IMPROVING CATASTROPHE MODELING FOR BUSINESS INTERRUPTION INSURANCE NEEDS

by

Adam Rose
Price School of Public Policy
University of Southern California
Los Angeles, CA 90089

Charles Huyck
eCityrisk
Ashtead, Surrey, UK KT21 2BT

April 20, 2012

IMPROVING CATASTROPHE MODELING FOR BUSINESS INTERRUPTION INSURANCE NEEDS

Adam Rose and Charles Huyck*

Abstract

While CAT modeling of property damage is well developed, CAT modeling of business interruption (BI) is still in a relative state of infancy. One reason is the complication of behavioral and recovery policy decisions relating to resilience during the recovery process. Another is the crude nature of functional relationships that translate property damage into BI. This paper proposes a framework for improving the estimation of ordinary and contingent BI. Improved data collection on individual facilities within a company and application of more detailed and realistic resilience adjustments can improve estimation accuracy. We then illustrate the difference this can make in a case study example. We also explain how some macroeconomic modeling approaches are best suited to estimating contingent BI because they can model critical aspects such as supply chain and infrastructure interdependence, as well as the ability to estimate the economic decline following a disaster that affects the demand for goods and services.

I. INTRODUCTION

From its inception, the focus of catastrophe (CAT) modeling has been property and content damage. This has primarily been stimulated by the needs of CAT models to adequately assess the financial risks of greatest concern to insurers. More recently, however, there has been a growing market for business interruption (BI) insurance and hence an emphasis on measuring BI stemming from hazards. Ordinary BI refers to the loss of revenue from reduction of the *flows* of services from reductions in the capital *stock* (property damage), while "contingent" BI stems from disruptions stemming from off-site sources such as the supply chain or infrastructure. Studies of recent and projected disasters have ascertained that the sum of ordinary and contingent BI losses can rival and even exceed property damage. Estimates of property losses from Hurricane Katrina are nearly $100 billion (National Weather Service, 2010), but capital BI losses now exceed a $100 billion and counting (Hallegate, 2008), because these losses just start at the time the disaster strikes and continue to rise until the regional economy has recovered to its pre-disaster trajectory or to a "new normal". Total property damage (insured and uninsured) from the September 11 terrorist attacks on the World Trade Center are estimated at about $25 billion (Grossi, 2009), but the consensus estimates of total BI losses are between $40 and $100 billion (Rose and Blomberg 2010). Estimates of property damage from a hypothetical 8.2 Southern San Andreas Fault earthquake are $100 billion, with the associated BI losses at $67 billion (Jones et al. 2008; Rose et al. 2011). Of course, a larger proportion of property damage losses are insured than are the BI losses, but the market potential for the latter is enormous.

The estimation of BI losses is more complicated than standard CAT modeling in part because BI depends greatly on public and private decisions during recovery with respect to resilience--tactics that mute the losses by using remaining resources more efficiently to maintain and enhance business function and to recover more quickly (Bruneau et al., 2003; Rose, 2009). Examples include: business relocation, conservation of scarce inputs, use of inventories, input substitution, and production rescheduling (recapture). Many of these actions are required as due diligence to file insurance claims.

BI insurance is sold as an additional policy provision to standard insurance, and thus is not as prevalent as standard property and casualty insurance. The increased awareness of the magnitude of BI losses, however, is likely to stimulate the demand for this risk-spreading option. This increases the need for more accurate methods to estimate BI. Such estimates are needed not only for total business interruption losses but also to pinpoint various components of BI and their causes. Resilience is not just an amorphous strategy, but is best implemented by tactical steps pegged to detailed aspects of business operations. For example, Rose et al. 2009 estimated that 72 percent of the potential BI losses associated with September 11 attacks were avoided by the prompt relocation of 95 percent of the tenants of the WTC area. A strong potential exists for reduction of BI losses for a range of past and potential future events, such as electric power outages (Rose and Lim 2002; Rose et al. 2007), water service disruptions (Rose et al. 2011), port closures (Rose and Wei 2011), and massive flooding (Wing et al. 2010). Improved CAT modeling that pinpoints the various causes and effects can not only improve accuracy of loss estimates but also identify ways insurance companies can be proactive about reducing losses, such as through contingency planning. This would be a direct counterpart of insurance industry successes at inducing policyholders to implement pre-event mitigation targeted at reducing property damage.

The purpose of this paper is to outline a framework for estimating BI losses from disasters and then to apply the framework to improving CAT model estimates. This framework will identify and impart structure to the various causal factors that lead to losses and the various resilience tactics that can reduce them. We focus on two major considerations. The first is the contribution of improved data on business operations in estimating BI losses. Improved accuracy can be attained from data on individual facilities within a company. For example, activities in an office headquarters are less likely to cause BI than activity in the company's factory. Moreover, office activities might more readily be relocated than factory production. Second, more detailed examination of resilience options like relocation can greatly improve loss estimates. The potential and actual implementation of resilience is a function of several factors, including preparedness, type of good or service, type of facility affected, and insurance policy incentives for implementation. In this paper, we stress the two latter factors. Finally, we explore the important CAT modeling distinctions between ordinary and contingent BI. The latter are best addressed by macroeconomic models that incorporate aspects such as supply chain and infrastructure interdependence, as well as general economic conditions that can estimate the likely major decline in the demand for goods and services following a disaster.

The proposed capability should prove useful to insurers, reinsurers, risk managers, and insurance brokers in assessing BI risk. It also provides a basis for reducing BI losses over time by educating and incentivizing policyholders to build resilience capacity ahead of disasters and execute contingency plans during the post-disaster recovery period. Ideally, these methods could be used to reduce insurance fraud by identifying potential moral hazard where policyholders do not practice due diligence in implementing available types of resilience.

The framework has direct value to risk managers, as it helps assess economic vulnerability, and perhaps will lead to a greater appreciation of the need for business interruption insurance. The framework applies equally to loss estimation undertaken by the public sector to understand risk. It will be of service to state and local governments who seek to reduce disaster losses, so as to reduce the apparent risk-proneness within their jurisdiction and improve their business climate. For federal governments, it can be used to better understand the conditions that lead to resiliency and to emboldening vulnerable communities through mitigation programs such as the Hazard Mitigation Grant Program (HMGP) administered by FEMA.

II. ANALYTICAL FRAMEWORK

A comprehensive analytical framework would distinguish between the following several interconnected aspects of BI losses:

1. BI losses stemming from direct damage to plant and equipment. This capitalizes on functional relationships between physical capital and the flow of goods and services they help produce (e.g., ATC 13 damage relationships (Rojan, 1985), ImageCat's Seismicat and CODA damage functions (Graf, 2009), FEMA's HAZUS™ MH loss estimation tool. There exists a lower threshold (usually 5 to 10 percent) that must be breeched to result in any BI losses, and then an upper threshold (often as low as 50 percent)

exists at which point the facility completely shuts down for structural repairs or even demolition (NIBS, 2011a, b). For example, a factory can still operate with many of its windows broken, but not without a roof. We suggest it is advantageous to identify the function of individual buildings and related facilities of a firm at a given production site, because the effect on production differs depending on whether damage is sustained by an office building, a building housing an assembly line, a warehouse, an on-site source of electricity generation, etc. For example, a given oil company may identify the "occupancy" of all of its facilities as petrochemical, whereas the function of an office compared to a refinery is far different in terms of both BI vulnerability and resilience potential.

2. Multi-plant relationships. Business operations are more resilient to BI losses if they are part of a multi-plant firm for several reasons. First, production can be shifted to a location that has suffered less damage or for which inputs are less affected. Second, the facility has greater access to working capital or mobile physical capital that can hasten its recovery.

3. Infrastructure dependence. All businesses are dependent on key types of infrastructure such as water, power, transportation and communication, such that these are designated as "lifelines." An inventory of vulnerabilities for existing lifelines and infrastructure, as well as their substitutes, is thus warranted (e.g., shifting from coal to natural gas in duel-fired boilers or the use of portable diesel generators). At a grander scale, the vulnerability of the New Orleans levee system to surge was known before Hurricane Katrina, and thus could have been used to forecast business interruption and justify mitigation measures.

4. Supply-chain considerations. Even factories that are physically unscathed may be forced to curtail their operation if critical inputs are curtailed. This pertains not only to their immediate suppliers but also those farther removed up the supply chain. Comprehensive assessments here would involve not only the existing supply chain but also potential alternatives for the same inputs or for substitutes. Also, not only is the availability of the goods in question important but so also is their price. Increased costs of inputs or their transportation will force firms into some combination of increasing their prices or absorbing the cost into their profits. Any increase in price, however, will decrease sales revenue and hence profits indirectly as well. Macroeconomic models, such as input-output analysis or computable general equilibrium analysis, are especially adept at tracing out the supply chain considerations (Santos, 2010; Rose et al., 2009).

5. Employee profiles and access. This pertains to key characteristics of employees, including the uniqueness or versatility of their training, home locations vis-a-vis the prime business location and multi-plant or backup sites, communication capability, and social networks. Communications are very important in the short run because workers typically make their family's safety rather than their jobs the

priority in the immediate aftermath of a disaster. Long term, employees are more likely to be able to return to work and to maintain a high level of productivity if they are members of an extended family located near their residence or place of work (Wein and Rose, 2011).

6. Regional macroeconomic considerations. The entire regional or national economy is likely to be adversely affected by a disaster. The induced recession will lower the demand for the products of firms that sell primarily in the affected market(s). It may cause a bidding up of wage rates as firms compete for workers in some cases, or a decline in wage rates if property damage is far more extensive than the comparative monetary effects of death and injury. Lifeline services may witness price increases, or, where subject to price regulation, may be subject to rationing. Other key goods affecting the pace of recovery may be influenced, especially construction, in terms of a demand surge phenomenon (see, e.g., Olsen and Porter, 2011; Rose and Liao, 2011; Rose et al., 2011).

III. DATA

Data required to adequately model business interruption goes beyond data pertaining directly to the insured's properties, or even the sum total of insured properties in the effected region. Where the characterization of direct damage seldom incorporates off-site parameters, business interruption is highly dependent on economic resilience, which is in turn dependent on damage experience thorough the area of impact. An Insured Exposure Database (IED) is typically used by CAT modelers to reflect the anticipated effects on the insurance industry, but a Global Insurance Database (GED) is required to reflect the entire economy. A GED is available for the U.S. in FEMA'S HAZUS™ MH program, with the data comprised principally of aggregated Dunn and Bradstreet business records and U.S. Department of Census building and housing statistics. Vulnerability of the building stock in HAZUS is determined through "mapping schemes" that match occupancy to probable building types. High-rise building stock is not adequately represented in HAZUS, but can be added through adjustments to the mapping schemes in urban cores by sampling aerial photography available through Google Earth. HAZUS-MH provides a baseline inventory that can be merged with regional inventories to adequately reflect the built environment.

County tax assessor data are also a resource for building stock data, although the quality of data varies drastically amongst counties (ABS Consulting and ImageCat, 2006). Generally, each county uses a different data structure, which complicates processing (notable exceptions are the counties within Florida, who all use the same data structure, and supply the data to the State for redistribution). When detailed analysis is warranted, we recommend the acquisition of tax assessor data. A handful of companies now supply data for key buildings that can be incorporated with default residential building stock in HAZUS to generate a far superior GED. Obtaining these datasets requires extensive negotiations, research, and funding, but may be justified if an adequate BI modeling platform is developed and costs can be shared amongst end users.

Lifeline data are typically harder to obtain than building data, and the impacts are harder to model (Huyck et al., 2002). Despite this challenge, severe lifeline interruption can be the tipping point that exacerbates recovery and leads to low levels of resilience or cascading effects. Examples include levee failure following Hurricane Katrina, and Damage to the Kobe port following the 1995 Great Hanshin Earthquake. An index of lifeline vulnerability and interdependence for major urban areas based on an expert opinion could be used to scale anticipated business interruption losses, but even a qualitative assessment would require significant effort and data from lifeline engineers. Given the relative importance and complexity of modeling lifelines, an acceptable solution may be to incorporate published scenarios such as ShakeOut, or apply lessons learned from historic events.

Data provided by insurance and reinsurance companies for the purpose of risk assessment are tailored to run within the CAT models provided by commercial firms such as AIR, EQECAT, or RMS. There are limitations dictated by file format that determine what data can be stored in the data files, and thus limit what information is transferred amongst insurers and reinsurers. If data for a given facility do not match the occupancy class options, for example, vulnerability cannot be assessed correctly. Occasionally, occupancy classes are added to the models to refine vulnerability estimates based on additional information, such as clarifying whether a given condo property is a unit owned by an occupant or a condominium building owned by a homeowner's association. Other changes have been made for hotels and educational institutions, typically after catastrophic events impact high-value facilities with these occupancy types. However, key facility attributes are still required to accurately assess vulnerability that are not typically tracked, such as: 1) the difference between insuring a suite in a building or insuring the entire building, 2) designating the appropriate information for collections of buildings at a single site, and 3) specifying the accuracy of the latitude and longitude coordinate data (i.e., matched to a tax parcel, geocoded to the address level, or defaulting to a lower degree of accuracy). Aside from the limitations of coding a portfolio into a format suitable for CAT modeling, a typical portfolio will have many additional problems (Ghosh, 2009), such as incomplete data and bulk coding default data. If data are not available, they are often filled with default data based on assumptions that may or may not be valid. There may be bias implicit in these assumptions, such as defaulting to a less vulnerable structural type. This is particularly the case for detailed structural attributes (e.g., roof type, year built, anchoring, retrofitting) that are not collected or known with certainty at the point of sale. The databases do not provide the ability to track the assumptions made in coding any specific field, and ancillary data tracking the history of edits are not maintained. Detecting bulk coding error, thus, is a complex process requiring expert interpretation, as well as regional statistics and comparison data sets (Huyck et al., 2004). Finally, if data are not provided, the CAT models themselves will assume a default for modeling purposes-- either based on a composite vulnerability or typical construction in the area. These defaults are part of the internal and proprietary CAT modeling exposure database, and are not provided to the user. These assumptions may skew results and underestimate uncertainty, but the extent is not known because of the closed nature of the CAT models.

Ultimately, the results of a CAT modeling exercise can be driven by the similarities of the data coding for a portfolio in question to the actual characteristics of the facilities, or, by default, to the assumptions made internal to the CAT models. This "Garbage-in, garbage out" element of the CAT modeling process is not characterized by the uncertainty quoted by the modelers, which generally pertains to other factors such as ground motions, wind speeds, and building vulnerability. Awareness of the importance of quality exposure data has increased following underestimation of losses in the aftermath of Hurricane Katrina, where poor data quality was a key factor. Insurance companies, regulators, and modelers alike are gaining understanding of the risk and uncertainty implications of bad or limited data.

IV. ECONOMIC RESILIENCE

In the past few years, nearly every analysis of the impacts of a catastrophe in the U.S. has highlighted the "resilience" of the economy. Resilience is sometimes used to explain why regional or national economies do not decline as much as might be expected after disasters, or why they recover more quickly than predicted. However, the concept of resilience is often poorly specified, or is defined so broadly that it could apply to any and all measures undertaken to reduce disaster losses. Most analysts use resilience in a non-rigorous fashion, and many discussions make no reference to the various research traditions that inform current resilience thinking (cf. Rose, 2009).

The concepts and definitions discussed next represent the synthesis of knowledge on the topic of economic resilience, both within economics and in other disciplines, with an emphasis on measures that reduce losses after a disaster begins. *Static economic resilience* (*SER*) is the ability or capacity of an entity or system to maintain functionality (e.g., continue producing) when shocked (Rose, 2007). It is thus aligned with the fundamental economic problem--efficient allocation of scarce resources, which is exacerbated in the context of disasters. *SER* pertains to ways to use the resources still available as effectively as possible. In contrast, *dynamic economic resilience* refers to the ability to hasten the speed at which an entity or system recovers ("bounces back") from a severe shock to achieve a desired state. This version of resilience is relatively more complex because, unlike static resilience, it involves a long-term investment problem associated with repair and reconstruction.

A basic operational measure of static economic resilience is the extent to which the reduction in business interruption deviates from the likely maximum potential reduction given an external shock. An analogous definition pertains to resilience taking into account indirect or macroeconomic effects.[1]

In addition to resilience at the individual business, or microeconomic level, resilience applies at the meso and macro levels. Moreover, residence at all three levels can take on both inherent and adaptive forms. The marketplace capability of reallocating goods to their highest value use is a major example of inherent resilience. An example of meso adaptive resilience would be the establishment of clearinghouses to match customers who have lost their suppliers with suppliers who have lost their customers. At the macro level, many background conditions represent inherent resilience, including a high level of economic diversification, which cushions the blow from a disruption to select sectors.

Dynamic resilience can be examined as well in terms of reducing the time to recovery. This is implemented by the prompt clearing of debris, repair and reconstruction. These actions are in turn facilitated by expedited government and private sector aid, mutual assistance programs, prompt insurance payments, and effective planning and management.

The following types of resilience should be factored into estimating BI losses:

- *Conservation* -- maintaining production with fewer inputs
- *Input substitution* -- shifting input combinations to achieve the same function or level of productivity
- *Inventories* -- both emergency stockpiles and ordinary working supplies of production inputs.
- *Excess capacity* --idle plant and equipment (a special case is *redundancy* that refers to back-up systems that do not increase productive capacity, but rather compensate for damaged capital).
- *Relocation* -- changing the site of business activity.
- *Resource independence* -- the portion of business operation that can continue without a critical input.
- *Import substitution* -- importing resources from other regions, including new contractual arrangements.
- *Technological change* -- easier manipulation to restore function, to increase production, change hours of operation, and to respond to altered product demands.
- *Production recapture* -- working overtime or extra shifts to recoup lost production.
- *Delivery logistics* -- reducing impediments to the delivery of goods and services.[2]

Not all residence tactics pertain to all parts of a business's operations. Table 1 provides a summary of resilience types and the building types to which they pertain. Below, we will combine enhanced data on individual buildings with considerations of resilience to improve the accuracy of loss estimates.

Table 1. Alignment of Resilience Tactics and Building Types

Resilience Tactic	Building Type
Conservation	All buildings
Input Substitution	Production lines; Power plants on site; Infrastructure off site
Inventories/Stockpiles	Warehouses; Storage tanks Multi-plant affiliates
Excess Capacity	Production lines
Relocation	Back-up sites; Multi-plant affiliates
Resource Independence	Office buildings
Import Substitution	Production lines; Power plants
Technological Change	Production lines; Office buildings
Production Recapture	Production lines
Delivery Logistics	Transport infrastructure; Garages
Management Effectiveness	All Buildings
Speeding Recovery	All Buildings

VI. BI INSURANCE AND RESILIENCE

Implementing resilient actions during a business interruption is a critical step in recovery. As BI insurance becomes more important for business continuity planning, understanding the necessary actions to take to reduce losses will help businesses develop economic resilience and better plan for disasters. In addition, many resilience tactics to mitigate losses are necessary actions required of the insured business by its property insurance coverage. However, there is some ambiguity in the regulations governing these matters, in addition to tensions between insurance company and client motivations. These issues are summarized in Table 2 (at the end of the paper) and explained below.

A. Necessary Elements for BI Insurance

In the event of disaster or other covered cause of property damage, there are four elements in BI coverage (Schirle, 2007):

1) Direct damage or destruction of named property for a covered cause of loss;
2) A necessary slowdown or suspension of operations resulting from the damage;
3) A period of interruption
4) An actual loss of income.

The first element is necessary because BI insurance coverage resides under the overarching property damage insurance policy. The period of interruption is defined as the lesser of the actual or theoretical time to repair, rebuild or replace the damaged property, or the time to permanent relocation (Lewis and Farrell, 2005). Finally, an actual loss of income is needed to make a BI claim. The insured's ability to recover from these three elements—by repairing and restoring property damage, resuming operations, and documenting and proving an actual loss of income-- fall under the insured's due diligence in mitigating its losses and presenting its claim.

B. Insured's Duty to Reduce Losses

Most policies require their insureds to practice due diligence in mitigating losses. Insureds are incentivized to implement resilience tactics because insurance companies will only pay for losses to the extent that losses cannot be reduced (Johnson and O'Tool, 2005). Resilient actions by the insured help to define the period of interruption and the actual loss of income, the two most important elements in defining the amount of the BI claim.

In determining the period of interruption, the actual time a business takes repair, rebuild or replace damaged property may be compared to a reasonable theoretical or hypothetical time developed by the insurance company. As such, businesses must practice due diligence in speeding restoration (Torpey et al., 2011). Temporary relocations that help to resume business operations are covered as necessary expenses to reduce income loss. However, insurance companies may regard a temporary relocation as permanent and use it to define a shorter period of interruption (Lewis and Farrell, 2005).

A business must implement a variety of resilience tactics as a part of its duty to reduce losses. These tactics include using similar or same substitutes for production, using inventories, utilizing extra capacity, and make-up sales in later periods (Johnson and O'Tool, 2005; Northwestern States Portland Cement Co. v. Hartford Fire Ins. Co., 1966). In mitigating losses, a business does not have to buy inferior inputs or act in any way that harms it operations, e.g., cost it market share, aid its competitors, or compromise its intellectual property rights (Bell, 2011). However, the insurance company will only cover actual loss of income, not just loss of production. In Lyon Metal Products v. Protection Mutual Insurance, the court ruled that the manufacturer was already compensated for damaged inventory under property damage coverage and could not claim an additional loss of income because it could not sell the inventory to a customer (Lyon Metal Products, LLC v. Protection Mutual Insurance Co., 2001). The insurance company will also reduce actual loss of income by any recouped or increased sales and profits after the period of interruption (Schirle, 2007).

Resilience tactics relating to management effectiveness can play a large role by having an effective staff with multiple competencies—engineers and repair specialists, risk management, financial management, operations management, sales and marketing, legal counsel, and forensic accountants—will make both the restoration and claims process run more smoothly (Torpey et al., 2011). Reducing operating impediments by giving notice to the insurance company, clearly documenting extra expenses, and providing clear evidence of income loss through financial statements and profit projections will also help to mitigate losses and speed a claim through settlement (Sylvester et al., 2011).

C. Special Coverage Provisions

Several additional insurance coverage provisions can incentivize or discourage resilience actions by businesses. “Extra Expenses” or “Expense to Reduce Loss” coverage will pay for policyholder's efforts to avoid or minimize loss and encourages business with this coverage to implement resilience tactics (Torpey et al., 2011).

Contingent business interruption coverage insures BI resulting from property damage to named dependent suppliers or customers under four types of endorsements (Torpey et al., 2011):

1) Contributing locations that supply critical inputs for the insured;
2) Recipient locations that accept the insured’s products;
3) Manufacturing locations that provide products for delivery to the insured’s customer;
4) Leader locations that attract customers to the insured’s business, such as an anchor store in a mall.

Contingent business interruption coverage could discourage resilience actions of input, import and export substitutions. However, the insured business still has the duty to mitigate its losses.

D. Calculating BI losses

Calculations of business interruption losses are based on historical performance and projected sales, which are inherently counterfactual and speculative (Schirle, 2007). Projected sales takes into consideration all of the following factors: the length of time of the covered loss, the projected and annual lost units/sales, future changes in performance, seasonality, changes in market conditions and consumer demand, and launches of a new product or planned expansion during the period of interruption. Despite the potential complexity, BI value is often expressed as a percentage of sales, with the loss calculated by multiplying the net value of lost sales by the BI value percentage.

The effect of resilience on BI is evaluated on an ad hoc basis by insurance companies. Only a small amount of formal research has been devoted to the subject, and, with few exceptions (e.g., Rose et al., 2009; Cox et al., 2010), these studies are applied to hypothetical cases through simulation modeling. Moreover, the vast majority of these studies gauge potential maximum resilience effectiveness rather than likely outcomes. The *actual* effectiveness of resilience will depend on several factors such as preparedness, type of economic activity, type of facility affected, and insurance policy incentives and disincentives for implementation. This section of the paper has identified several of these incentives/disincentives. For lack of actual data or definitive studies on the likelihood of implementation, we will apply some rough qualitative judgments to illustrate the implications for BI estimation by invoking the scale below. Note that it applies to individual resilience options, and that a recovery strategy will involve several options. At the same time recovery strategies will differ between various components (facilities) of a company.

Estimating Factors for Resilience Implementation

Incentives/Disincentives	Effectiveness
Yes/No	80%
Yes/Yes	60%
No/No	40%
No/Yes	20%

Overall effectiveness will also be dependent on the number of relevant resilience tactics for any single facility and their *potential* effectiveness. For now, this *potential* will have to be measured by reference to various simulation studies cited above. For example, Rose et al. (2007) evaluated the relative prominence of 5 major sources of resilience in response to a major electricity outage (conservation, substitution for electricity, independence of a facility from electricity requirements, use of back-up generators, and production rescheduling). These and other factors will be multiplied by the implementation effectiveness from the chart above.

VI. AN ILLUSTRATION OF DATA AND METHOD ENHANCEMENTS

A. Higher Resolution Data

As an illustrative example, a single large-scale food processing corporation in the Southeast was modeled for hurricane risk using a combination of tools and methods. This company was chosen primarily due to the breadth of operations and physical concentration of the entire manufacturing and distribution process. Within two states the company manages, grows, processes, and distributes raw food products in facilities that include agricultural structures and processing plants, as well as two offices and a large warehouse located in a high hazard area near a port. The company sells its product both through retail and wholesale channels, including major food service chains. Data on the company were obtained from an insurance schedule, with permission granted to use these facilities as a sample as long as the data are kept anonymous both in terms of location and facility details. Table 3 provides basic information on the insurance and configuration of the company.

To characterize key parameters required for modeling wind vulnerability, the location data were reviewed along with government documents, company literature, and aerial photographs of the facilities. Occupancies and construction details, including year built, height in stories, and construction class, were modified or verified. It is particularly important to characterize occupancy correctly. Frequently with facilities such as these, all structures are identified as food processing due to the nature of the business, rather than identifying the individual occupancy at each facility. Depending on the sensitivity of the damage functions to changes in occupancy, the difference in modeled damage and downtime can be very significant. The engineering-based models used in this illustrative example are fairly insensitive to changes in occupancy, whereas empirically-based commercial models developed from claims data tend to be highly sensitive to occupancy.

Table 3: Anonymous Facility Details and Approximate Insurance Coverage for a Food Processing Company in the Southeast U.S.

ID	Occupancy	Building Construction	Building Replacement Coverage	Building Contents Coverage	Business Interruption Coverage*
1	Warehousing	Steel, Pre-Engineered Metal Building, Large	-	50,000	250,000
2	Agriculture	Steel, Pre-Engineered Metal Building, Large	5,000,000	3,500,000	2,000,000
3	Food Processing	Masonry, Low-Rise	2,500,000	15,000	250,000
4	Office	Steel, Engineered Commercial Building, Low-Rise	250,000	25,000	25,000
5	Food Processing	Steel, Engineered Commercial Building, Low-Rise	5,000,000	20,000,000	10,000,000
6	Food Processing	Steel, Engineered Commercial Building, Low-Rise	10,000,000	1,000,000	1,000,000
7	Food Processing	Steel, Engineered Commercial Building, Low-Rise	5,000,000	5,000,000	5,000,000
8	Office	Steel, Engineered Commercial Building, Low-Rise	200,000	500,000	50,000
9	Agriculture	Masonry, Low-Rise	1,500,000	1,000,000	2,500,000

* Per annum coverage as represented in client portfolio.

The HAZUS™ MH Hurricane Model was used to estimate the percent damage of each structural type (NIBS, 2011b). HAZUS™ estimates probability of a given building being in several damage states (none, slight, moderate, extensive, complete). HAZUS™ is used to illustrate both: 1) probabilistic damage using the expected wind speeds encountered at each site for a 100 year event, and 2) probable losses from a repeat of a 1916 Category 3 hurricane that made landfall in the region. Results from the probabilistic run are not scenario-based and do not reflect probable results from the worst event expected within 100 years, as would be represented in an exceedance probability curve. HAZUS™ does not support running a full series of storm tracts. Therefore, the results are based upon calculating property loss from peak gust wind speeds with an estimated probability of occurrence every 100 years as a proxy. If the food processing company had a distributed geographic exposure that, for example, included facilities in the Northeast, using probabilistic hazard data as a proxy for a scenario would not be an acceptable approach. However, given the small spatial footprint, this issue is not expected to be significant, and it is interesting to note that by selecting the largest event affecting this region from the historical archive of approximately 100 years, losses are quite similar to the 100 year probabilistic results. The results should, however, be viewed as conservative.

The model runs include both an estimate using occupancy class gleaned at the census tract-level and a site-level analysis using structural class updated by using various exposure data-cleaning techniques developed by eCityrisk. The results for property damage in Table 4 indicate an approximate difference of a factor of 2 on average, driven by significant changes to the data made at key facilities. Losses to building contents for user-defined facilities are not analyzed within HAZUS™

Table 4. HAZUS™ MH Hurricane "Ground-up" Loss to Buildings and Contents
(thousands of 2012 dollars)

			Probabilistic 100-Year Losses		Deterministic Losses Repeat Landfall of 1916 CAT 3	
ID	Occupancy		Census Level	Site Level	Census Level	Site Level
1	Warehousing	Mean Damage:	12%	9%	10%	9%
		Bldg Damage:	*	*	*	*
		Contents:		$23.5		$18.4
2	Agriculture	Mean Damage:	2%	9%	3%	12%
		Bldg Damage:	$ 80.0	$462.5	$ 127.5	$582.5
		Contents:		$93.6		$151.3
3	Food Processing	Mean Damage:	3%	8%	1%	5%
		Bldg Damage:	$ 77.5	$ 193.1	$ 32.5	$ 127.6
		Contents:		$3.8		$2.5
4	Office	Mean Damage:	6%	3%	3%	1%
		Bldg Damage:	$ 14.5	$ 7.9	$ 7.6	$ 3.1
		Contents:		-		-
5	Food Processing	Mean Damage:	3%	3%	1%	1%
		Bldg Damage:	$ 155.0	$ 157.5	$ 65.0	$ 62.5
		Contents:		$1,253.4		$752.3
6	Food Processing	Mean Damage:	1%	1%	1%	1%
		Bldg Damage:	$ 75.0	$ 70.0	$ 130.0	$ 130.0
		Contents:		$3.3		$7.2
7	Food Processing	Mean Damage:	1%	1%	1%	1%
		Bldg Damage:	$ 37.5	$ 35.0	$ 65.0	$ 65.0
		Contents:		$13.3		$28.6
8	Office	Mean Damage:	2%	1%	3%	1%
		Bldg Damage:	$ 4.2	$ 1.4	$ 6.2	$ 2.6
		Contents:		$2.2		$4.7
9	Agriculture	Mean Damage:	~0%	~0%	~0%	~0%
		Bldg Damage:	-	$ 750	-	-
		Contents:		$2.6		-
Total		Bldg Damage:	$443.7	$928.2	$433.8	$973.3
		Contents:		$1,372.3		$946.6

* No Coverage.

MH Hurricane. This shortcoming was addressed by modeling content loss at the site level through a custom application developed utilizing the damage functions accessed through SQL Server. Table 4 presents the resulting loss estimates for buildings and contents in “Ground up” terms (i.e. without regard to deductibles and limits).

Because HAZUS™ MH Hurricane does not provide estimated down times for repair, recovery, and reaching 100% functionality, we utilized HAZUS™ MH Earthquake to provide this capability (NIBS, 2011a). Restoration time for a given facility with a given amount of damage is expected to vary depending on the peril. However, there are countless variables that impact downtime that are not currently captured by the occupancy-based restoration functions in either HAZUS™ MH or state of the art commercial CAT models. These include an assessment of the overall impact of an event by economic sector, an assessment of the supply chain, and the configuration of the properties in question in relation to intensity of damage. Given the expected error is on the order of the error anticipated from these analytical methods and that hurricane specific restoration times are not available in the public domain, downtime was calculated using damage calculated from the hurricane model and earthquake restoration time by detailed occupancy class as a proxy for hurricane restoration.

Downtime for business interruption was calculated using the number of days until 100% recovery, which ignores that some production may be possible during repair and recovery. Thus, these estimates represent a conservative approach that does not account for partial operation at this point, although the framework does account for company resilience in general, as will be addressed in the following section. The annualized business interruption coverage provided by the carrier was used to calculate business interruption. Production for a given occupancy could have been estimated using labor- or capital (property)-output ratios, but these approaches are unlikely to approach the accuracy of estimates by the company itself in determining its adequate amount of insurance coverage. Thus, our method to estimate BI losses was simply to divide the per annum insurance coverage by 365 and then multiply by the number of days estimated for full recovery. The results of this analysis are presented for both the probabilistic 100-year losses and the 1916 category 3 hurricane. Again, we note that the probabilistic results are conservative, given that an event catalog is not available. Deductibles are not considered, and results less than $1,000 have not been presented.

The results presented in Tables 4 and 5 have been calculated using both census level data and augmented site level data. Census level results are calculated through occupancy alone, which uses a conglomerate vulnerability based on probable structures types. As is often the case, occupancy was available in the portfolio but very little information was provided pertaining to structural class,

Table 5. Business Interruption, without Consideration of Resilience
(in days and thousands of 2012 dollars)

			Probabilistic 100-Year Losses		Deterministic Losses Repeat Landfall of 1916 CAT 3	
ID	Occupancy		Census Level	Site Level	Census Level	Site Level
1	Warehousing	Days to Recover:	72	216	55	196
		BI:	$49.0	$147.9	$37.3	$134.4
2	Agriculture	Days to Recover:	1	5	1	6
		BI:	$4.2	$25.3	$ 6.7	$31.9
3	Food Processing	Days to Recover:	9	60	3	32
		BI:	$5.7	$ 37.5	$ 1.8	$ 19.8
4	Office	Days to Recover:	15	12	8	4
		BI:	$ 1.1	-	-	-
5	Food Processing	Days to Recover:	9	9	3	3
		BI:	$ 193.1	$ 197.4	$ 59.4	$ 57.3
6	Food Processing	Days to Recover:	4	2	3	3
		BI:	$ 10.4	$ 3.9	$ 7.3	$ 7.3
7	Food Processing	Days to Recover:	4	2	3	3
		BI:	$ 38.2	$ 14.3	$ 26.7	$ 26.7
8	Office	Days to Recover:	6	2	8	4
		BI:	$ 1.1	-	$ 1.6	-
9	Agriculture		-	-	-	-
	Total		$302.7	$426.3	$140.8	$277.3

building height, or era of construction. On the other hand, occupancy correctly reflected the function of the individual facilities, rather than the company as a whole, and was confirmed through the company website. Slight adjustments were made, and the occupancy classes were converted to HAZUS™ classes for analysis. Location data were provided at the site level and confirmed through Google Earth. Visual interpretation of the facilities, ancillary databases, and inspection of aerial photography were used to refine structural information. Site level data augmentation clearly provides more accurate results, as the structural classes match the engineering-based vulnerability functions more accurately. The impact of these changes modifies both the total direct damage and the business interruption by a factor of two. These results are fairly typical given extensive research at the site level and illustrate the importance of factoring the uncertainty of data quality into reinsurance pricing, which can be reduced given diligent data scrubbing and enhancement.

B. Improved Measurement of Resilience

In this section, we provide a comparison of the estimation of resilience for two levels of data presented in the previous sub-sections. The availability of data on individual facilities allows us to more clearly identify which of the many types of resilience are applicable in the CAT modeling.[3]

The effectiveness of individual resilience tactics will depend on factors such as the likelihood that they will be implemented and their loss reduction potential, which are presented in Table 6. The first column of numbers applies the implementation likelihood factors from the chart in the previous section to individual resilience tactics .[4] The second numerical column is a synthesis of findings on resilience potential from a combination of studies of actual events, such as the Northridge Earthquake, September 11 Terrorist Attacks, and the London subway bombings (Tierney 1997; Rose and Lim, 2002; Rose et al 2009; Cox et al., 2011), and simulations of hypothetical events, such as terrorist attacks on water and power systems (Rose et al 2007a, b) and port shutdowns (Rose and Wei, 2011). "Resilience

Table 6. Resilience Implementation and Effectiveness Factors

Resilience Tactic	Implementation Likelihood	Loss Reduction Potential	Resilience Effectiveness
Conservation	80%	2-6%	3.2%
Input Substitution	60	4-8	3.6
Inventories/Stockpiles	80	3-5	3.2
Excess Capacity	60	10-20	9
Relocation	60	20-80	30
Resource Independence	80	10-20	12
Import Substitution	60	5-25	9
Technological Change	50	5-15	5
Production Recapture	60	20-80	30
Delivery Logistics	50	2-6	2
Management Effectiveness	80	8-16	9.6
Speeding Recovery	80	10-20	12

Effectiveness" in the last column of the Table is the multiplication of the figures in column 1 times the mid-point of the range of estimates in column 2. These factors range from very low percentages to 30 percent reductions for the application of Relocation and of Production Recapture. Note that the application is not additive given overlaps in effects (see, e.g., Rose et al., 2007a). Based on previous studies, in the estimation below we divide total estimates of resilience in half to account for this.

The Resilience Effectiveness factors for each resilience type are applied, as applicable, to the Probabilistic 100-year Losses in Table 5, with the results presented in Table 7. (Recall that the applicability of each type of resilience on a building type basis is presented in Table 1). There are two sets of columns in Table 7 corresponding to the two levels of data: Census and Site-specific. For each, we compare the Base level losses (without resilience) from Table 5 to the loss estimates with resilience factored in. For both the Census and Site-specific data, the greatest reductions in losses are found in Food Processing facilities because the largest number of resilience tactics is applicable to them, including the

Table 7. Business Interruption with Resilience
(thousands of 2012 dollars)

		Probabilistic 100-Year Losses			
		Census Level		Site Level	
ID	Occupancy	Base	w/Resilience	Base	w/Resilience
1.	Warehousing	$49.0	$35.3	$147.9	$106.5
2.	Agriculture	4.2	1.8	25.3	10.6
3.	Food Processing	5.7	1.1	37.5	7.0
4.	Office	1.1	0.6	0	0
5.	Food Processing	193.1	35.9	197.4	36.7
6.	Food Processing	10.4	1.9	3.9	0.7
7.	Food Processing	38.2	7.1	14.3	2.7
8.	Office	1.1	0.6	1.6	0.9
	Total	$302.7	$84.3	$426.3	$165.1
	Adjusted Total	n.a.	$193.6	n.a.	$296.5

two tactics with the greatest potential—relocation and production recapture. Looking at the adjusted totals (those that eliminate overlaps in between the various types of resilience), the resilience reductions differ only slightly between the Census and Site-specific data ($109.1 vs. $129.8 thousand). Resilience is estimated to reduce losses for the former by 36 percent, but only by 30 percent for the latter. The main reason is that the Site-specific data include a base BI estimate for a Warehouse nearly three times that of the Census data, but that the Warehouse is much less likely to gain from resilience than other building types. For example, without the resilience adjustment, a major food processing facility is the largest BI loss ($197.4 thousand, or, more than 33 percent higher than the BI losses estimate for the warehouse), but, after the resilience adjustment, the warehouse becomes the highest single site of BI (nearly three times the size of the largest food processing facility)

Overall, the bottom-line results for the Site-specific data are 53 percent higher than the Census data (see the last row of Table 7). This is combination of the influence of the improved data and the inclusion of resilience. The former resulted in a base (without resilience) estimate of BI losses 41 percent higher for Site-specific data than the Census data. Ironically, factoring in resilience reduces the absolute gap between estimates, because they reduce the levels of both, the resilience adjustment has the effect of increasing the percentage difference between the results for the two sets of data. Reduction of errors related to the use of higher resolution data cancel each other out somewhat resulting in only a minor improvement in total estimates in our example. However, it should be obvious to the reader that the variation for individual facilities is great, and that in other instances errors will not offset one another, thereby making data improvements all the more worthwhile.

VIII. IMPROVED DATA AND METHODS FOR ESTIMATING CONTINGENT BI

Contingent BI refers to economic losses to a firm that stem from factors other than property damage to its own facilities, such as supply chain disruptions, infrastructure failures, impediments to employee access on the supply side, and the post-disaster overall economic decline on the demand side. Here, the data requirements are seemingly enormous. Only a portion of these sources are covered by BI insurance[5] but all should be addressed to obtain an estimate of total (direct plus indirect) BI losses. One reason for estimating the total does apply to BI insurance—loss of demand form a general economic decline.

Fortunately, several modeling approaches that typically contain most of the requisite data can be used to address the issue. This refers to multi-sector macroeconomic models focusing on economic interdependence that have been applied to estimating the economic impacts of natural and made-made disasters, although none have systematically been incorporated into CAT models commonly sold in the insurance industry. These include input-output (I-O) analysis (Okuyama, 2007; Rose and Wei, 2011), computable general equilibrium (CGE) analysis (Rose and Liao, 2005; Rose et al., 2009; Dixon et al., 2010; Giesecke et al., 2012), and Macroeconometric (ME) modeling (Rose et al., 2009; Werling and Horst, 2009). All of these approaches have their relative strengths and weaknesses, and none of the models is superior in all respects. Choice of the modeling approach is dependent on the problem at hand, the need for accuracy, and limitations of time and resources.

I-O is the most basic of the modeling approaches. It refers to a model of all purchases and sales between sectors of an economy based on the technological relations of production (Miller and Blair 2009). The I-O table at the heart of the model depicts the economy as one large set of interdependent supply chains. This is the most widely used approach to economic impact analysis of all types in the U.S., in part because I-O models are very simple and inexpensive to construct and to use. It has been applied to evaluating impacts from disaster losses in a range of applications (see, e.g., Gordon et al., 2006; Park et al., 2008; Rose and Wei, 2011). Unfortunately, this approach suffers from restrictive assumptions of linearity and absence of behavioral content and market considerations. It captures only a limited amount of inherent resilience and its inflexibility and lack of behavioral features make it difficult to incorporate adaptive resilience

CGE is a multi-market model of the behavioral responses of individual businesses and households to price signals and external shocks, within the limits of available capital, labor, and natural resources (Dixon and Rimmer, 2002). At its core are functional relationships, much more flexible and complex than those of an I-O table, that mimic how firms combine various labor, capital, energy, and material inputs to produce goods and services. This offers great insight into the implications of disruptions to the supply of these inputs, and various ways to cope with these shortages, such as business relocation, conservation, use of inventories, etc. (Rose and Liao, 2005). CGE models can be thought of as a major extension of I-O analysis. They retain many of the major advantages of I-O (multi-sector detail, full accounting of all inputs, focus on economic interdependence), but overcome many of I-O's limitations by infusing into the model behavioral considerations, nonlinearities, and the explicit workings of prices and markets (Shoven and Whalley 1992). CGE and ME models are considered the state of the art approach. However, although these models offer clear advantages, application is complicated by data requirements, especially in the case of ME models since thy require an extensive time series. Application of both CGE and ME models,, which incorporate the many diverse features of the workings of an entire economy, requires specialized skills and is by no means straightforward.

ME models analyze the entire economy of a region or nation in terms of aggregate variables of consumption, investment, government spending, exports and imports. More recent advances have strengthened these model by incorporating various microeconomic foundations, including behavioral considerations relating to the choices made by businesses and households, and providing multi-sector detail. In the real world applications, these models have typically been constructed by utilizing a time series of data and a consistent, multi-equation econometric estimation of major parameters. As such, these models typically have excellent statistical properties and forecasting abilities. Of course, a formulation like this is not adept at exploring shocks, since they are a departure from the past. Application of econometric models to estimating the total economic impacts of disasters is somewhat limited. Rose et al. (2009) used the Regional Economic Models, Inc. (REMI) Model to analyze the macroeconomic impacts of shutting down the U.S. borders in response to a security of public health threat but found it necessary to modify the model considerably to account for various obvious types of resilience to this policy. Werling and Horst (2009) applied the INFORUM model to the estimation of the economic impacts of 9/11.

We are continuing to refine the use of CGE Models in estimating contingent BI. CGE is especially promising because of its comprehensiveness, flexibility, and data content. It can address all six aspects of the Modeling Framework we summarized in Section II. We do not provide an illustration of its application here, but simply identify steps that would be undertaken to supplement the results presented in the previous section.

1. BI losses stemming from direct damage to plant and equipment. This would extend our estimation of pre-resilience losses to all sectors.

2. Multi-plant-relationships. This would require distinguishing firms according to single-plant and multi-plant categories, and identifying what proportion of the latter are outside the impacted region.

3. Infrastructure dependence. This is an inherent part of the CGE model and does not require any further work beyond initial estimation of infrastructure downtime.

4. Supply-chain considerations. This is an inherent part of the CGE model.

5. Employee profiles and access. This is an inherent part of CGE models that contain a matrix of occupational requirements for each sector. This would have to be supplemented by further data on occupational supply (including identification of personnel who have multiple occupational skills), as well as GIS data on home vs. work locations.

6. Regional macroeconomic considerations. This is an inherent part of the CGE model.

We note that modeling of contingent BI must factor in the influence of interdependencies on the likelihood and effectiveness of implementing resilience. Kunreuther (2006) points out that these externalities are likely to lower the motivation to undertake mitigation, and Kunreuther and Muermann (2008) recommend "at fault" insurance rather than "no fault" insurance to internalize the externality. A similar motivation effect could take place on the post-disaster side with respect to resilience and would require additional investigation. However, modeling approaches like CGE could estimate the implementation effectiveness through the calculation of general equilibrium (extended supply chain) effects.[6]

IX. CONCLUSION

This paper offers a framework for improving the estimation of ordinary and contingent BI. We have explained how improved data collection on individual facilities within a company and application of more detailed and realistic resilience adjustments can improve estimation accuracy. We then illustrated the difference this can make in a case study example. We also explain how some macroeconomic modeling approaches are best suited for estimating contingent BI, because they can model key considerations such as supply chain and infrastructure interdependence, as well as the ability to estimate the economic decline following a disaster that affects the demand for goods and services.

The devastating floods in Thailand inundated many areas from September to December in 2011. Total insured loss estimates have been as high as $108 billion, with a significant portion attributed to BI. Several key major industrial facilities, concentrated in fewer than 10 industrial park locations, were flooded. However, the cascading effects to worldwide production have been tremendous. A considerable amount of time and effort has been expended by the insurance industry to identify facilities that have been flooded, the tenants and who they supply, and the likely economic impacts. Not only was it unclear to most insurers what facilities were located in the exposed areas, it was also unclear what portions of their Thai portfolios were located in the exposed area north of Bangkok. It is now clear that key manufacturing facilities there supply critical hi-tech components and automotive parts for a significant proportion of the electronic and automotive industries worldwide. These 2011 losses, along with liquefaction in New Zealand and tsunami hazard in Japan are considered "unmodeled" by the industry, and discussions are now turning to what other unanticipated risks may affect global portfolios.

Although BI loss calculations are a complicated endeavor, the potential benefits to risk pricing and diversification, as well as to identifying resilience and mitigation strategies, are likely to far exceed the costs of additional data collection and analysis identified in this paper. Nevertheless, we acknowledge these methods are simply an initial foray into a largely unexplored field of research. BI losses dominate in low-probability, extreme events "at the tail" of the loss distribution, where cascading effects are often to blame for catastrophic and unmodeled losses. And, although it is possible to reasonably model cascading effects through the consideration that damage to lifeline networks, such as power systems and transportation systems, can have on supply chains by integrating systems analysis with CAT models, in practice data to support these detailed methods are simply not available for commercial accounts. Novel methods are required to bridge the gaps. To this end, one approach may be to adapt data and techniques from multi-sector macroeconomic models that characterize economic interdependence in lieu of conventional supply-chain data. Another is to develop regional resilience factors that characterize overall economic health, the robustness and redundancy of lifeline infrastructure, and system interdependencies that might lead to cascading effects. Lastly, data fusion methods both at the regional and site-specific level can be combined with many analytical methods to help bring risk into focus. It is our hope that future research into BI may lead to the full development of a framework that truly supports risk pricing and diversification, as well aiding identification of resilience and mitigation strategies. The status quo will only perpetuate inefficient risk diversification and financial instability due to periodic devastating losses.

ENDNOTES

*The authors are, respectively, Research Professor, Price School of Public Policy, and Coordinator for Economics, Center for Risk and Economic Analysis of Terrorism Events (CREATE), University of Southern California, Los Angeles, CA; and Director, eCityrisk, Ashtead, Surrey, UK and Executive Vice-President, ImageCat, Inc., Long Beach, CA,. The authors thank Oswin Chan for his valuable research assistance.

[1] An example of the application of this simple resilience metric is the assessment of the economic consequences of the September 11 terrorist attacks (Rose et al., 2009b). More than 1,100 firms in the World Trade Center impact area suddenly found their places of business destroyed. Had all of those businesses closed permanently, the direct business interruption losses (in terms of lost GDP) would have been $43 billion in the first year (the maximum potential loss). However, 95 percent of the businesses relocated to space in Midtown Manhattan or Northern New Jersey. Had relocation been immediate, the actual loss would have been zero. However, it took affected businesses an average of a few weeks to move, resulting in a loss of $12 billion. Avoided losses were thus $31 billion. According to the formula, then, 72 percent of the losses to affected businesses were avoided due to business relocation, much of which took advantage of the existence and utilization of spare office space, representing a resilience factor of 72 percent. At the same time, it is noteworthy that this sort of excess capacity is rarely mentioned in current research on the compilation of resilience indicators.

[2] This list has omitted some types of resilience that pertain to contingent BI. *Export substitution* -- selling goods to other regions that cannot be sold otherwise to local customers—is one example.

[3] Most CAT models or hazard loss estimation models do not include more than a token number of features relating to resilience. One exception is HAZUS, though the inclusion of resilience is often opaque and generally limited. For example, the Direct Economic Impact Module (DELM) contains features of business relocation and production recapture, while the Indirect Economic Loss Module (IELM) contains adjustments for inventories and import substitution. The recapture factors are crude, and do not allow for the fact that this resilience alternative degrades over time as customers begin to look elsewhere. The relocation adjustment cannot be modified either. In addition, there are an absence of adjustments for resilience tactics such as conservation, input substitution, and improving management effectiveness.

[4] Insurance clause information was lacking for two of the resilience tactics, so we assumed an "equal likelihood" of 50 percent.

[5] Contingent BI covers the full BI loss value only for BI resulting from property damage to "named" dependent properties. Unnamed dependent properties are covered as well, but are treated as "miscellaneous locations." The standard insurance form for contingent BI only pays for 3% of the BI loss value for miscellaneous locations.

Under the standard contingent BI form, roads, bridges, tunnels, waterways, airfields, pipelines or other similar structures" are not considered miscellaneous locations, and contingent BI due to property damage to these are not covered. Also, contributing locations cannot be properties that deliver water supply services, power supply services, or communication supply services.

Employee access is otherwise covered by ingress/egress clauses, which exists as additional coverage for ordinary BI. Ingress/egress coverage for dependent properties does not exist. For example, if the insured did not suffer property damage but access to its factory was blocked due to damage to a critical road, ingress/egress coverage would trigger. However, if a named dependent property did not suffer property damage but access to the dependent property was blocked due to damage to a critical road, there would be no ingress/egress coverage and no contingent BI coverage under the standard form.

[6] A similar phenomenon exists with respect to another form of insurance—non-interruptible service premiums for electricity, where customers pay a surcharge to receive priority in case of supply curtailments. Rose and Benavides (1999) point out that where a system of individually structured non-interruptible service premiums may not be socially optimal, because individual businesses make decisions on whether to pay the premium on the basis of their own benefits, but ignore benefits to their direct or indirect suppliers and customers. In this context, resilience is not only a function of individual business or household actions but also all the entities that depend on them or that they depend on directly or indirectly. A classic case in point is San Francisco Airport, which paid the premium for years, but its major jet fuel supplier did not, and came close to not being able to deliver its product to SFO in the aftermath of the Loma Prieta Earthquake.

REFERENCES

ABS Consulting and ImageCat, Inc. 2006, Data Standardization Guidelines for Loss Estimation – Populating Inventory Databases for HAZUS®MH MR-1, prepared for the California Governor's Office of Emergency Services.

Bell, B. P. 2011. "Time Element (Business Interruption) Insurance," *New Appleman on Insurance Law Library Edition*, Chapter 46. Retrieved March 26, 2012, from LexisNexis Insurance Law Community.

Best's Briefing. 2011. "Thai Flooding Brings Industrial, Business Interruption Claims," A.M. Best Company, Inc.

Bruneau, M., Chang, S., Eguchi, R., Lee, G., O'Rourke, T., Reinhorn, A., Shinozuka, M., Tierney, K., Wallace, W., and von Winterfeldt., D. 2003. "A Framework to Quantitatively Assess and Enhance Seismic Resilience of Communities," *Earthquake Spectra* 19**:** 733-52.

Burns, C. 2011. "INN's Annual Top 5 Trends for 2012 - Data Quality," *Insurance Networking News*. December 1.

Cox, A., F. Prager and A. Rose. 2011. "Transportation Security and the Role of Resilience: A Foundation for Operational Metrics," *Transport Policy* 18(1): 307-17.

Czajkowski, J. H. Kunreuther and E. Michele-Kerjan. 2012. *A Methodological Approach for Pricing Flood Insurance and Evaluating Loss Reduction Measures: Application to Texas*. White Paper, Wharton School, University of Pennsylvania, Philadelphia, PA.

Dixon, P., and M. Rimmer. 2002. *Dynamic General Equilibrium Modelling for Forecasting and Policy: A Practical Guide and Documentation of MONASH.* Amsterdam: North-Holland.

Dixon, P., B. Lee, T. Muehlenbeck, M. Rimmer, A. Rose, and G. Verikios, "Effects on the U.S. of an H1N1 Epidemic: Analysis with a Quarterly CGE Model," *Journal of Homeland Security and Emergency Management* 7(1): Article 75.

Ghosh, S. 2009. "Data Quality in Focus, Managing Enterprise Risk & Delivering Competitive Advantage with Improved Exposure Data," eCityrisk.

Giesecke, J., W. Burns, A. Barrett, E. Bayrak, A. Rose, P. Slovic and M. Suher. 2012. "Assessment of the Regional Economic Impacts of Catastrophic Events: A CGE Analysis of Resource Loss and Behavioral Effects of a Radiological Dispersion Device Attack Scenario," *Risk Analysis*, forthcoming.

Gordon, P., H. Richardson, J. Moore II, J. Park and S. Kim. 2007. "Economic Impacts of a Terrorist Attack on the U.S. Commercial Aviation System," *Risk Analysis* 27(3): 505-12.

Graf, W.P., and Lee, Y., 2009, "Code-Oriented Damage Assessment for Buildings," *Earthquake Spectra* 25 (1): 17-37.

Hallegatte, S. 2008. "An adaptive input–output model and its application to the assessment of the economic cost of Katrina," *Risk Analysis* 28 (3): 779–99.

Huyck, C.K., Castner L.L., Bouabid J., and Eguchi R.T. 2002. "A Comprehensive Seismic Vulnerability and Loss Evaluation of the State of South Carolina Using HAZUS: Part V Lifelines, Essential Facilities, and Hazardous Materials Sites," 7th National U.S. Conference on Earthquake Engineering, Boston, Massachusetts, July.

Huyck, C.K., Ghosh, S., Seligson, H.A., and Bortugno, E, 2004. "Tips and Tricks for Customizing HAZUS-MH (Hazards U.S.-Multihazard)", ESRI User Conference Proceedings, Redlands CA.

Johnson, S., and O'Tool, K. 2005. “Common Business Interruption Measurement Disputes,” *The John Liner Review* 19(3): 59-83.

Jones L.M.,R. Bernknopf, D. Cox, J. Goltz, K. Hudnut, D. Mileti, S. Perry, D. Ponti, K. Porter, M. Reichle, H. Seligson, K. Shoaf, J. Treiman, and A. Wein. 2008, The ShakeOut Scenario, U.S. Geological Survey Open File Report 2008-1150 California Geological Survey Preliminary Report 25.

Kunreuther, H. (2006). “Risk and Reaction: Dealing with Interdependencies,” *Harvard International Review* 28(3): 38-42.

Kunreuther, H. (2008). “Reducing Losses from Catastrophic Risks through Long-Term Insurance and Mitigation,” *Social Research* 75(3): 905-930.

Lewis, R. P., and Farrell, J. M. 2005. Disaster and Business Interruption Coverage in the Aftermath of Katrina.

Lyon Metal Products, LLC v. Protection Mutual Insurance Co., 2-00-0587 (Appellate Court of Illinois, Second District April 16, 2001).

Malecki, D. 2011. “Business Interruption: Exclusions Make Finding the Right Coverage Difficult,” *Rough Notes*. 154(5): 4-15

Miller, R. and P. Blair. 2009. *Input-Output Analysis: Foundations and Extensions* (2nd ed.). New York: Cambridge.

Muerman, A. and Kunreuther, H. (2008). “Self-protection and Insurance with Interdependencies,” *Journal of Risk and Uncertainty* 36(2): 102-123.

National Weather Service (NWS), 2006. “Service assessment: Hurricane Katrina, August 23–31, 2005,” National Oceanic and Atmospheric Administration, U.S. Department of Commerce, Silver Spring, MD.

Neligan, M. 2012. "Lloyd's Faces third-biggest Loss from Thai Flood." http://uk.reuters.com/article/2012/02/14/uk-lloydsoflondon-idUKTRE81D0C420120214

National Institute of Building Sciences (NIBS). 2011a. Multi-hazard Loss Estimation Methodology, Earthquake Model – HAZUS™ MR4 Technical Manual. Prepared for the Federal Emergency Management Agency (FEMA) Mitigation Division, Department of Homeland Security (DHS) Emergency Preparedness and Response Directorate.

National Institute of Building Sciences (NIBS). 2011b. Multi-hazard Loss Estimation Methodology, Hurricane Model – HAZUS™ MR4 Technical Manual. Prepared for the Federal Emergency Management Agency (FEMA) Mitigation Division, Department of Homeland Security (DHS) Emergency Preparedness and Response Directorate.

Northwestern States Portland Cement Co. v. Hartford Fire Ins. Co., 360 F2d 531 (8th Circuit Court May 13, 1966).

Olsen, A. H. and K. A. Porter. 2011. What we know about demand surge: Brief summary. *Natural Hazards Review* 12(2): 62-71.

Park, J., Gordon, P., Moore II, J., and Richardson, H. 2008. “The State-by-State Economic Impacts of the 2002 Shutdown of the Los Angeles-Long Beach Ports,” *Growth and Change* 39(4): 548-72.

Rojahn, C., 1985. *ATC-13: Earthquake Damage Evaluation Data for California,* Applied Technology Council, Redwood City, CA.

Rose, A. 2007. “Economic Resilience to Disasters: Multidisciplinary Origins and Contextual Dimensions,” *Environmental Hazards: Human and Social Dimensions,* 7(4), 1-16.

Rose, A. 2009. *Economic Resilience to Disasters.* Community and Regional Resilience Institute (CARRI) Research Report #8, ORNL.

Rose, A. and J. Benavides. 1999. “Optimal Allocation of Electricity After Major Earthquakes: Market Mechanisms vs. Rationing,” in K. Lawrence et al. (eds.) Advances in Mathematical Programming and Financial Planning, Greenwich, CT: JAI Press, 1999.

Rose, A. and B. Blomberg. 2010. “Total Economic Impacts of a Terrorist Attack: Insights from 9/11,” *Peace Economics, Peace Science, and Public Policy* 16(1): Article 2.

Rose, A. and S. Liao. 2005. “Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions,” *Journal of Regional Science* 45(1): 75-112.

Rose, A. and S. Liao. 2011. "Demand/Supply Surge in the aftermath of Disasters," Center for Risk and Economic Analysis of Terrorism Events (CREATE), USC, Los Angeles, CA.

Rose, A. and D. Lim. 2002. “Business Interruption Losses from Natural Hazards: Conceptual and Methodology Issues in the Case of the Northridge Earthquake,” *Environmental Hazards: Human and Social Dimensions* 4: 1-14.

Rose, A. and D. Wei. 2011. *Measuring Economic Risk Benefits of USCG Marine Safety Programs*. Final Report to U.S. Department of Homeland Security, Center for Risk and Economic Analysis of Terrorism Events (CREATE), University of Southern California, Los Angeles, CA.

Rose, A., S. Liao and A. Bonneau. 2011. “Regional Economic Impacts of a Verdugo Earthquake Disruption of Los Angeles Water Supplies: A Computable General Equilibrium Analysis,” *Earthquake Spectra* 27(3): 881-906.

Rose, A. G. Oladosu, and S. Liao 2007. "Business Interruption Impacts of a Terrorist Attack on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout," *Risk Analysis* 27 (3): 513-31.

Rose, A., D. Wei, and A. Wein. 2011. "Economic Impacts of the ShakeOut," *Earthquake Spectra Special Issue on the ShakeOut Scenario* 27(2): 539-57.

Rose, A., G. Beeler Asay, D. Wei, and B. Leung. 2009. "Economic Impacts of Shutting Down the U.S. Borders in Response to a Security or Health Threat," in H. Richardson, P. Gordon, and J. Moore (eds.) *Global Business and Terrorism,* Cheltenham, UK: Edward Elgar.

Rose, A., G. Asay, D. Wei, and B. Leung. 2009a. "Economic Impacts of Shutting Down the U.S. Borders in Response to a Security or Health Threat," in H. Richardson, P. Gordon, and J. Moore (eds.) *Global Business and Terrorism*, Cheltenham, UK: Edward Elgar.

Rose, A., Oladosu, G., Lee, B., and Beeler-Asay, G. 2009b. “The Economic Impacts of the 2001 Terrorist Attacks on the World Trade Center: A Computable General Equilibrium Analysis,” *Peace Economics, Peace Science, and Public Policy* 15(4), Article 4.

Schirle, C. 2007. “Time Element Coverages in Business Interruption Insurance,”*The Brief* 37(1): 32-41.

Shoven, J. and J. Whalley. 1992. *Applying General Equilibrium.* New York: Cambridge.

Sue Wing, I., A. Rose, and A. Wein. 2011. *Economic Impacts of the ARkstorm Scenario*. Final Report to the U.S. Geological Survey, CREATE, USC, Los Angeles, CA.

Suess, O. and Bandel, C. 2011. "Floods, Tsunami May Dent ‘Black Box’ Supply-Chain Insurance. http://www.businessweek.com/news/2011-12-22/floods-tsunami-may-dent-black-box-supply-chain-insurance.html

Toothill, J. and Voronkoff, M. 2004. “A Watery Solution.” Globalreinsurance.com, September..

Tierney, K. 1997. “Impacts of Recent Disasters on Businesses: The 1993 Midwest Floods and the 1994 Northridge Earthquake,” in B. Jones (ed.), *Economic Consequences of Earthquakes: Preparing for the Unexpected*. Buffalo, NY: National Center for Earthquake Engineering Research.

Torpey, D., D. Lentz and A. Melton. 2011. *Business Interruption: Coverage, Claims, and Recovery* (Second Edition). Cincinnati, OH: The National Underwriter Company.

Wein, A. and A. Rose. 2011. "Economic Resilience," *Earthquake Spectra: Special Issue on the ShakeOut Earthquake Scenario* 27(2): 559-73.

Werling, J. and R. Horst. 2009. "Macroeconomic and Industry Impacts of 9/11: An Interindustry Macroeconomic Approach," *Peace Economics, Peace Science and Public Policy* 15 (2): Article 5.

TABLE 2. Resilience Tactics and Due Diligence for Business Interruption Insurance

Resilience Option	Policy Clauses Requiring Action	Policy Clauses Discouraging Action	Incentives to Implement	Disincentives to Implement	Comments
General Applicability	Insured have a duty to mitigate their losses. Insured also have the initial burden of proof for proving income loss.[1]	BI insurance is only triggered with "necessary suspension of operations"; then efforts to mitigate losses that allow the business to continue operating will not trigger BI coverage.[2]	Insurer will only cover losses to the extent that they cannot be mitigated by resilience tactics.[1] The policy clause "necessary or potential suspension" has been interpreted to allow for a partial suspension of business, e.g. continued operations at a lower level.[2] Loss Mitigation Rule of general insurance law reimburses the policyholder's costs in avoiding or mitigating losses.[3] "Extra Expenses" or "Expense to Reduce Loss" clauses pay for policyholder's efforts to avoid or minimize loss.[4]		BI insurance was not meant to cover all negative effects from covered perils and is no substitute for actual income. Calculating business interruption losses are speculative and difficult to prove.[1]
Input Substitution	Insured's duty to mitigate losses includes using same or similar substitutes.[1]			In mitigating losses, businesses are not required to act in ways that are harmful to its business, i.e. use inferior inputs.[5]	
Inventories	Insured's duty to mitigate losses includes using inventory as a means for reducing a business loss.[6]				
Excess Capacity	Insured's duty to mitigate losses includes using other plants or overtime hours to recapture production.[6]			BI only covers actual loss sustained. If there was a loss of production without loss of actual earnings, there is no covered loss.[7]	

TABLE 2. Resilience Tactics and Due Diligence for Business Interruption Insurance

Resilience Option	Policy Clauses Requiring Action	Policy Clauses Discouraging Action	Incentives to Implement	Disincentives to Implement	Comments
Relocation	Period of Restoration is the lesser of the theoretical time that destroyed property could be repaired, rebuilt or replaced, the actual time it takes to repair, rebuild or replace property, or when operations are resumed at a new permanent location.[3]			Disputes with insurance companies may arise out of what is a temporary or permanent relocation, or the value of the business' location to its business model.[3]	
Import Substitution	Insured's duty to mitigate losses includes using same or similar substitutes.[1]	Contingent BI coverage resulting from property damage to suppliers, including foreign suppliers.[8]			
Export Substitution		Recipient locations endorsement covers business income loss resulting from property damage to locations that accept the insured's product or services.[9]	Insurers often seek to determine if lost income during the period of BI has been recouped through increased sales and profits in subsequent periods.[2]	Courts have held that when mitigating losses, businesses are not required to act in ways that are harmful to its business, i.e. cost it market share, aid its competitors, or compromise its intellectual property rights.[5]	
Production Recapture	Insured's duty to mitigate losses includes using other plants or overtime hours to recapture production.[6]		Insurers often seek to determine if lost income during the period of BI has been recouped through increased sales and profits in subsequent periods.[2]	BI only covers actual loss sustained. If there was a loss of production without loss of actual earnings, there is no covered loss.[2]	
Management Effectiveness	Having detailed proof and documentation of income loss (financial statements, ex-ante profit expectations and extra expenses) will provide an audit trail to help expedite claim.[4]		Having a team to manage the entire restoration and claims process will expedite payment of claims.[9] Must give notice of claim ASAP to allow adjusters to begin claim process and ensure no delays on the business' part.[4]		Team could include engineers and repair specialists, management from risk, financial and operations, sales, legal counsel, forensic accountants. [9]

TABLE 2. Resilience Tactics and Due Diligence for Business Interruption Insurance

Resilience Option	Policy Clauses Requiring Action	Policy Clauses Discouraging Action	Incentives to Implement	Disincentives to Implement	Comments
Speeding Restoration	Period of Restoration is the lesser of the hypothetical time that destroyed property could be repaired, rebuilt or replaced, the actual time it takes to repair, rebuild or replace property, or when operations are resumed at a new permanent location.[3]		Insurers may dispute the actual time of repair by referring to the hypothetical or theoretical time it should take. Practicing due diligence in speeding restoration will avoid such disputes.[9]		

[1] Johnson and O'Toole (2005).
[2] Schirle and Clark (2007).
[3] Lewis et al. (2005).
[4] Sylvester, et al. (2010).
[5] Bell (2011).
[6] Northwestern States Portland Cement Co. v. Hartford Fire Ins. Co.
[7] Lyon Metal Products, LLC v. Protection Mutual Insurance Co.
[8] Malecki (2011).
[9] Thompson (2006).