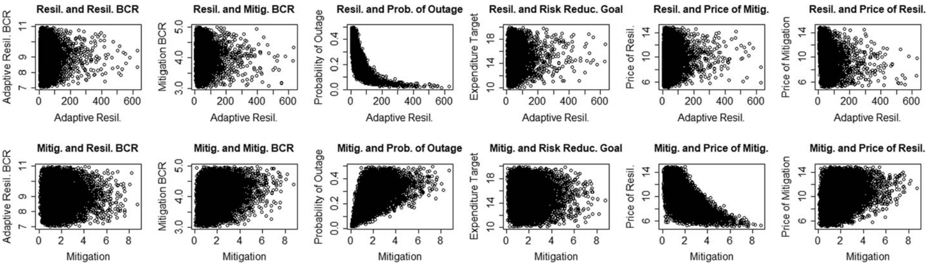

Fig. 4 Sensitivity of Mitigation and Adaptive Resilience to Parameter Assumptions with ρ = 0.5

mitigation. As in the Cobb-Douglas case, the optimal level of each risk reduction strategy declines as its own price increases, but in the CES functional form the budget shares change as well as the absolute quantity. As a result, there is a substitution effect towards the other risk reduction strategy as prices increase. As ρ increases, the substitutability between mitigation and resilience rises, so that changes in prices result in larger changes in the mix between mitigation and resilience.

Figures 4 and 5 show the relationship between the optimal level of mitigation and resilience and each of the key parameters under assumptions of ρ = 0.5 and ρ = 1.5, respectively. When ρ = 0.5, price effects are quite modest for resilience and larger for mitigation. When ρ = 1.5, the optimal level of resilience is much more responsive to changes in mitigation and resilience prices. Note that because expenditures on resilience are only made with probability, P, the effect of a change in the price of resilience is scaled by P - a \$1 increase in the price of resilience would only result in a \$1*P increase in ex ante resilience expenditure. As a result, mitigation is much more responsive to relative price changes than resilience though this effect declines as the ρ parameter rises.

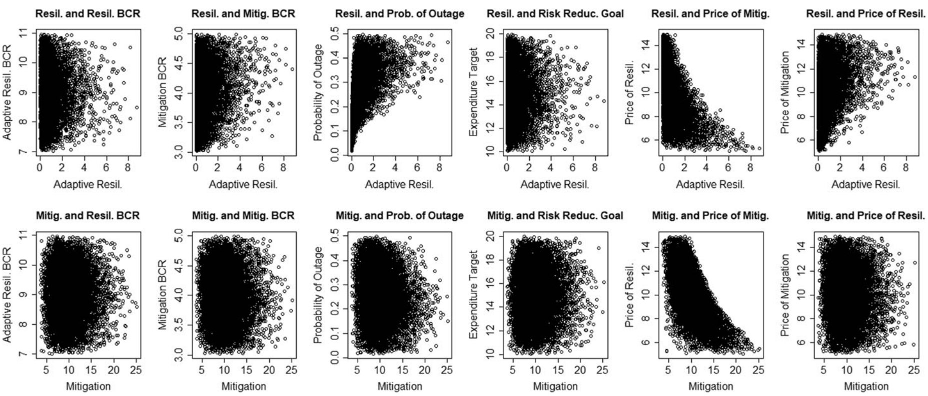

Fig. 5 Sensitivity of Mitigation and Adaptive Resilience to Parameter Assumptions with ρ = 0.5

Conclusion

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

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

There are several important extensions of this paper that should be considered. First, it would be useful to further generalize the assumed damage function and to instead rely on fully specified production functions for mitigation and resilience. There is little empirical research on the complementarity of mitigation and resilience though. It would also be useful to consider a distribution of outage types in order to better reflect the range of potential outages. This could be achieved by allowing for heterogeneous γ parameters that are drawn from a probability distribution. Finally, this paper assumed a single benevolent social planner sets the levels of mitigation and resilience in order to minimize total expected damages, subject to an expenditure constraint. While this assumption allows mitigation and resilience to be aggregated across heterogenous actors (e.g., utilities and consumers), in reality different actors make their optimization decisions separately and with uncertainty about other actors' decisions. It would be useful to reconsider the mitigation and resilience tradeoff in the context of a game-theoretic model, in cases where utilities and their customers consider purchasing mitigation and resilience with public goods attributes.

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