Integrated Disaster Risk Management

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Economic Consequence Analysis of Disasters

The E-CAT Software Tool

Springer

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About the Series

Just the first one and one-half decades of this new century have witnessed a series of large-scale, unprecedented disasters in different regions of the globe, both natural and human-triggered, some conventional and others quite new. Unfortunately, this adds to the evidence of the urgent need to address such crises as time passes. It is now commonly accepted that disaster risk reduction (DRR) requires tackling the various factors that influence a society's vulnerability to disasters in an integrated and comprehensive way, and with due attention to the limited resources at our disposal. Thus, integrated disaster risk management (IDRiM) is essential. Success will require integration of disciplines, stakeholders, different levels of government, and of global, regional, national, local, and individual efforts. In any particular disaster-prone area, integration is also crucial in the long-enduring processes of managing risks and critical events before, during, and after disasters.

Although the need for integrated disaster risk management is widely recognized, there are still considerable gaps between theory and practice. Civil protection authorities; government agencies in charge of delineating economic, social, urban, or environmental policies; city planning, water and waste-disposal departments; health departments, and others often work independently and without consideration of the hazards in their own and adjacent territories or the risk to which they may be unintentionally subjecting their citizens. Typically, disaster and development tend to be in mutual conflict but should, and could, be creatively governed to harmonize both, thanks to technological innovation as well as the design of new institutions.

Thus, many questions on how to implement integrated disaster risk management in different contexts, across different hazards, and interrelated issues remain. Furthermore, the need to document and learn from successfully applied risk reduction initiatives, including the methodologies or processes used, the resources, the context, and other aspects are imperative to avoid duplication and the repetition of mistakes.

With a view to addressing the above concerns and issues, the International Society of Integrated Disaster Risk Management (IDRiM) was established in October 2009.

The main aim of the IDRiM Book Series is to promote knowledge transfer and dissemination of information on all aspects of IDRiM. This series will provide comprehensive coverage of topics and themes including dissemination of successful models for implementation of IDRiM and comparative case studies, innovative countermeasures for disaster risk reduction, and interdisciplinary research and education in real-world contexts in various geographic, climatic, political, cultural, and social systems.

More information about this series at http://www.springer.com/series/13465

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To our families

Foreword to the IDRiM Book Series

In 2001, the International Institute for Applied Systems Analysis (IIASA) and the Disaster Prevention Research Institute (DPRI) joined hands in fostering a new, interdisciplinary area of integrated disaster risk management. That year, IIASA and DPRI initiated the IIASA–DPRI Integrated Disaster Risk Management Forum Series, which continued over 8 years, helping to build a scholarly network that eventually evolved into the formation of the International Society for Integrated Disaster Risk Management (IDRiM Society) in 2009. The launching of the society was promoted by many national and international organizations.

The volumes in the IDRiM Book Series are the continuation of a proud tradition of interdisciplinary research on integrated risk management that emanates from many scholars and practitioners around the world. In this foreword, we briefly summarize the contributions of some of the pioneers in this field. We have endeavored to be inclusive but realize that we have probably not identified all those worthy of mention. This foreword is not meant to be comprehensive but rather indicative of major contributions to the foundations of IDRiM. This research area is still in a continuous process of exploration and advancement, several of the outcomes of which will be published in this series.

Japan

Disaster Prevention Research Institute

The idea of framing disaster prevention in risk management terms was still embryonic even among academics in Japan when Kobe and its neighboring region were shaken by the Great Hanshin–Awaji Earthquake (GHQ) in 1995. For example, Okada (1985) established the importance of introducing a risk management approach to reduce flood and landslide disaster risks. Additionally, it was not until late 1994 that the Disaster Prevention Research Institute (DPRI) of Kyoto University

Table 1 Conventional disaster plan vs. 21st century integrated disaster planning and management

Reactive	Proactive
Emergency and crisis management	Risk mitigation plus preparedness approach
Countermeasure manual approach	Anticipatory/precautionary approach
Pre-determined planning (if known events)	Comprehensive policy-bundle approach
Sectoral countermeasure approach	Adaptive management approach
Top-down approach	Bottom-up approach

had reorganized to add a new cross-disciplinary division of Sogo Bosai, or "integrated disaster management."

The new division of DPRI undertook a strong initiative among both academics and disaster prevention professionals to substantiate what is meant by integrated disaster management and to communicate to society why it is needed and how it helps. Many of these efforts were based on evidence and lessons learned from the GHQ. Japan's disaster planning and management policy changed significantly thereafter. Table 1 contrasts the approaches before and after that cataclysmic event. The current approach stresses strategies that are proactive, anticipatory, precautionary, adaptive, participatory, and bottom-up. The rationale is that governments in Japan had been found to be of relatively little help immediately after a high-impact disaster. Lives in peril had more often been saved by the actions of individuals and community residents than by official governmental first responders.

To understand a significant change in disaster planning and management in Japan, one must understand the contrasts among Kyojo ("neighborhood or community self-reliance"), Jijo ("individual or household self-reliance"), and Kojo ("government assistance"). Realizing limitations in the government's capacity after a large-scale disaster, Japan has shifted more toward increasing both Kyojo and Jijo self-reliance roles, and to depend less on the former, which in the past was the major agent to mitigate disasters.

One of the additional lessons learned after the 1995 disaster was to address the need for a citizen-led participatory approach to disaster risk reduction before disasters, as well as for disaster recovery and revitalization after disasters.

International Collaboration

In 2001, the International Institute for Applied Systems Analysis (IIASA) and DPRI started to join hands in fostering a new disciplinary area of integrated disaster risk management. That year, IIASA and DPRI agreed to initiate the IIASA–DPRI Integrated Disaster Risk Management Forum Series. Eight annual forums were held under this initiative, helping to build a scholarly network that eventually evolved into the formation of the IDRiM Society in 2009.

These activities, which were designed to be cross-disciplinary and international, have seen synergistic developments. Japan's accumulated knowledge, led by DPRI, became merged with IIASA's extensive expertise and became connected with inputs from the USA, the UK, other parts of Europe, Asia, and other countries and regions.

Major Research Contributions

Among many, the following contributions merit mention:

Conceptual Models Developed and Shared for Integrated Disaster Risk Management Okada (2012) proposed systematic conceptual models for understanding the Machizukuri (citizen-led community management) approach. Figure 1 illustrates the multilayer common spaces (an extension of the concept of infrastructure) for a city, region, or neighborhood community as a living body (Okada 2004). This conceptual model has been found to be useful to address multilayer issues of integrated disaster risk management at various scales. For example, in the context of this diagram, Machizukuri is more appropriately applied on a neighborhood community scale rather than on a wider scale, such as a city or region. Applied to a neighborhood community in the context of a five-storied pagoda model, it starts with the fifth layer (daily life), followed by the fourth (land use and built environment) and the third (infrastructure). By comparison, Toshikeikaku (urban planning) focuses mainly on the fourth and third layers. Another point of contrast is that Machizukuri requires citizen involvement to induce attitudinal or behavioral change, while this issue is not essential for Toshikeikaku.

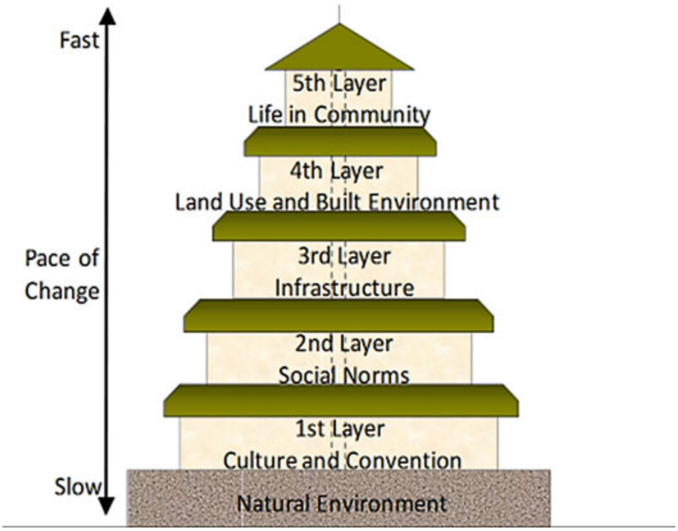

Fig. 1 Five-storied pagoda model (Source: Okada 2006)

Economic Modeling of Disaster Damage/Loss and Economic Resiliency Extensive research has been carried out by Tatano et al. (2004, 2007) and Tatano and Tsuchiya (2008) to model and analyze economic impacts of disruptions to lifelines and infrastructure systems caused by a large-scale disaster. For instance, simulating a hypothetical Tokai–Tonankai earthquake in Japan, a spatial computable general equilibrium (SCGE) model was constructed to integrate a transportation model that can estimate two types of interregional flows of freight movement and passenger trips. Kajitani and Tatano (2009) investigated a method for estimating the production capacity loss rate (PCLR) of industrial sectors damaged by a disaster to include resilience among manufacturing sectors. PCLR is fundamental information required to gain an understanding of economic losses caused by a disaster. In particular, this paper proposed a method of PCLR estimation that considered the two main causes of capacity losses as observed from past earthquake disasters, namely, damage to production facilities and disruption of lifeline systems. To achieve the quantitative estimation of PCLR, functional fragility curves for the relationship between production capacity, earthquake ground motion, and lifeline resilience factors for adjusting the impact of lifeline disruptions were adopted, while historical recovery curves were applied to damaged facilities.

Disaster Reduction-Oriented Community Workshop Methods The Cross-Road game developed by Yamori et al. (2007) proceeds as follows. During a game session, a group of five players read 10–20 episodes that are presented on cards one at a time. Each episode is derived from extensive focus group interviews of disaster veterans of the GHQ and describes a severe dilemma that the veterans of Kobe actually faced. Individual players are required to make an either/or decision (i.e., yes or no) between two conflicting alternatives in order to deal with the dilemma.

The Yonmenkaigi System Method (YSM) by Okada et al. (2013a, b) is a unique participatory decision- and action-taking workshop method. It is composed of four main steps: conducting a strength–weakness–opportunity–threat (SWOT) analysis, completing the Yonmenkaigi chart, debating, and presenting the group's action plan. The YSM is an implementation- and collaboration-oriented approach that incorporates the synergistic process of mutual learning, decision-making, and capacity building. It fosters small and modest breakthroughs and/or innovative strategy development. The YSM addresses issues of resource management and mobilization, as well as effective involvement and commitment by participants, and provides a strategic communication platform for participants.

Collaborative Research and Education Schemes Based on the Case Station-Field Campus (CASiFiCA) Scheme Acknowledging that diverse efforts have been made for disaster reduction, particularly in disaster-prone areas (countries), many professionals have been energetically and devotedly engaged in field work to reduce disaster risks. They recognize also that more community-based stakeholder-involved approaches are needed. A crucial question arises as to why we cannot

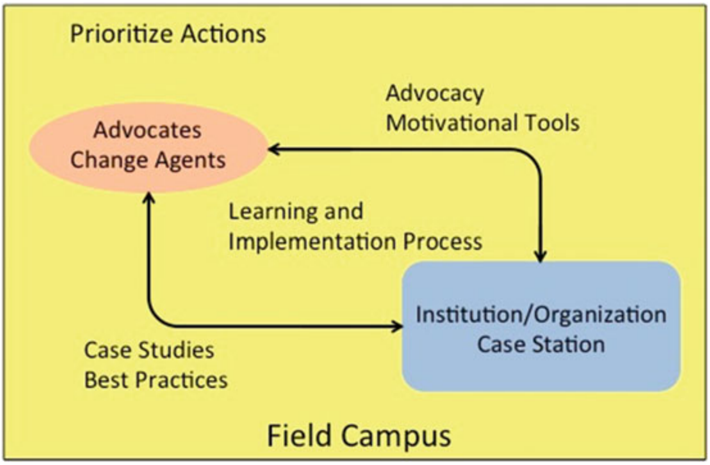

Fig. 2 Case Station-Field Campus scheme

conduct field work more creatively. One promising solution might be the CASiFiCA scheme originally proposed by Okada and Tatano (2008). As diagrammed in Fig. 2, the CASiFiCA scheme is characterized by a set of local case stations and field campuses and their globally networked linkages that are expected to operate synergistically to achieve the following objectives: promotion of IDRiM education at all levels, multilateral knowledge sharing and knowledge creation, and implementation of knowledge and gaining knowledge from implementation.

Europe

Integration via Regulation: European Union Experience

The integrated risk management of technological and natural hazard-triggered technological accidents (known as Natechs) has been a major theme addressed during the IIASA–DPRI Integrated Disaster Risk Management Forum Series since the first forum in 2001. In 2007 and 2008, the forum was hosted by the Major Accident Hazards Bureau at the Joint Research Centre of the European Commission in Italy, further strengthening the need for integration across natural and technological disaster risk management.

Integration was not (and, generally, still now *is not*) a self-evident concept when the first European Union Conference on Natural Risk and Civil Protection was launched in 1993, in Belgirate, Italy (Horlick-Jones et al. 1995). As the rapporteur-general wondered:

> Whilst one objective of the conference was to encourage dialogue between researchers and practitioners, it quickly became clear that the group structure was rather more complex than simply comprising natural scientists and civil protection experts. The 'tribes' present included natural hazard scientists, civil protection theorists – mostly social, behavioural and management scientists, industrial risk specialists, protection administrators and civil protection practitioners. The hazards and civil protection 'community' included a number of professional groups with distinct traditions and cultures. The term 'tribe' is used in an attempt to capture some sense of how strong is this divide.

Communication between the groups was rather difficult and most surprising for people not directly involved in scientific disputes. The discovery of the strong opposing views existing between different research directions within the same "hard" discipline (e.g., in seismology the debate on earthquake predictability) made even the agreement on an agenda for the conference challenging. These difficulties were unanticipated, because previous events concerning industrial hazards—organized in a similar manner on emergency planning (Gow and Kay 1988) and risk communication (Gow and Otway 1990)—found a rather cooperative atmosphere.

Despite the fact that the organization of the conference involved three directorate-generals of the European Commission (Research and Education, Environment, and Joint Research Center), natural hazards activities were not covered by an institutional legal basis. Also, at the time, there was no mutual assistance/compensation agreement in the case of a natural disaster, but only an initial exchange of experiences among emergency response services of EU member states. On the other hand, the existence of a sound regulatory process that obliged the different actors to be involved in the risk management framework was the reason for the successful cooperation in the latter mentioned events.

The new regulatory process for chemical accident prevention is an example. The process was reactive rather than anticipatory. It was triggered by a number of major accidents—e.g., the dioxin release at Seveso (Italy) in 1976 and the explosion at Flixborough (UK) in 1974. These had in common the features that local authorities did not know what chemicals were involved and in what quantities. They did not know enough about the processes to understand what chemicals/energy could be produced or released under accident conditions, and there was a general lack of planning for emergencies. Given this background, the first 1982 Seveso I Directive (82/501/EEC) was largely concerned with the generation and the control of an adequate and sufficient information flow among the different actors in the risk management process (Otway and Amendola 1989). This covered industrial activities that handle hazardous materials and introduced an integrated risk management scheme with identification of the actors and their obligations (control/licensing authorities—operators) or rights to know (the public). It requires that potential major accidents involving hazardous materials be identified, adequate safety measure be taken to prevent them, and on-site emergency plans be implemented. The competent authorities (CAs) have to control the adequacy of such measures and provide for external emergency plans. The public should be "actively" informed of the safety measures and how to behave in the event of an accident. The operator is required to report any major accident to the CAs, and the CAs have to notify the European Commission, which keeps a register of accidents so that member states can benefit from this experience for the purposes of prevention of future accidents.

The Seveso I Directive was the background for further discussions at the international level, such as the Organisation for Economic Co-operation and Development (OECD) and the United Nations Economic Commission for Europe (UNECE), which resulted in further recommendations and conventions on trans-boundary effects related to major accidents (United Nations 1992).

Reacting to the tragedy in Bhopal, India and other issues identified during its implementation, the need for a revision was identified, particularly concerning the lack of provisions for land-use planning (De Marchi and Ravetz 1999), resulting in the Seveso II Directive (96/82/EC). It completed the transparency process, beginning with the obligation of disseminating information to the public on how to behave in case of an accident, and, in a relatively short time, changed the "secrecy" in most countries surrounded by chemical risks into unprecedented transparency (for the "evolutionary construction of a regulatory system" for an extensive discussion of all Seveso II requirements, see Amendola and Cassidy 1999). It established that the public should be consulted for land-use planning and emergency planning with respect to accident risks and therefore should be more directly involved in risk management decisions. Furthermore, the safety report and accident reporting systems became accessible by the public.

The Seveso II Directive focused much more on the socio-organizational aspects of the control policy:

- The concept of an industrial *establishment* was introduced, characterized by the presence of dangerous substances. The focus is on the interrelations among installations within such an establishment, especially those related to organization and management. Further, attention is given to situations liable to provoke so-called *domino effects* between neighboring establishments. This led to integrated assessments of industrial areas. Furthermore, it implicitly called for the analysis of external threats, such as natural hazards.
- The socio-organizational aspects of an establishment were strongly affected by the introduction of the obligation for a major accident prevention policy (MAPP), to be implemented by means of safety management systems (SMS) (Mitchison and Porter 1999). These provisions were introduced after the awareness that most of the major accidents of which the commission was notified over the years under the major accident reporting system (MARS) had root causes in faults of the management process (Drogaris 1993).
- The introduction of the obligation for a *land-use planning policy* with respect to major accident hazards has had important socio-organizational consequences, as a broader body of authorities, especially those dealing with local urban planning, are becoming involved in decisions about the compatibility of new development with respect to existing land use (Christou et al. 1999). This has been integrated with the requirement that the public shall be consulted in the decision-making process. This has also led to integration of planning policies with respect to other kinds of hazards, such as natural ones, assuring that appropriate distances are

kept between establishments, residential areas, and areas of particular "natural sensitivity."
- The provisions for *emergency planning* and *public information* have been reinforced, as the *safety report* becomes a public document, and the public must be consulted in the preparation of emergency plans.

The Seveso II Directive also approached management as a continuous process, because it did not limit the regulatory action to providing a license or a permit to operate. Instead it assigned the obligation to the operator to adopt management systems as a continuous process for feedback in the procedures relating to operating experience and managing the changes over time. Also, land-use planning addresses not only "siting" a new establishment but also considers the compatibility of major changes with the existing environment as well as the control of urbanization around an establishment. Furthermore, it promoted common efforts among authorities, operators, and risk analysts to improve the risk assessment procedures and achieve better risk governance processes (Amendola 2001).

As mentioned above, the Seveso II Directive called for the analysis of external hazards as part of the hazard assessment process. Both domino effects and land-use controls are of particular importance when addressing the risk reduction of chemical accidents triggered by external natural hazard events (Natechs). In fact domino effects may be more likely during natural disasters than during normal plant operation (Cruz et al. 2006; Lindell and Perry 1997). Their likelihood will depend on the proximity of vulnerable units containing hazardous substances, and the consequences will undoubtedly increase with the proximity of residential areas. The European Commission published guidelines to help member states fulfill the requirements of the Seveso II Directive (see Papadakis and Amendola 1997; Mitchison and Porter 1998; Christou and Porter 1999). However, the guidelines do not provide specific actions or methodologies that should be taken to prevent, mitigate, or respond to Natechs (Cruz et al. 2006).

In 2012, the European Commission published the Seveso III Directive, which amended and subsequently repealed the Seveso II Directive. The major changes included in the Seveso III Directive included strengthening of a number of areas such as public access to information and standards of inspections. Furthermore, the latest amendment now explicitly addresses Natech risks and requires that environmental hazards, such as floods and earthquakes, be routinely identified and evaluated in an industrial establishment's safety report (Krausmann 2016).

International Institute for Applied Systems Analysis (IIASA)

"Risk" has been part of IIASA's activity profile since the institute's foundation. This theme is critical, as the prospect of unintended consequences from technological, environmental, and social policies continues to stir intense debates that shape the future of societies across the world. Relying on probability calculations, risk became a theoretical focus designed to bolster a scientific, mathematically based approach toward uncertainty and risk management.

Early controversies in the 1970s and 1980s on nuclear power, liquid natural gas storage, and hazardous waste disposal—all early research topics at IIASA—made clear to the expert community, however, that probabilistic calculations of risk, although essential to the debates, are not sufficient to settle issues of public acceptance. In response, IIASA has pioneered research on risk perception (Otway and Thomas 1982), objective versus subjective assessments (Kunreuther and Linnerooth 1982), systemic cultural biases (Thompson 1990), and risk and fairness (Linnerooth-Bayer 1999).

As a critical part of this history, IIASA is widely recognized for its advances in stochastic and dynamic systems optimization (e.g., Ermoliev 1988), treating endogenous uncertainty and catastrophic risks in decision-making processes (reviewed in Amendola et al. 2013) and advancing statistical methods for probabilistic assessment (e.g., Pflug and Roemisch 2007). The hallmark of IIASA's risk research is the integration of these multiple strands of mathematical and social science research.

One important in-house model taking an integrated perspective in the RISK program at IIASA is the so-called Catastrophe Simulation (CatSim) Model, which focuses on the government and its fiscal risk in the face of natural disaster events. It is a mainstay of the program's methodological and policy research and was first developed to aid public officials in developing countries to assess catastrophic risks from natural hazards and analyze options to enhance their country's financial resiliency. The model takes a "systems approach" by integrating catastrophe risk modeling with financial and economic modeling. It enables users to explore the impact of traditional and novel financial instruments, including reinsurance and catastrophe bonds, in terms of the costs of reducing the risk of a financing gap. CatSim has proven useful in other contexts as well, e.g., for allocating climate adaptation and development funds to support disaster resilience in the most vulnerable countries. Based on the model framework, assessed exposure and financial vulnerability to extreme weather events on the global scale can be performed as well (Hochrainer-Stigler et al. 2014).

Beyond modeling, IIASA has pioneered the exploration of novel financing instruments to provide safety nets to vulnerable communities and governments facing climate risks (Linnerooth-Bayer and Amendola 2000). These instruments now feature prominently on the agendas of development organizations and NGOs, and they are also gaining attention in the climate change adaptation community (Linnerooth-Bayer and Hochrainer-Stigler 2015). In an early influential policy paper, IIASA scientists argued that donor-supported risk-transfer programs, some based on novel instruments, would leverage limited disaster-aid budgets and free recipient countries from depending on the vagaries of post-disaster assistance (Linnerooth-Bayer et al. 2005).

As a final mention, IIASA's contributions to integrated disaster risk management have included the design and implementation of new forms of bottom-up governance, most notably stakeholder processes which co-design policy options with experts and explicitly recognize large value differences.

The USA

Multidisciplinary Center for Earthquake Engineering Research

The National Center for Earthquake Engineering Research (NCEER) was established at the State University of New York at Buffalo in 1986, with funding from the US National Science Foundation (NSF), the state of New York, and industrial partners. NCEER's original vision focused on multidisciplinary research and education aimed at reducing earthquake losses. Although the Center's main priority was to support research in structural, civil, and geotechnical engineering, it also provided funding for research in the fields of economics, urban planning, regional science, and sociology. Despite NCEER's ambitious vision, much of the research conducted during the 10-year period of initial grant support remained discipline-specific, although with the passage of time there was greater integration across disciplines, particularly in areas such as earthquake loss estimation, which required collaborative approaches.

When NCEER leaders decided to enter a new competition for NSF funding in the mid-1990s, there was general agreement that investigators should step up their multidisciplinary collaborative efforts based on an understanding that earthquake risk reduction and risk management require contributions from a range of areas of expertise beyond traditional engineering fields. This was made explicit when the leadership decided to change the Center's name to the Multidisciplinary Center for Earthquake Engineering Research (MCEER). Participation in multidisciplinary teams was strongly encouraged as MCEER investigators increasingly tackled problems that were beyond the scope of individual disciplines. Experts in remote sensing and in structural engineering worked together on the development of building inventories and, later on, rapid post-earthquake damage assessment methods using remotely sensed data. Engineers, economists, and sociologists worked on improving earthquake loss estimation methods, focusing, for example, on estimating potential damage to urban lifeline systems as well as resulting direct and indirect economic losses. Collaborating teams developed earthquake recovery models and explored the economic, political, and institutional obstacles that stand in the way of adopting and implementing risk reduction policy. Researchers studied hospitals both as critical physical systems and as organizations. A multidisciplinary group consisting of engineers, policy experts, and decision scientists developed decision-support tools designed to help facility owners make informed choices about alternative seismic risk reduction measures.

In the late 1990s, another team of researchers from various fields began a series of projects focused on the conceptualization and measurement of earthquake (and general disaster) resilience. Recognizing that resilience itself is a multidisciplinary and even a transdisciplinary concept, researchers surveyed a wide range of studies in fields ranging from ecology to psychology, identified common concepts and indicators, and developed one of the first frameworks that applied the resilience concept to natural hazards. One early product resulting from that collaboration was the article "A Framework to Quantitatively Assess and Enhance the Seismic Resilience of

Communities" (Bruneau et al. 2003). Authors of that paper represented the fields of civil, geotechnical, and structural engineering, operations research, economic geography, decision science, and sociology.

These successful collaborations were the result of several factors. Research activities were problem focused, and the researchers involved recognized that the earthquake problem is multidimensional. Methodological tools such as geographic information systems were useful in bringing about integration across disciplines. The longevity of NCEER and MCEER was also important; long-term funding made it possible for investigators to engage with one another over prolonged periods. This also meant that over time, researchers came to better understand and appreciate the approaches and methods employed by their counterparts in other disciplines. Additionally, the intent of the funding source was a significant influence; NSF made it clear that it was looking for research that was capable of overcoming disciplinary silos.

A major example of integrated research at MCEER was the first New Madrid (Earthquake Zone) electricity lifeline case study (Shinozuka et al. 1998), which focused on the site of the largest earthquake to strike North America in its recorded history. The study team was composed of engineers, geographic information scientists, economists, regional scientists, planners, and sociologists. They addressed the complexity of the interaction of various systems in the Memphis Tennessee Metropolitan Area. This included the vulnerability of the lifeline network, business response to physical damage and production disruption, estimation of direct and indirect losses in the region and throughout the USA, and policy analysis and implementation. At the core of the research were models of economic, social, and spatial interdependence, such as input–output analysis, multisector mathematical programming, and social accounting matrices (all precursors of the now state-of-the-art approach of computable general equilibrium analysis). This research was performed around the same time as the development of FEMA's loss estimation software tool HAZUS (FEMA 1997, 2016), which was another example of an integrated assessment model (see also Whitman et al. 1997). The capabilities included in HAZUS had to be simplified in order to be incorporated into a decision-support system that could be used by a wide spectrum of emergency managers and analysts on a desktop PC. In contrast, the MCEER research was intended to advance the state of the art in improving the scope and accuracy of hazard loss estimation. As such, it proved valuable in future extensions and upgrades of HAZUS and informed other research and public and private decision-making. One of its major points was the prioritization of electricity service restoration according to various societal objectives such as minimizing lost production and employment. As one of the study authors noted: "Not taking advantage of such opportunities results in an outcome as devastating as if the earthquake actually toppled the buildings in which the lost production would've originated" (p. xvii).

MCEER was directed by Masanobu Shinozuka, George Lee and Michel Bruneau. Researchers who contributed to the integration of various disciplines under its umbrella, in addition to the directors, included Barclay Jones, Kathleen Tierney, Tom O'Rourke, Bill Petak, Charles Scawthorn, Detlof von Winterfeldt, Stephanie Chang, Ron Eguchi, and Adam Rose. Two sister centers of MCEER were established with NSF Funding in the mid-1990s: the Pacific Earthquake Engineering Center (PEER), headquartered at the University of California, Berkeley, with a focus on performance-based engineering; and the Mid-American Earthquake Center (MAE), headquartered at the University of Illinois, Urbana, with a focus on a multi-hazard approach to engineering.

Natural Hazards Center

The Natural Hazards Research and Applications Information Center at the University of Colorado Boulder—now called the Natural Hazards Center (NHC)—was founded in 1976 by Gilbert F. White, a geographer, and J. Eugene Haas, a sociologist. Center activities were built upon the foundation that White and his collaborators from many disciplines had already established, as outlined in the books *Natural Hazards: Local, National, and Global* (White 1976) and *Assessment of Research on Natural Hazards* (White and Haas 1975). In the *Assessment*, White and Haas argued that efforts to prevent and reduce disaster losses relied far too much on technological approaches, without taking into account research in the social sciences. Their position was that such research could offer important insights into societal responses to hazards and disasters while also shedding light on whether technological approaches aimed at reducing losses were likely to produce their intended outcomes. Early research assessments focused on "adjustments" to hazards that communities and societies can adopt either singly or in combination: relief and rehabilitation, insurance, warning systems, technological adjustments such as protective works, and land-use management. In the view of the founders, a key task for researchers was to better understand the conditions under which particular adjustments would be adopted and their subsequent impact on disaster losses. Early in its history, the NHC produced its own series of books, monographs, and special reports, many of which focused on findings from US National Science Foundation-sponsored research carried out by investigators in the social, economic, and policy sciences. That practice was discontinued as specialized journals began to proliferate and an increasing number of academic and commercial publishers began to show an interest in publishing research monographs and textbooks in the disaster field.

From its inception, the NHC has had a dual mission. First, it serves as a clearinghouse and information provider for social science research on hazard mitigation, preparedness, response, and recovery, again with an emphasis on alternative adjustments to hazards. The idea of an information clearinghouse arose out of recognition of the difficulties associated with getting research applied in real-world settings. Clearinghouse activities include the production and distribution of the NHC newsletter, the *Natural Hazards Observer,* library and information services, and the annual NHC workshop, which has grown over the years. From the beginning, the annual workshop was designed to bridge communication gaps among researchers and graduate students from a variety of physical, social science, and engineering disciplines, government decision-makers, and emergency management practitioners. The NHC also administers a small-grant quick-response research program that enables researchers and students to go into the field immediately following disasters and then publishes the results of those studies. Second, NHC faculty and graduate students conduct their own research, with support from the National Science Foundation and other sponsors.

Both the activities associated with the production of the original *Assessment* and subsequent center activities involved the training of young researchers from a variety of social science disciplines. The first generation of center graduate trainees included well-known researchers such as Harold Cochrane (economics); Eve Gruntfest and John Sorensen (geography); Dennis Mileti, Robert Bolin, and Patricia Bolton (sociology); and Michael Lindell (psychology).

During the 1990s, the NHC conducted the second assessment of research on natural hazards under the leadership of director Dennis Mileti. The second assessment, which involved contributions from approximately 120 researchers, students, agency personnel, and other public officials, resulted in five books and numerous published articles and reports, again reflecting a range of social science perspectives (e.g., Mileti 1999). Like its predecessor, the second assessment provided training for another generation of researchers.

Since the early 2000s, the NHC has been increasingly involved in multidisciplinary research projects. Examples include collaborations with computer scientists and other social scientists on new technologies for emergency management, with economists on post-disaster business and economic resilience, with researchers from the National Center for Atmospheric Research on warning systems, with investigators from a number of social science disciplines on homeland security-related issues, with engineering researchers on recovery from the 2004 Indian Ocean tsunami, and with engineers, earth scientists, and policy scientists on the problem of induced earthquakes.

The NHC has served under the able directions of its founders and successor directors geographer William Riebsame (now William Travis), sociologists Dennis Mileti and Kathleen Tierney, and, beginning in January 2017, sociologist Lori Peek.

Center for Risk and Economic Analysis of Terrorism Events (CREATE)

Soon after the September 11, 2001, terrorist attacks in the USA, the nation's National Academy of Sciences performed an assessment of how the scientific community, broadly defined, could contribute to reducing the terrorist threat. One of their recommendations was to establish university centers of excellence (COEs) in research and teaching. The first of these was the Center for Risk and Economic Analysis of Terrorism Events (CREATE), established in 2004 and headquartered at the University of Southern California but being a geographically distributed entity with more than a dozen affiliates at other universities and research organizations throughout the USA and some overseas. These faculty affiliates came from the

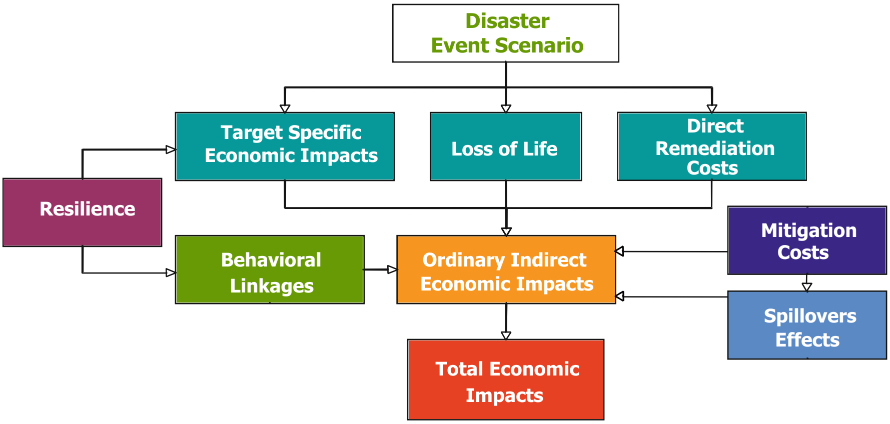

Fig. 3 CREATE economic consequence analysis framework

disciplines of decision analysis, risk analysis, psychology, economics, business, regional science, planning, operations research, public policy, public administration, public health, computer science, and communications. Founding directors were Randolph Hall and Detlof von Winterfeldt; subsequent directors were Stephen Hora and Ali Abbas, with von Winterfeldt returning after serving as director of IIASA.

Despite the restrictive nature of its title, CREATE was intended to be an "all hazards" center, although research in areas other than terrorism has been in the minority. CREATE was initially based on three themes: risk assessment, economic consequence analysis (and related topics in economics), and risk management. Risk communication was later inserted into the base of the framework. Much of the research has been multidisciplinary and some of it interdisciplinary.

One of the major interdisciplinary contributions was the development of a comprehensive framework for economic consequence analysis (ECA), as depicted in Fig. 3. This framework expanded ordinary economic impact analysis and hazard loss estimation substantially, first, by incorporating resilience. Building on his research at MCEER, Rose refined the concept of economic resilience into its static and dynamic versions, which are analyzed in the context of business interruption (BI), and focused the research on the demand, or customer, side, in terms of how businesses, households, and government agencies utilize remaining resources more efficiently and recover more quickly (see, e.g., Rose 2009 and this volume in the IDRiM Book Series). CREATE researchers performed many case studies using the operational metric that resilience effectiveness of any given strategy was equal to the averted BI as a proportion of the total potential BI in the absence of implementing the strategy. A major example was the finding that 72 % of the potential BI losses stemming from the destruction of the World Trade Center were averted by the rapid relocation of its business and government tenants (Rose et al. 2009).

Subsequent research has established the basis of an economic resilience index based on actionable variables (Rose and Krausmann 2013).

Another innovation was to incorporate "behavioral linkages," primarily off-site, post-disaster responses caused by such phenomena as the social amplification of risk and stigma effects. Many of these reactions are related to fear, as exemplified by the large BI following 9/11 from the decline of airline travel and related tourism (von Winterfeldt et al. 2006; Rose et al. 2009). A more in-depth and integrated analysis was undertaken to examine the BI losses from a simulated dirty bomb attack on the Los Angeles Financial District (Giesecke et al. 2012). This study examined the costs of potential wage and investor rate of return premia and customer discounts needed to attract people back to the targeted areas and inserted these costs in the state-of-the-art tool of economic consequence analysis—computable general equilibrium (CGE) modeling. The study results indicated that behavioral effects were 15 times larger than the ordinary direct and indirect economic impacts typically measured.

More recently, the framework has been "transitioned" to a user-friendly software tool known as E-CAT (Rose et al. 2017—a forthcoming volume in the IDRiM Book Series). A further extension of ECA on a parallel track to enhance the US government's terrorism risk assessment capability is being completed by Dixon and Rimmer (2016).

Other examples of interdisciplinary research at CREATE include work on adaptive adversaries, risk perceptions, risk messaging, and the value of information in risk management. This includes numerous case studies for academic and policy advising purposes that have been undertaken by CREATE researchers. One set of these has been the collaborative efforts between CREATE and the US Geological Survey (USGS) on analyzing disaster scenarios, such as a catastrophic earthquake, severe winter storm, tsunami, and massive cyber-disruption (see, e.g., Porter et al. 2011).

CREATE is one of a dozen COEs, with others involved in interdisciplinary research being the Consortium for the Study of Terrorism and Responses to Terrorism (START) and the Coastal Hazards Center. The centers have involved major researchers in the USA on both terrorism and natural hazards, such as Dennis Mileti, Kathleen Tierney, Susan Cutter, and Gavin Smith. An example of pioneering research is that on community resilience by Norris et al. (2008).

Low-Income Countries

It is difficult to pinpoint the beginning of academic research on natural hazards and disasters in low-income countries. The humanitarian system has deep historical roots, but the emergence of a humanitarian knowledge community is more recent and began to accelerate in the 1970s (Davey et al. 2013: 29). The 1970s and 1980s saw significant attention given to food emergencies and famine (Comité d'Information Sahel 1973; Sen 1981) and also to floods and cyclone impacts (White

1976). The rapid growth of academic research in the 1970s and 1980s was arguably driven by the greater visibility and political saliency of disasters such as the famines in the West African Sahel and Ethiopia, huge loss of life in Bangladesh due to cyclones, and deadly earthquakes in Guatemala and China (Kent 1983; Wisner and Gaillard 2009). However, it was only in what the British call "development studies" that disaster vulnerability became a core concern during this early period, with, for instance, Chamber's introduction of the concept of vulnerability in the context of "integrated rural poverty" (1983) and theme issues of the *Bulletin of the Institute of Development Studies* devoted to problems of seasonality and to food security and the environment (Lipton 1986; Leach and Davies 1991). The international, interdisciplinary journal *Disasters* was launched in 1976. Geographers, political economists, anthropologists, students of international relations, and community health specialists were among the early contributors. Epidemiologists and other public health researchers were active in defining disasters as a new focus of research at about the same time (de Ville de Goyet 1976); however, they worked alone or in small groups. The large academic center devoted to interdisciplinary, integrated approaches to understanding and managing disasters in low-income countries is a more recent development.

National Interdisciplinary Centers in the Global North

In the early twenty-first century, dedicated research centers now exist whose staff and collaborators span disciplines from the earth science and geoinformatics, social work, engineering, and public health to psychology, economics, sociology, politics, and geography, among others. Their approach is generally applied to and focused on the policy and practice of management of disaster prevention and risk reduction, warning, response and relief, and recovery. Two examples are the IRDR at University College London and IHRR at Durham University.

The Institute for Risk and Disaster Reduction (IRDR https://www.ucl.ac.uk/rdr) at University College London draws from a wide range of the University's institutes and departments, including the Institute for Global Health, Development Planning Unit in the Bartlett School of Architecture, Faculty of Engineering Sciences, the Leonard Cheshire Disability and Inclusive Development Centre, and departments of earth science and psychology, among many others. IRDR affiliates conduct research on the public perception of risk and how diverse societies deal with disaster, understanding health risks and pandemics, the study of extreme weather and the climate forcing of geological hazards, innovative design and construction, planning and design codes, and issues of resilience and recovery. One UCL partner with IRDR, the UCL Hazard Centre, has placed Ph.D. student researchers in nongovernmental development organizations (NGOs) in order to enhance NGO effectiveness (https://www.ucl.ac.uk/hazardcentre/ngo).

The Institute of Hazard, Risk and Resilience (IHRR https://www.dur.ac.uk/ihrr/) covers a similar range of research topics and also engages staff and research students across many disciplines at the University of Durham. IHRR plays a central role in the Earthquakes Without Frontiers research program in a number of countries in the Alpine–Himalayan Belt. This work involves earth scientists, social scientists, a historian, and a professor of social work and seeks to understand secondary earthquake hazards such as landslides, as well as risk governance and perception of earthquake risks by stakeholders at a number of scales (http://ewf.nerc.ac.uk/). IHRR researchers are also investigating such health aspects of disaster management as the effectiveness of respiratory protection during volcanic eruptions and economic questions such as how well small and medium enterprises recover from flooding.

International Centers

Because the elimination of poverty and promotion of security for people from food shortage, disease, and natural hazards are among the mandates of a number of UN organizations and international organizations, it is not surprising that research on integrated disaster risk reduction and management also takes place in these institutional homes. The World Bank and United Nations Development Programme (UNDP) are keenly aware of risk and are active on issues of human security (World Bank 2014; UNDP 2014). The World Health Organization (WHO) and the World Food Programme (WFP) also commission and conduct research on the early warning and management of epidemics and food emergencies, respectively (WHO 2016; WFP 2016). The Intergovernmental Panel on Climate Change (IPCC) has addressed the impacts of climate change on poor people in poor countries, particularly in its major report on climate-related disasters (IPCC 2012).

Also at the international scale, a good deal of the work of IIASA has been important in shaping policy and practice of risk management in low-income countries, for example, in the area of disaster insurance. The Center for Research on the Epidemiology of Disasters at the Catholic University of Louvain (CRED) in Belgium has evolved from a collector and repository of disaster data into a multifunctional academic institution that also produces occasional reports of relevance to integrated disaster risk management. One example is its 2016 report on poverty and disaster deaths (CRED 2016).

The International Council for Science has launched an initiative on the integrated study of disaster risk (http://www.irdrinternational.org/). Based in Beijing, China, the program of Integrated Research on Disaster Risk (IRDR) is active worldwide, especially in the Global South. It encourages young scientists, and it is currently engaged in an international assessment of integrated research on disaster that may lead to the IRDR's becoming the hub of a community of practice for such work. Its other research areas include knowledge sharing on the assessment of disaster loss and of the factors involved in the ways that people make decisions regarding disaster risk. In all of these functions, the emphasis is on serving a networking and facilitating function among researchers.

Another major program at IRDR has been to develop a framework for the forensic analysis of disasters called Forin (IRDR 2015). It seeks to focus researchers' attention on the root causes of disaster that go beyond the physical triggering phenomena and simple human exposure. Forin is grounded in a theory of social construction of disaster risk (Wisner et al. 2004, 2016; Tierney 2014). While keenly aware of physical and biological processes that manifest as hazards, Forin focuses on the process of development itself as a locus of risk creation (Oliver-Smith et al. 2016).

The forensic approach of the IRDR's Forin framework is not unusual. For many researchers who come to disaster risk from a background of work on poverty and marginalization in low-income countries, disaster is understood as a manifestation of failed or distorted development (Lavell et al. 2012) and the accumulation of risk in everyday life (Bull-Kamanga et al. 2003). Data collected beginning in the early 1970s shows that marginalized and excluded social groups in formerly colonized and other low-income countries are more severely impacted by natural hazards (Wisner et al. 2004). Women die in greater numbers in floods and coastal storms. Small farmers and fishers end up losing their land and boats to more wealthy neighbors and money lenders and find it more difficult to reestablish viable livelihoods.

The perspective of research grounded in daily realities of the urban and rural poor has also revealed that local knowledge and ways of adapting to hazards have been overlooked by planners and managers. In the last two decades, there has been much research on how local knowledge of hazardous environments can be brought together with outside specialist knowledge (Wisner 1995, 2010, 2016). The concept and practice of community-based disaster risk management (CBDM) or risk reduction (CBDR) have become common among both academic researchers and a large number of nongovernmental organizations, and collaboration between civil society and academia has begun in this domain (Wisner et al. 2008; Kelman and Mercer 2014).

National and Regional Centers in the Global South

Interdisciplinary research is also being conducted by institutions within low- and medium-income countries themselves. In the Americas, the network of researchers known as La Red was a pioneer (http://www.desenredando.org/). Created in 1992, La Red has a relationship with FLACSO, the graduate faculty of social sciences shared by ten Latin American countries. La Red publishes a journal, *Sociedad y Desastres* (http://www.desenredando.org/public/revistas/dys/), suspended for a time, but now relaunched, and has incubated some of the world's most innovative work on participatory action research for disaster reduction and on deep analysis of the links between development and disaster. Many of these innovations, while originally focused on the region and published in Spanish, have taken on an international role in shaping how disaster is understood and measured. A disaster monitoring and inventory tool known as DesInventar (http://www.desinventar.org/) was created by associates of La Red. It makes use of sub-national media and civil society sources to catalogue small- and medium-scale hazard events that have been shown to have a major impact on livelihoods and human security. Since its earliest application in Colombia, it is now used in many parts of the world.

In South Africa, Stellenbosch University and North-West University have interdisciplinary centers devoted to disaster risk management. At Stellenbosch, the Research Alliance for Disaster Risk Reduction (RADAR) began in 2013 to build on 17 years of research and networking on the continent when the director was based at Cape Town University. A large body of work on urban disaster risks such as shack fires and risk management in South Africa has resulted, as well as work on flooding. In addition, Peri Peri University is coordinated from a base in RADAR (http://www.riskreductionafrica.org/partners-and-programmes/stellenbosch-university-stellenbosch-south-africa/). Peri Peri U is a network of 11 universities in sub-Saharan Africa that share knowledge on disaster-focused pedagogy and research methods. North-West University is home to the African Centre for Disaster Studies (ACDS http://acds.co.za/). Established in 2002, ACDS conducts research on disaster risk governance, gender and disasters, water-related risks, and climate change. It is also home to a peer-reviewed, open-access journal, *Jàmbá: Journal of Disaster Risk Studies* (http://www.jamba.org.za/index.php/jamba).

In South Asia, a group of researchers pulled from civil society, journalism, and academia produces the occasional *South Asia Disaster Report* (e.g., Practical Action 2010) coordinated by the NGO called Duryog Nivaran and facilitated over the years by the INGO, Practical Action.

Many of the participants in these various research efforts in the Asia-Pacific region, the Middle East, Africa, Latin America, and the Caribbean have collaborated over the years with research into local, lived realities of disaster risk and risk reduction. The Global Network of Civil Society Organisations for Disaster Reduction (GNDR www.gndr.org) has in this way been able to mount large surveys that involved 800 civil society organizations in 129 countries, tapping the knowledge of more than 85,000 respondents in its Views from the Frontline series (http://www.gndr.org/programmes/views-from-the-frontline/vfl-2013.html), as well as even more detailed studies of local risk perception and action in its Frontline and Action at the Frontline series (Gibson and Wisner 2016).

Summary

The examples provided above are not exhaustive. Groups of researchers in many universities, civil society organizations, and government departments in low- and medium-income countries carry out work on disaster risk, albeit some of it more and some less integrated and interdisciplinary, given differences in the history of relations among academia, news media, and government and differences in bureaucratic flexibility within higher education and government. The important takeaways from this brief overview are that:

- A vital and growing focus on disaster risk in low- and medium-income countries has emerged
- A consensus is growing that disaster risk in such countries is to a great degree a manifestation of failed development
- The applied focus on practice and policy leads such research toward an integrated management approach
- Systemic changes in governance and in the relations among academia, civil society (including the media), and government are necessary if research on integrated risk management is to flourish in low- and medium-income countries themselves, and elsewhere in the Global South, as opposed to relying primarily on work within rich-country institutions and international organizations in the Global North

Other Contributions

The brief summaries of research contributions on integrated disaster risk management presented above are not all-inclusive. They focus to a great extent on work performed through major research institutions. As such, they omit contributions by several who have contributed to the IDRiM cause before the formation of the organization and since. Some examples are noted below.

The interrelationship between disasters and development was given a significant boost by the establishment of a program in disaster and development studies at Northumbria University (UK) in 2000 (see also the Department of Geography/ Disaster and Development Network, DDN). This also co-emerged with integration of more specialized fields such as health and well-being-centered disaster risk reduction and communities and resilience, all of which are based on integrated approaches. Early work by Andrew Collins and others focused specifically on infectious disease risk management, bringing together microbial ecology, socio-behavioral, and contextual analyses to identify best-integrated risk management practices in Mozambique and Bangladesh (see http://www.ukcds.org.uk/the-global-impact-of-uk-research/communities-against-disasters). A broader set of universities are involved in the UK Alliance for Disaster Research (UKADR) (www.ukadr.org).

In Austria, BOKU University has a long tradition in the research of water resources, including current involvement in the South East Europe (SEE) project CC-WARE (Mitigating Vulnerability of Water Resources Under Climate Change). It is led by the forest section of the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management and includes 17 partners from 10 countries. The main objective of CC-WARE is the development of an integrated transnational strategy for water protection and mitigating water resources vulnerability as a basis for the implementation of national and regional action plans (http://www.ccware.eu/). See also Löschner et al. (2016).

DPRI, with funding from the government of Japan under its GCOE Human Security Engineering (HSE) initiative, promoted field-based research projects on disaster risk management in Asian megacities. The Mumbai project, 2009–2013, focusing on vulnerable hot-spot communities, was established with the objective of evolving scientific methodology on participatory grassroot-level disaster risk management. The project, a first of its kind in India and one among a few globally, was undertaken in collaboration with the Mumbai city government (MCGM); School of Planning and Architecture, New Delhi; the Tata Institute of Social Science; IIT Bombay; and JJ School of Architecture, Mumbai. One outcome is a breakthrough in process methodology that empowered the two hot-spot poor communities to play the lead role in what is known as community-based disaster risk management (CBDRM). IDRiM founding member Bijay Anand Misra served as the senior adviser and coordinator of the project (see Misra 2013).

IDRiM member Manas Chatterji has overlapped research on integrated disaster risk management with work on conflict management and peace science (see, e.g., Chatterji et al. 2012).

Several research centers working on aspects of integrated disaster risk management operate in Iran, such as the International Institute of Earthquake Engineering and Seismology, under the founding and long-term leadership of Professor Mohsen Ghafory-Ashtiany, who also serves as the Chairman of the SP Insurance Risk Management Institute.

As one major example of research in China, in 2011, the Risk Governance Group of the Chinese National Committee on International Dimensions Programme on Global Environmental Change (CNC-IHDP) launched its Integrated Risk Governance (IHDP-IRG) Project. As a ten-year international cooperative research effort, its mission is to improve the governance of new risks that exceed current human coping capacities by focusing on the transitions in and out of the occurrence of relevant risks in the global climate changes. Under this project Beijing Normal University, with the leadership of Peijun Shi and others, has led comprehensive scientific research that included the several case studies, a community risk governance model, and a proposed paradigm of catastrophe risk governance in China. See, e.g., Shi et al. (2013) for a comparative study of the Wenchuan Earthquake and Tangshan Earthquake, centering on hazard, exposure, disaster impacts and losses, disaster rescue and relief, and recovery and reconstruction.

Limitations of space restrict us from mentioning all those working on the topic of resilience, but, in addition to the people and organizations mentioned above, we note the following whose research is in the spirit of integrated disaster risk management: Erica Seville, co-Leader of the Resilient Organisations community in New Zealand, Stephane Hallegatte of the World Bank, and Swenja Surminski of the Overseas Development Institute.

Conclusion

Further efforts needed in the future to advance integrated disaster risk management include:

- Extending research perspectives and constructing new conceptual models
- Developing new methodologies
- Exploring yet uncovered and newly emerging phenomena and issues
- Engaging in proactive field studies in regions that face high disaster risks, but, where investigations have not yet been undertaken, performing field studies that incorporate research advances in disaster-stricken regions

Obviously, the above approaches are rather interdependent, and thus integrated disaster risk management is best promoted by combining them. For instance, emerging mega-disasters, which are caused by an extraordinary natural hazard taking place in highly interconnected societies, may require a combination of both the second and third points above, such as mega-disaster governance based in part on mathematical models of systemic risks. Also, long-range planning for societal implementation of integrated disaster risk management inevitably requires encompassing most of the above approaches.

The IDRiM Book Series as a whole intends to cover most of the aforementioned new research challenges.

Nishinomiya, Japan	Norio Okada
Milan, Italy	Aniello Amendola
Laxenburg, Austria	Joanne Bayer
Uji, Japan	Ana Maria Cruz
Laxenburg, Austria	Stefan Hochrainer
Los Angeles, CA, USA	Adam Rose
Boulder, CO, USA	Kathleen Tierney
Oberlin, OH, USA	Ben Wisner

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Preface

The twenty-first century has been ushered in by unprecedented disasters throughout the world. We have witnessed known events occurring with higher frequency and/or severity, as well as new forms of disasters. The September 11, 2001 terrorist attacks in the United States used commercial airliners as a weapon to wreak havoc on human lives and our collective psyche, with the additional intent to cause extensive economic harm. Hurricane Katrina's wind and flood damage were unprecedented in US history, as was the failure of the government response at all levels. The Deep Water Horizon oil spill greatly damaged fragile eco-systems along the Gulf Coast and led to a dramatic drop in tourism and fishing activities. We can add to this the increase in the number and magnitude of tornadoes and wildfires in recent years. Other parts of the world were also hit by especially devastating disasters, such as the Wenchuan China earthquake of 2008, the Chilean earthquake of 2010, and the Thai floods of 2011. Most devastating of all was the compound event of the Tohoku earthquake, ensuing tsunami, and subsequent Fukushima nuclear reactor meltdown in Japan in 2011. On the horizon is the prospect of the accelerating threats stemming from climate change and space weather. As our world becomes increasingly interconnected, we also become more vulnerable to widespread cyber disruptions.

Decision-makers in the private and public sectors need information on the economic consequences of these disasters and others. This will allow them to better allocate resources across multiple disasters for mitigation and resilience capacity-building prior to the events, and to reallocate resources and provide recovery assistance during their aftermaths. Ideally, these estimates would be accurate, quick, and comparable across multiple threats. This volume presents the development of advanced economic modeling methods and their transition into a user-friendly software system for this purpose. The modeling involves several stages, but the major ones are the identification of a broad range of drivers of many types of direct impacts, refinement of a state-of-the-art approach to economy-wide modeling that can incorporate the drivers and estimate the ripple effects, conversion of the complex modeling results into a reduced-form statistical equation, and incorporation of these equations into a user-friendly software system.

The research presented in this volume is the culmination of 10 years of work at the Center for Risk and Economic Analysis of Terrorism Events (CREATE), an independent Center of Excellence in Research and Education originally established by major funding from the US Department of Homeland Security (DHS) Office of University Programs (OUP). This research has involved the broadening of economic consequence analysis, enhancement of economy-wide modeling, and application to dozens of case studies, all of which have been vetted in the peer-reviewed literature.

A foundation of the research is the CREATE Economic Consequence Analysis (ECA) Framework (Rose, 2015). A few decades earlier, hazard loss estimation was formulated, primarily by engineers and statisticians, with an emphasis on loss of life and property damage emanating from physical damage. A major advance in the 1980s was the consideration of direct impacts on gross domestic product (GDP) and employment, as well as the estimation of ordinary indirect, often referred to as multiplier, effects (see, e.g., Gordon and Richardson, 1992; FEMA, 1997; Rose et al., 1997; Shinozuka et al., 1998). CREATE researchers first added resilience to their framework. While this concept had been studied by hazards researchers for a decade (see, e.g., Chang et al. 2001; Bruneau et al., 2003), I developed a rigorous definition and an operational metric grounded in economic principles (Rose, 2007), and, together with my research team, applied it most notably in a study of the economic impacts of 9/11 (Rose et al., 2009) and in subsequent analyses of disruptions to water and power systems (Rose et al., 2011a), epidemics (Dixon et al., 2010; Prager et al., 2016), earthquakes (Rose et al., 2011b), port shutdowns (Rose and Wei, 2013), and tsunamis (Rose et al. 2016a).

The second major addition was behavioral responses, primarily stemming from fear, that have the potential to greatly exacerbate the consequences. Rose et al. (2009) found that the rapid relocation of businesses and government agencies housed in the World Trade Center reduced business interruption (BI) by 72 %, but that 80 % of the remaining BI was due to a nearly 2-year reduction in airline travel and related tourism. Subsequent research by Giesecke et al. (2012) and Rose et al. (2016b) found that behavioral effects could increase ordinary BI by 1–2 orders of magnitude.

Finally, large expenditures on decontamination and remediation after major oil spills and chemical/biological/radiological/nuclear (CBRN) threats were brought into the CREATE ECA Framework. Here ECA differs from benefit–cost analysis (BCA) in that it does not automatically relegate such expenditures to the cost side of the ledger, but instead uses modeling to determine the bottom-line effects on GDP and employment, in the context of whether the economy is operating at full employment or not (Rose 2015).

The major recent innovation in the CREATE ECA Framework relates to the identification of a comprehensive set of impact drivers for any disaster. There are generally two approaches to loss estimation or consequence analysis. One is a detailed examination of a few major drivers, while the other undertakes less-detailed examination of a broader range of them. For major disasters, it is our premise that the latter is likely to result in greater overall accuracy. We developed an approach that enumerates all of the potential drivers and thus provides a comprehensive check-list of factors that need to be considered (Rose et al., 2015; Prager et al., 2016).

The next major innovation was to transform the results of a complex economic simulation model into a form that could be incorporated into a software system to be used by non-experts. Computable General Equilibrium (CGE) models, our major model of choice, contain thousands of equations reflecting relationships within, among, and between businesses, households, and various institutions. What we have done for this volume is to develop a "reduced-form" approach by which we run at least 100 simulations for each threat type, varying drivers and parameters according to a sophisticated sampling system, to yield synthetic data to which we apply regression analysis to yield a single estimating equation. The equation is then entered into an Excel Visual Basic Applications (VBA) platform as the core of the user-friendly E-CAT software system that yields rapid estimates of consequences on GDP and employment presented in the context of various depictions of uncertainty.

This volume owes a debt to many people and institutions. I was indeed fortunate to have an outstanding research team to further refine the CREATE ECA Framework and models and to transition them into a software system over the past 2 years. The other three senior authors, especially, made this volume possible.

Fynn Prager led the latest round of refinements of the US CGE Model and its update. He coordinated a good deal of the work on the research with special emphasis on overseeing the quantitative scoring of the enumeration tables for many of the threats, linking the enumeration table impact categories with CGE model drivers, and translating them into user interface variables. He also led the work on the influenza CGE analysis, which served as a template for the work on other threats. He is the lead author of Chaps. 4 and 5 and of the CGE model description in Appendix A.

Zhenhua Chen worked closely with Fynn on the CGE model refinement and updating, as well as on the development of the user interface variables. He was the lead on the programming and execution of the complex reduced-form analysis and the programming of the E-CAT User Interface, as well as carrying out the validation tests. He is the lead author of Chaps. 6 and 9 and of the E-CAT Software Tool in Appendix C.

Sam Chatterjee led the output uncertainty design and analysis, as well as the input sampling procedure. He was the lead programmer and architect of the initial E-CAT User Interface prototype, and also designed the major validation test. He is the lead author of Chap. 7.

The associate authors Dan Wei, Nat Heatwole, and Eric Warren contributed to key aspects of the volume. All three participated in the design of the threat scenarios and the identification of the upper and lower bound cases in the enumeration tables and their quantitative scoring. Dan Wei did extensive work on the detailed underpinnings of the influenza threat scenario in Appendices 4A and 4B. Nat Heatwole performed an analysis of the nuclear threat, the details of which cannot be presented

because of their sensitive nature. Eric Warren took the lead on the quantification of the enumeration of several other threats.

I am also indebted to the long line of pioneers in the hazard loss estimation field. I have benefited greatly from them in general and through my affiliation with the U.S. National Science Foundation-sponsored Multidisciplinary Center for Earthquake Engineering Research (MCEER). These include Masanobu Shinozuka, Stephanie Chang, Kathleen Tierney, Ron Eguchi, Bill Petak, and Tom O'Rourke, and my graduate students at Penn State University, primarily Debo Oladosu, Shu-Yi Liao, Gauri Guha, Dongsoon Lim, and Juan Benavides.

At the University of Southern California (USC), my research accelerated by my affiliation with CREATE. I am grateful especially to Detlof von Winterfeldt, who has served two terms as Director and who established an atmosphere of independent research and a high-quality standard. I also thank CREATE Director Steve Hora and CREATE Research Director Isaac Maya for encouraging the reduced-form approach and to Erroll Southers, CREATE Director for Transition, who supported the final leg of the relay. I must say that I resisted the suggestion for quite some time because I questioned its ability to generate new research advances. I am however happy to say that it has done so in addition to yielding the obvious practical decision-support tool.

I am also grateful to Debra Elkins, formerly of the DHS Office of Policy, which commissioned E-CAT in the first place, and to Joseph Simon, for their guidance, and to Scott Farrow, CREATE Coordinator for Economics, for his guidance and input as well in the formative stages of this research. I also thank several professional colleagues at CREATE with whom I have collaborated on ECA research, most notably Peter Dixon, Maureen Rimmer, James Giesecke, Dan Wei, and Peter Gordon, and those in related areas such as Bill Burns, Paul Slovic, and Heather Rosoff. Post-docs and graduate students, some of whom are co-authors of this volume, made valuable contributions, including Fynn Prager, Zhenhua Chen, Sam Chatterjee, Nat Heatwole, Misak Avetysian, Noah Dormady, Bumsoo Lee, and JiYoung Park. Other able research assistants not listed as co-authors include Noah Miller and Joshua Banks, who contributed to the quantification of the enumeration tables, and Lillian Anderson, who undertook the tedious tasks of proofreading and reformatting the manuscript.

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Finally, I thank my many IDRiM colleagues who have provided valuable feedback of an interdisciplinary nature on my research at annual conferences. These include Norio Okada, Hiro Tatano, Elisabeth Krausmann, Joanne Bayer, and Ana Maria Cruz, among others.

Los Angeles, CA, USA Adam Rose
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Chapter 1
Introduction

1.1 Objectives

Policymakers and analysts in disaster risk management need consistent and rapid estimates of the economic consequences of multiple threat types, including terrorism events, natural disasters, and technological accidents. Consistency is important to be able to compare the many threats for the purpose of allocating resources among them to reduce overall risk as efficiently as possible. To date, research on the economic consequences of disasters is generally conducted on a threat-by-threat basis, but comparing results from these studies is problematic because the analyses use different models, employ unique sets of assumptions and parameters, and present results in terms of different economic indicators. Rapid turnaround is important for facilitating analyses across many threats, but even more so for allocating post-disaster assistance. However, models that can quickly provide reasonably accurate estimates of economic consequence of most threats are lacking. This volume overcomes these limitations.

The purpose of this book is to develop a methodology for rapidly obtaining approximate estimates of the economic consequences from the nearly 40 threats listed in the U.S. Homeland Security National Risk Characterization (HSNRC) Risk Register. The tool is intended for use by various decision-makers and analysts to obtain estimates almost instantly. It is programmed in Excel with Visual Basic for Applications (VBA) to facilitate its use. This tool is called “E-CAT” (Economic Consequence Analysis Tool) and accounts for the cumulative direct and indirect impacts (including resilience and behavioral factors that significantly affect base estimates) on the national economy from terrorism, natural disasters, and technological accidents. Implementation of E-CAT in Excel using VBA makes the tool accessible to a wide variety of users. E-CAT is intended to be a major step toward advancing the current state of economic consequence analysis (ECA), and also contributing to and developing interest in further research into complex but fast turnaround approaches.

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9_1

The essence of the methodology involves running numerous simulations in a computable general equilibrium (CGE) model for each threat, yielding synthetic data for the estimation of a single regression equation based on the identification of key explanatory variables (threat characteristics and background conditions). This approach transforms the results of a complex model (CGE), which is beyond the reach of most users, into a "reduced form" model that is readily comprehensible. We have built functionality into E-CAT so that its users can switch various consequence categories on and off in order to create customized profiles of economic consequences of numerous risk events. E-CAT incorporates uncertainty on both the input and output side in the course of the analysis. A premium has been placed on making E-CAT user friendly and transparent.

This book is a major milestone in CREATE's 10-year progression of research on economic consequence analysis and leverages its recent research for the Office of Health Administration National Biosurveillance Integration Center (OHA/NBIC) on broadening its range of impacts (Rose et al. 2015) and the Defense Nuclear Detection Office (DNDO) on analyzing the duration and time-path of radiological/nuclear events (Heatwole et al. 2014). It builds upon prior work on developing a reduced form model to predict the economic consequences of earthquakes (Heatwole and Rose 2013) and reduced form modeling for DNDO. It also builds on the CREATE Urban Commerce and Security (UCASS) Project as well, where CREATE developed a user-friendly spreadsheet program to facilitate the performance of ECA (Rose et al. 2014).

1.2 The CREATE Economic Consequence Analysis Framework

CREATE's expanded framework for estimating economic consequences of terrorist attacks and natural disasters is shown in Fig. 1.1. It has been formulated to account for several standard and new considerations that affect bottom line economic impacts (Rose 2009a, 2015).

Until recently, the estimation of losses from disasters focused almost entirely on standard target-specific (Direct) Economic Impacts and Loss of Life, and, to some extent, Ordinary Indirect Effects in terms of multiplier (quantity supply-chain), general equilibrium (multi-market quantity and price interactions) or macroeconomic (aggregate behavioral) effects. With respect to Fig. 1.1, prior estimation approaches have focused on the teal boxes as inputs to ordinary indirect economic impacts.

The first major refinement to these standard economic consequences is the inclusion of *Resilience*, which refers to actions that mute business interruption and hasten recovery. Rose (2009b) has proposed an operational metric of resilience: the avoided losses resulting from implementing a given resilience tactic as a proportion of the maximum potential losses for a given event in the absence of

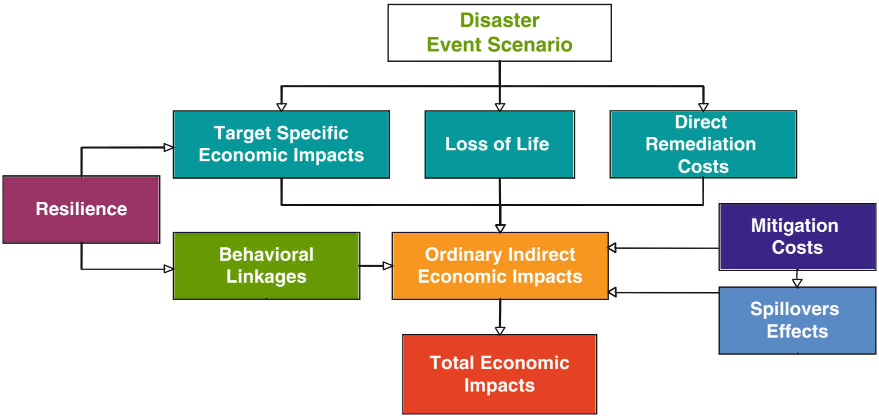

Fig. 1.1 Economic assessment framework overview

that tactic. Rose et al. (2009) measured the resilience of the New York Metropolitan Area economy to the 9/11 World Trade Center attacks at 72 % as a result of business relocation. This stemmed from the fact that 95 % of the businesses, comprising 98 % of the employment, in the World Trade Center area did not shut down but rather relocated their operations, mainly within the New York Metro Area. The losses are simply due to the time lags in the relocation.

In the past decade, the major extension of economic consequence analysis has been to include *Behavioral Linkages*. A prime example is the "fear factor," which refers to changes in risk perception that translate into changes in economic behavior and may amplify damages instead of reducing them as happens through resilience. Rose et al. (2009) measured the effect of the nearly 2-year downturn in air travel and related tourism in the U.S. following 9/11 at $85 billion, which accounted for over 80 % of the estimated business interruption losses stemming from the event. A recent study by Giesecke et al. (2012) of a potential radiological dispersal device (RDD, or "dirty bomb") attack on the financial district of Los Angeles would lead to social amplification of risk and stigma effects that could exceed the conventional "resource loss" effects by 14-fold.

The framework includes three other aspects necessary for a comprehensive analysis, the implications of which are often misinterpreted. The first is *Remediation*, which is typically not part of traditional economic impact analysis and has a conventional role in hazard loss estimation as simply repair and reconstruction. In the case of a terrorist attack, this can take on a much larger role, especially if the attack is caused by an insidious chemical, biological, radiologic or nuclear (CBRN) agent. For example, Baker (2008) found that the cost of remediation for a radionuclide attack on a reservoir of a small city of 100,000 was equal to the sum of the property and business interruption losses because of the extensive spread of the contamination and the high standards of remediation set by the U.S. Environmental Protection Agency (EPA).

The second, *Mitigation*, or public and private actions prior to the event that reduce impacts, also enters the picture of a comprehensive economic consequence framework in its move toward a full-blown counterpart to benefit-cost analysis (BCA). The interesting consideration here is the interpretation by many that remediation and mitigation have benefits stemming from their direct expenditures alone (aside from the standard benefits of avoided losses). This perspective is often criticized because it appears to ignore the basic principle that resources are expended in the course of implementing remediation or mitigation, and that these resources typically must be diverted from productive use elsewhere. Of course, if the economy is not at full employment (the typical situation), or, at the regional level, where in-migration of new workers is likely, then indirect effects can be included, as admitted by most authorities on BCA (see, e.g., Boardman et al. 2001). ECA does not make an a priori judgment on this question and simply explores whether the employment adds, detracts, or is neutral with respect to the bottom-line, e.g., its impact on gross domestic product (GDP). The answer has a great deal to do with whether the economy is initially at full employment, but is also influenced by whether higher-order effects of resource diversion are larger or smaller than those associated with mitigation or remediation.

Thirdly, the mitigation effort can generate various types of "non-market" *Spill-over Effects* in the form of congestion, delays, inconveniences, changes in property values, changes in the business environment, and changes in the natural environment. These are difficult to measure, but have been found to be significant in both negative and positive directions, e.g., closed-circuit television surveillance is minimally intrusive, and its improvement in the business environment due to the public feeling safer from both terrorism and ordinary street crime can outweigh the intrusion on privacy (Rose et al. 2014).

The presence of *Resilience* and *Behavioral Responses* imparts significant variability to the economic consequences of terrorism in relation to attack mechanisms and targets. Simple rules of thumb cannot be used as in the relatively straightforward areas of ordinary economic impact analysis. CGE modeling is relatively superior to other model forms because of its ability to incorporate resilient actions (see, e.g., Rose and Liao 2005) and the behavioral consequences of changes in risk perceptions (see, e.g., Giesecke et al. 2012).

1.3 Reduced Form Analysis

A "reduced-form" model refers to a simplified version of a more complex model that can readily be operated by users with a limited amount of knowledge of economics and with a rapid turnaround. Dixon and Rimmer (2013) have developed examples of these models for CGE models and Rose et al. (2011) have done so for macroeconometric models.

In E-CAT, for a given scenario, the CGE model is run hundreds of times for variations in key variables. This provides the "synthetic" data for the statistical regression equations that render the reduced–form model. The dependent variable is a major consequence type (e.g., GDP losses or employment losses), while the independent variables are threat characteristics (such as magnitude, duration, location, economic structure, etc.), which explain these losses to the best extent possible.

Three factors should be considered in performing this reduced-form analysis. First is the soundness of the theoretical underpinnings. This is guaranteed to a great extent by the fact that CGE models, which have been vetted on both a theoretical and empirical plane, generate the synthetic data. CGE models reflect the behavioral responses of businesses and households within an economy to changes in prices, as well as taxes, regulation and other external shocks, all within the constraints of labor, capital, and natural resource assets. CGE models are based on economic theory relating to producer and consumer choice and the workings of markets. They are able to estimate not only the direct responses but also indirect ones leading to total economic impacts, or consequences, referred to as "general equilibrium". In this modeling approach these impacts relate to price and quantity interactions in upstream and downstream markets. CGE models are constructed on the basis of a comprehensive set of economic accounts for production, household and institutional sectors, as well as some parameters, such as price and substitution elasticities, from the literature.

The soundness of the CGE model helps to ensure that results are likely to be reasonably accurate. However, we should note that accuracy depends on more than just sound theoretical underpinnings and internal consistency of the model, but also depends on the key variables that are included or omitted as well. For each threat we consider 16 categories of direct impacts that might be relevant and quantify those that are likely to have significant effects on the results. This "Enumeration" approach is discussed in the following chapter.

The third consideration is ease-of-use. While the complexity of the underlying CGE model is a plus, because it enables the representation of subtle and interactive behaviors across the economy, the opposite requirement is needed here. CGE models include thousands of variables, while the reduced form regression equations are based on a limited number of independent variables that are transparent, easier to interpret, and for which numerical values with appropriate representations of uncertainty can readily be obtained. The user thus need only plug these variables into the estimating equation, and a simple multiplication by parameter values yields the value of the dependent variable. The reduced form equations have also been constituted in a user-friendly spreadsheet format to facilitate this application.

1.4 Overview

This study presents each of the seven steps involved in the E-CAT research framework, as outlined in Fig. 1.2. An additional Step 8 is necessary to transition the research results and model into a tool usable by the intended community. In Chap. 2, Enumeration Tables for each threat are filled out according to upper and lower bounds identified from searches of relevant historical data of prior threat

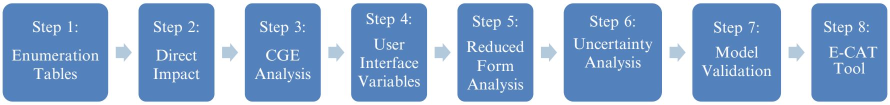

Fig. 1.2 Seven-Step E-CAT Research Framework, plus the Eighth Step for Tool Development

incidents, related literature, and/or expert judgment. In Chap. 3, lower and upper bound Direct Impact numerical values are estimated for each of the Enumeration Table categories that are determined to be above the "Low Influence" threshold.

In Chap. 4, Direct Impact values are input into our CGE model of the US economy (USCGE), which captures the combined and interactive effects of these impacts through price changes and substitution effects across multiple economic institutions – 58 sectors, 9 household groups, government institutions, and international traders. GDP and employment impacts for up to the first year of consequences are generated.

In Chap. 5, unique sets of User Interface Variables are identified for each threat and grouped under the following categories: Magnitude, Time of Day, Duration, Economic Structure, Location, Other, Behavioral Avoidance, Behavioral Aversion, Resilience Recapture, and Resilience Relocation. Randomized draws of a large number of User Interface Variable combinations generate uniformly distributed values between range boundaries for the Magnitude variable and different options for the other variables relevant to each threat. These multiple draws are then converted to CGE inputs via a series of linkages. CGE model simulations are run for each of the multiple random draw scenarios, and, where relevant, the Economic Structure of the impacted region is also factored in by scaling the national average results across three different example regional economy structures to render hundreds unique GDP and employment results.

In Chap. 6, multivariate regression analysis is conducted to estimate the influence of each of the User Interface Variables on the dependent variables of GDP and employment impacts, respectively. This analysis produces a reduced-form equation on the basis of Ordinary Least Squares and Quantile regression analysis, allowing for estimates of mean, 5th percentile, 25th percentile, 50th percentile, 75th percentile, and 95th percentile results.

In Chap. 7, these reduced-form equations are combined to model the mean response and uncertainty surrounding the GDP and employment results for any given combination of User Input Variables. Uncertainty distributions are determined by user inputs of the parameters of a triangle distribution (i.e. a low-bound, a mid-point, and an upper-bound) for the Magnitude variable, alongside user inputs of the other variables for that particular threat.

In Chap. 8, validation criteria and methods applicable to CGE modeling are presented. Two of the methods are then applied to a transportation system disruption threat, and indicate the reduced form results are reasonably accurate.

In Chap. 9, the coefficients from the reduced-form equations are input into E-CAT. The Tool is designed to be a user-friendly interface with which to explore the deterministic and probabilistic results of the reduced-form analysis of the CGE modeling for each threat. Users first select a threat and the level of detail for the results they would like. The resulting E-CAT User Interface provides an Input Area, whereby the user selects values for each of the relevant User Input Variables, and an Output Area, where economic impact results for GDP and employment are presented in both tabular and graphical formats and with respect to both point estimates and distributions.

1.5 Conclusion

This study develops an Economic Consequence Analysis Tool (E-CAT), which is a reduced-form model of a given threat, based on state-of-the-art CGE modeling. The E-CAT User Interface is programmed in Excel VBA and is appropriate for use in risk assessments of natural, man-made and technological threats to the U.S. economy. It is intended to be easy to use, quick, reasonably accurate, and transparent. It also incorporates functionality such that end users can create tailor-made profiles of economic consequences, with associated measures of uncertainty.

We note some of the limitations of E-CAT. Although each threat is evaluated carefully, we make no pretense about pinpoint accuracy of the estimates; this is a major reason we have performed various sensitivity and uncertainty analyses, which will enable the user to ascertain the confidence to be placed in the results. Second, our estimation of economic consequences is performed with a CGE model, which has many strengths but also some weaknesses to be discussed in more detail below. Third, the economic impacts, even though they may emanate from a given local area or region, are only estimated in relation to the entire national economy of the U.S. Finally, the impacts are only assessed for the first year; while this is likely to be the vast majority if not the entirety of impacts for the majority of threats, it omits many of the latent and long-term consequences of threats such as nuclear attacks and accidents, large oil spills, and droughts.

Although this research has been performed in the United States and oriented toward the needs of government agencies there, the framework, specific methods, insights, and software platform are applicable to any country faced by external shocks to its economy and security. We understand the many cultural differences around the world, but economic principles and concepts such as economic structure, interdependence, resilience, and behavioral responses, transcend national boundaries. The major challenge for applying E-CAT analysis to other countries is data limitation, as the analysis requires reliable information to construct applicable threat boundaries for various direct impact drivers and appropriate CGE modeling framework to represent the corresponding national economy.

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Chapter 2
Enumeration of Categories of Economic Consequences

2.1 Introduction

The purposes of this chapter are to identify a broad range of categories of economic consequences of major threats and to develop a checklist tool that provides a framework for their examination in subsequent chapters in this report. The Enumeration approach described below intends to improve the accuracy of economic consequence estimation. Many studies delve deeply into the estimation of a narrow set of economic consequence types but compromise accuracy by the exclusion of others. The Enumeration approach is the opposite—it provides approximate estimates for a comprehensive set of consequence categories. We contend that for many threats, this breadth can achieve more accurate overall estimation than the in-depth estimation of a limited number of consequence categories.

We use a checklist of consequence categories for three biothreats to illustrate the methodology. A brief explanation of the qualitative scoring is provided for the Ebola Virus. Quantitative estimates of consequences based on a synthesis of the literature are presented for other threats in the following chapter.

The approach is useful in two ways. It can distinguish categories that are worthy of more precise estimation and those that are relatively minor. We also make use of the full list of categories in our enumeration of scenarios in later chapters to identify impacts that are being used to initiate changes in the CGE model and other categories that are assumed not to be changing.

2.2 Economic Consequence Categories

Table 2.1 identifies 16 categories of direct economic consequences and two general economic consequence categories that are applicable to various biothreats. Ten of the aggregate categories are broken down in further detail. Moreover, the table

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9_2

Table 2.1 E-CAT economic consequence enumeration table

Direct impact category[a]	Domestic influenza	Domestic FMD	Domestic ebola
1. Vaccination/inoculation	+/−M/L	+/− L	−VL
2. Evacuation and/or quarantine	−L	−L	−M
3. Clean-up/decontamination		+/− L	+/− M
4. Medical expenditures	+/− M/H		+/− M/H
5. Mortality/morbidity (humans)			
(a) Deaths	−H		−M/H
(b) Injuries/infected	−H		−M
(c) Other (caregivers)	−M/H		−M
6. Risk management			
(a) Information gathering	−L	−VL	−M/L
(b) Administration	−L	−VL	−L
7. Behavioral effects: avoidance			
(a). International travel—foreign visitors	−M/L		−M
(b) International travel—residents abroad	+L		+L
(c) Domestic tourism	−M		−M
(d). Public gatherings/places	−M		−M/H
8. Behavioral effects: aversion			
(a) Public anxiety[c]	−L		VH/H
(b) Wage premiums			−M/L
(c) Rate of return premiums			−M/L
(d) Other (customer discounts)			−L
9. Infrastructure interruption/aversion			
(a) Transportation	−M/L		
(b) Water			−M/H
(c) Natural Gas			
(d) Electricity			
(e) Education	−M		−H/M
(f) Agriculture		−M/L	
10. International Trade Impacts			
(a) Import (e.g., reductions, bans)			
(b) Export (e.g., reductions, bans)		−M/L	
11. Social disruption (non-economic)	−M/L		VH/H
12. Irreversibilities			
(a) Iconic structures and resources			
(b) Eco-systems			
13. Complex effects			
(a) Compound events			
(b) Cascading events			−L
14. International linkages			
(a) Foreign impacts on the U.S.	−L	−L	+/−L
(b) U.S. impacts abroad	−L	−L	−M/L

(continued)

Table 2.1 (continued)

Direct impact category[a]	Domestic influenza	Domestic FMD	Domestic ebola
15. Resilience[d]			
(a) Conservation			
(b) Substitution	+L	+M/L	+L
(c) Inventories			
(d) Relocation or excess capacity	+M/L		+M/L
(e) Production separation			
(f) Production recapture	+M/L		+M/L
(g) Other (ship diversion, export diversion)			
16a. Negative general direct economic disruption	−M	−M/L	−M/H
16b. Net general direct economic disruption	−M/L	−L	−M
17. Property damage			

Source: See Rose et al. (2015)

[a]All impacts have indirect or general equilibrium effects. The multiplier to translate direct impacts to total impacts at the national level is approximately 2.5

[b]Includes leisure (public gatherings)

[c]Refers to either: (i) public anxiety exemplified by panic buying/hoarding and is indicated by a plus sign, or (ii) general public fear, which is not quantified. Public anxiety in the form of aversion behavior is listed under Row 7

[d]Resilience refers to the ability to mute economic losses by using remaining resources more efficiently and recovering more quickly, and is bounded by the maximum level of economic disruption

presents qualitative indicators (Low, Medium, High) of the relative magnitude of the impacts. It also identifies the relevant geographic area (National, Regional, or Local). In the next two chapters, we discuss how these direct impacts are linked to economic modeling in relation to direct and indirect quantity and price effects.

The focus of the analysis is on *flow* losses, typically measured in terms of reductions in employment and GDP, or more generally characterized as business interruption (BI). This is in contrast to *stock* losses associated with destruction of capital assets, typically characterized as property damage. Property damage usually takes place during the short period of time when the threat is actualized (e.g. when the earthquake shaking occurs), but BI just begins at that point and continues until the economy has recovered or has reached a "new normal." As such, BI is more complicated than measuring the consequences of property damage because it is influenced heavily by public policy, institutional decision making, and human behavior (Rose 2009a). Attention to flow measures like GDP and employment have gained increasing attention in recent years on both the professional literature and the popular press, since BI losses exceeded property damage in the cases of 9/11 and Katrina, and nearly rivaled them in disaster simulations such as the Shakeout Catastrophic Earthquake Scenario (Rose et al. 2011).

Another important aspect is the link between mortality and morbidity, both stock measures, in relation to the flow measures (i.e., they pertain to changes in the labor force stock and are later translated into labor flow units like employment work-days). This involves translating these consequence categories into the flow of labor services they represent. Chemical/Biological/Radiologic/Nuclear (CBRN) threats are more likely to have protracted periods of these health-related stock losses than would natural hazards or blast-related events. Biothreats, more so than other CBRN threats because they typically cause relatively more deaths and injuries, are also likely to have a higher proportion of BI instigated from reduction of labor flows than from the reduced flow of services from buildings and infrastructure.

Key for enumeration letter values[*]

Letter	Description	Dollar value range	Deaths	Illness/Injuries
L	Low	<$100M	<100	<1000
M/L	Medium/Low	$100M–1B	100–1000	1000–10,000
M	Medium	$1–10B	1000–10,000	10,000–100,000
M/H	Medium/High	$10–100B	10,000–100,000	100,000–1,000,000
H	High	>$100B	>100,000	>1,000,000

[*]These values pertain to all bounds

All impacts have indirect or general equilibrium effects (not explicitly differentiated in Table 2.1). One can apply rule-of-thumb impact multipliers from I-O models or the results of CGE models, which depend on various factors, but primarily direct sector(s) impacted, the size of the geographic area, and its structure, self-sufficiency and level of economic development. All but two of the categories pertain to conditions outside the US. International Trade Impacts would be exemplified by a potential ban by other countries on imports from the US (our exports abroad). The other category, International Linkages, valuates impacts of the events in foreign countries, but only in relation their potential impacts on the US.

The consequence categories are consistent with impact types identified in an extensive literature search for the National Biosurveillance Integration Center (Rose et al. 2015) and for other sponsors of CREATE ECA analyses (S&T Chem-Bio, Domestic Nuclear Detection Office, Federal Emergency Management Agency (FEMA), and the U.S. Coast Guard). In general, the groupings consist of mitigation, remediation, morbidity and mortality, general economic disruption, behavioral impacts, special focus on infrastructure, trade impacts, social disruption, and resilience. Note that qualitative scoring in this table corresponds to cases of major outbreaks or events (see, e.g., Dixon et al. 2010; Oladosu et al. 2013).

The Mitigation and Remediation categories (Rows 1 through 4) are self-explanatory. What is unique about them is their economic impact. Evacuation/Quarantine results in negative impacts associated with lost economic activity (due to individuals not being able to engage in normal, pre-disaster economic activity such as work and consumption patterns); hence, the minus sign preceding the qualitative measures in Row 2. However, the other three categories represent expenditures, which could have a positive or negative bottom-line impact, depending on whether the economy is operating at full employment, hence the ambiguous +/− designations. One simplification is made here, however – the entry for vaccination and medical care reflect only the expenditures on these two items. They do include other effects, such as the reduction in morbidity and mortality, which we assume are taken into account in the estimates in Row 5.

Under the broad category of Mortality/Morbidity, Deaths and Infected individuals refer to the economic impacts of the reduction of labor services as explained above. This is also the case for the "Other" sub-category, best exemplified by caregivers, referring to those who are not able to work because they are taking care of ill household members and tending to sick or healthy children not attending school. All three of these sub-categories are major inputs into General Economic Disruption (Row 16), which includes the sum total of direct and indirect or general equilibrium effects.

Row 6 refers to Risk Management sub-categories. First is Information Gathering about the threat, vulnerability, consequences, and resilience to the biothreat. Even if employees already in place undertake much of this information gathering, the wages/salaries and overhead should be valued in their totality, because these staff could be devoting their time and other resources to other important pursuits. The same applies to the Administration and Coordination of the evaluation in response to the biothreat. Behavioral Effects in Row 7 pertain to Aversion to various public activities/gatherings, the first three of which come under the designation of impacts on the tourist industry. It is important to note that a decline in US residents traveling abroad, however, means more spending in the US, and hence is preceded by a plus sign.

Row 8 refers to the category of Other Behavioral Effects, which includes Public Anxiety (though this is not measured in economic terms and hence is not preceded by plus or minus signs). It also includes wage and investor premia required in some cases to attract workers and owners of capital back to the site of the biothreat, where applicable. These premia increase the cost of doing business and hence have a dampening effect on the economy. Note that an area may become stigmatized by the event, and hence these increased costs may last for years. The "Other" sub-category would include impacts such as retail stores and restaurants having to provide price incentives (discounts) in order to attract shoppers back to an area affected by an insidious biothreat.

Row 9 isolates key industries of an Infrastructure type, for which we include transportation, water, natural gas, and electricity infrastructure, as well as educational facilities, and agriculture. These can be affected both by outright interruption, as in the slaughter of animals in the face of a contagious disease, or from aversion behavior, such as finding alternatives to public transit.

International Trade Impacts listed in Row 10 have been discussed previously to some extent. We note here the possibility of the US banning imports from other countries (primarily agricultural products) for fear of further contamination from outside the US.

Social Disruption in Row 11 refers to changes in the ordinary course of life. It is given a qualitative designation but this does not refer to any economic impacts, which are subsumed by other categories.

Row 12 represents two types of irreversibilities in relation to structures, natural resources and the environment. The first refers to iconic targets of both the built environment, such as the World Trade Center, Statue of Liberty and Golden Gate Bridge; and natural resources, such as Arches National Park and Mount Rushmore. With the exception of events like an anthrax attack, for which decontamination is difficult and prolonged, this category is more likely for CBRN threats other than bio, but is presented here for the sake of generality. The second sub-category refers to Eco-Systems, which can be destroyed by purposeful biological contamination and natural predators, as well as other types of disasters and terrorist attacks. Many national parks are vulnerable to combinations of these two sub-categories.

Complex Event Impacts are represented in Row 13. The first sub-category refers to Compound Events, as exemplified by hurricanes, which generate both wind and flood damage, or by a technological accident that causes both blast damage and a subsequent accidental release of biological contamination. The second sub-category is Cascading Events, which are akin to the metaphor of falling dominos, with one disaster type causing another, which in turn leads to another disaster. This category is best exemplified by the 2011 Japanese earthquake/tsunami/nuclear reactor catastrophes. Another example would be a widespread epidemic that causes political instability, rare in the US, but not uncommon in developing countries.

Row 14 represents International Aspects not covered in the International Trade category in Row 10. It includes disasters in foreign countries that impact the US – for example, by raising fear of disease spread to domestically that results in aversion behavior or other forms of social disruption. It also includes the opposite flow—biothreats in the US that cause fear overseas and may reduce international travel or decreased foreign investment in the US.

Resilience, presented in several sub-categories in Row 15, refers to actions that reduce losses by using resources more efficiently or investing in a manner that hastens recovery (Rose 2009b). Their focus is on post-shock activities that reduce business interruption in contrast to pre-shock mitigation/interdiction. Medical Care is in essence a resilience tactic, since it reduces lost productivity, but is listed above in its typically separate role in Row 4. The magnitude of the resilience categories is bounded by the level of negative General Economic Disruption in Row 16a.

Net General Economic Disruption listed in Row 16b refers to the bottom line impacts of the biothreat, taking into account all of the negative *and* positive direct and indirect impacts that take place. It would ideally be measured in a common denominator (e.g. dollars), but it would also be important to measure the number of deaths and injuries/infected separately. The entries in this row are not just a summing of those above it in a given column. First, a couple of the other categories, such as Social Disruption, do not lend themselves easily to being expressed in dollars or by any simple indicator. Second, there may be interactive or synergistic effects between the categories.

Finally, we list property damage in Row 17. Again, it is not a flow, so it cannot be included in BI, but is included as a useful point of reference.

2.3 Application to the Ebola Virus

The qualitative scoring of the categories can be illustrated by the Ebola Virus case in the last column of Table 2.1. Again, the scoring in the table refers to major outbreaks or events. Also, with the exception of the entries in Row 14 and indirectly in Row 10, we refer to impacts only with respect to the US and hold incidents of the biothreat abroad constant.

There is no vaccine against the virus at the time of this writing, so the entry in the first row is very low (VL), referring to only an acceleration of research. Given the severe nature of the disease, quarantine is likely for infected populations and also those exposed to them, which could be many people. However, the severity of the disease is likely to spur vigilant action to contain it and thus lessen the impact.

The number of Deaths is likely to be contained and only slightly lower than the number of Infected because of its severity. Caregiver impacts are likely to involve even more people because of the infectious nature of the disease and the activities like tending children at home because of school closings.

Risk Management pertaining to the Ebola Virus would likely be more costly than that of more ordinary threats, such as Influenza, because of the severity of the former. Information gathering, especially with regard to tracking the spread of the disease, is likely to be especially impacted relative to others.

The seriousness of the Ebola Virus is likely to cause a relatively greater reduction of visitors to the US than other events in Table 2.1 through what we term “avoidance” behavior (see, e.g., Gordon et al. 2007). It is also likely to deter Americans from traveling abroad given the ease of spreading disease during travel, generating more spending within our borders; hence, the positive impact in Row 7b.

An Ebola epidemic is likely to lead to a high level of Public Anxiety, as well as the additional sub-categories of Behavioral Effects, which we refer to as “aversion” behavior (see, e.g., Giesecke et al (2012). These other effects are estimated to have a relatively lower impact because they would be redundant in the face of areas quarantined and because they would not linger in time, in contrast to anthrax, which is much harder to decontaminate.

In terms of Infrastructure Interruption, relating primarily to another type of aversion, it is likely to affect public transportation, and, at a higher level, schools. Trade Impacts are likely to be nil, except that the US is likely to produce fewer goods for export (but see Row 14 below). Social Disruptions are likely to be relatively high, but again this is not measured in economic terms.

Irreversibilities are not likely to be present, but Complexities could arise, if the epidemic causes some civil unrest or rampant discrimination against socioeconomic or racial/ethnic groups that have a higher incidence of the disease.

In terms of International Linkages, the presence of the disease in other countries could lead to negative effects by reducing demand for U.S. exports and raising prices of U.S. imports. It would also likely raise the price of U.S. exports thus stunting our export sales and dampening economic activity in other countries. The latter could lead to even further declines in the world demand for U.S. exports. On the outbound side, a downturn in the U.S. economy would have an impact on the world economy. It could also lead to reduced international travel to our country

Several sub-categories of Resilience are operative, including Substitution for goods/services whose production is lowered (e.g., in regions where the outbreak is centered), Relocation (outright or to branch facilities for businesses and telecommuting for workers), and Production Recapture (the ability to make up lost production once the epidemic is over). Again, the effectiveness of Resilience is bounded by the magnitude of the General Economic Disruption in Row 16a.

General Economic Disruption is not likely to be as high or as widespread as an Influenza epidemic, again because the Ebola Virus case is likely to result in a relatively much greater effort to contain it.

Each type of biothreat is unique in terms of its relevant impact categories and scoring, and the overall category of biothreats well differ greatly from other types of natural and man-made threats. For example, chemical threats are more likely to affect eco-systems than are biothreats, and terrorist attacks are likely to affect iconic targets than are other threats.

2.4 Estimating the Numerical Values of Biothreat Impact Categories

Once again, we emphasize that the numbers in Table 2.1 are intended for illustrative purposes only, and, are at best ballpark estimates. More research is needed in specifying and validating them.

Several strategies can be applied to this estimation. The first would be to perform a critical synthesis of the literature for numerical estimates. "Data-Transfer" techniques can be applied generalize the estimates or to apply them to a given context. Care must be taken in this endeavor.

The second would be to undertake new studies, especially for severe threats, as well as for categories of impacts that have been relatively neglected. It would be important to establish a standard lexicon, data protocols, assumptions, and other estimation concerns to reduce ambiguity and to promote accuracy.

Given the limited number of actual cases for many events, simulation techniques can be very helpful. It would be especially important to incorporate uncertainty in these analyses via sensitivity tests and other mathematical techniques.

Finally, expert elicitation could be used to populate the numerical values Table 2.1 for the broad range biothreats. Again, various protocols and good experimental design are necessary to yield reliable estimates.

2.5 Conclusion

We have identified, explained, and qualitatively estimated the major categories of economic consequences of man-made and natural disasters. These are summarized in a Check-List of Consequence Categories table, in which they are applied to three diverse biothreats. A brief explanation of the qualitative scoring is provided for the Ebola Virus. All of the estimates are only intended as illustrative.

The analysis is intended to serve several useful purposes. It can help identify gaps in the coverage of the approaches to economic consequence estimation. It can also help separate impact categories that have a major bearing on bottom line results from those that do not.

The analysis can serve as the basis for quick turn-around consequence estimation tool. Qualitative estimates, and even ballpark quantitative estimates, can be established for all impact categories through a synthesis of findings from actual and simulated threats or from expert elicitations, or a combination of the above. Moreover, its simplicity facilitates the ability to convert it into a user-friendly automated system.

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Chapter 3
Threat Scenarios and Direct Impacts

3.1 Introduction

The full set of U.S. Homeland Security National Risk Characterization (HSNRC) Threats is presented in Table 3.1. This chapter presents examples of scenarios and direct economic impacts for two example threats: earthquakes and human pandemic. Each section consists of a summary description of the scenario, conversion of concepts to drivers that can be used in our CGE model, and the filling in of both qualitative and quantitative entries in the Enumeration Tables discussed in the previous chapter.

We note two aspects of the presentation. First, we do not discuss all aspects of the conversion of direct impacts to CGE drivers here, but only those that involve special considerations. Second, we only quantify those direct impacts that score above the "low" (L) categorization. Impacts at the Low, as well as the null, level of impact are assumed not to have any significant influence on the overall consequence results. This assessment is based on a review of the literature.

3.2 Earthquakes

To evaluate the potential economic consequences from earthquake disasters, we use as the upper-bound scenario the Great Southern California ShakeOut Scenario that was formulated by the U.S. Geological Survey in 2008. This scenario is based on a hypothetical magnitude 7.8 earthquake on the southernmost 300 km of the San Andreas Fault, between the Salton Sea, Imperial County and Lake Hughes, Los Angeles County (Jones et al. 2008). The devastating physical and economic consequences of the earthquake are analyzed for the eight-county region comprising Southern California. Estimates of casualties and effects of the earthquake on the built environment are analyzed in HAZUS (FEMA's Disaster Loss Modeling Tool).

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9_3

Table 3.1 HSNRC risk register (listed alphabetically)

Terrorism/intentional acts	Natural hazards	Technological accidents/infrastructure failures
Aircraft as a weapon	Accidental biological food contamination	Accidental chemical substance spill or release
Armed assault	Animal disease outbreak	Accidental radiological substance release
Biological terrorism attack – non-food	Drought	Dam failure
Chemical/biological food contamination terrorism attack	Earthquake	Industrial accidents – explosions
Chemical terrorism attack – non-food	Extreme cold/snowstorm	Large oil spills
Cyber events that impede system operations	Flood	Pipeline failure
Cyber events that extract or alter information without system impacts	Heat/heat wave	Power grid failure
Cyber: data destruction results in degraded commercial viability or government service	Human pandemic outbreak	Small oil spills
Cyber: Distributed Denial of Service (DDOS) attack causes erosion of consumer confidence and economic loss	Hurricane	Transportation system failure
Disruptive strike/industrial action	Space weather	Urban conflagration
Explosives terrorism attack	Tornado	
Illegal immigration	Tsunami	
Illicit drugs	Volcano eruption	
Mass migration	Wildfire	
Nuclear terrorism attack		
Radiological terrorism attack		

The earthquake is estimated to result in about 1800 deaths (more than half is fire-related) and 53,000 injuries (including both "serious" injuries requiring specialized trauma or burn care and non-fatal injuries requiring treatment in emergency departments or outpatient care) (Jones et al. 2008). The total direct and indirect property damages are estimated to be \$114.9 billion (Rose et al. 2011). Direct property damages refer to the damages caused by the shaking. Additional collateral or indirect property damages result from ancillary fires caused by ruptured pipelines and frayed electrical wires, for example. It is estimated that property damage from ancillary fires is about 50 % greater than property damage from ground shaking.

Economic losses from business interruption occur not only because of property damage, but also persistent disruptions of utility lifelines, including interruptions of electric power, water, and natural gas services (Rose et al. 2011).

For the lower-bound scenario, we use the case of the 2001 Nisqually Earthquake in Washington State. The magnitude of the Nisqually Earthquake was 6.8, and was a significant earthquake in terms of the moment magnitude (as a comparison, the 1994 Northridge Earthquake was a 6.7 moment magnitude). However, since the hypocenter was deep under the surface of the earth (at a depth of about 32 mi) in a rural area, the physical and economic losses caused by the Nisqually earthquake were relatively low. There were about 400 people injured and no deaths caused directly by the earthquake (the one death reported in the table below was because of a heart attack at the time of the earthquake). The property damages were about $3 billion (in 2012$) (Meszaros and Fiegener 2002; Chang and Falit-Baiamonte 2002). We assume that business interruption losses are comparable to property damage. The impacts on lifeline services were minimal. There were no service disruptions for water and gas. Less than 20 % of the businesses in the earthquake affected area experienced electricity disruption. However, the service was restored to most of the customers within 1 day.

3.2.1 Conversion to CGE Drivers

Direct Impact values calculated above are then converted into “CGE Drivers”, i.e. values that can be input into the CGE model, as shown in Table 3.2. In this case, the lower bound Nisqually Earthquake values identified in the Enumeration Table below are inappropriate because that earthquake’s epicenter was in a rural area, and hence despite being a relatively large magnitude (6.8), the consequences were not as significant as an equivalent-magnitude earthquake in an urban area. To convert the Nisqually event data (presented in Table 3.4) into an appropriate lower bound, i.e. to the “Urban/Small earthquake” driver level, we use scaling factors identified from analysis of a large sample of earthquake impact data that relates earthquake magnitude to property damage costs, with respect to the population density of the impacted area (Heatwole and Rose 2013), as shown in Table 3.3. The exceptions here are evacuation costs, which are scaled down from ShakeOut estimates (based on Table 3.3 factors) and property damage costs, which are not scaled from the Nisqually Earthquake event, and are instead calculated directly from the average of an “Urban/Small earthquake” in the Heatwole and Rose (2013) dataset.

3.2.2 Enumeration of Impact Categories

Table 3.4 identifies categories of impacts considered in the earthquake simulations. The qualitative and quantitative values pertain to direct impacts (“CGE drivers”) only, with the total impacts being determined by the CGE simulations. Note that

Table 3.2 Summary of CGE drivers for earthquakes, lower and upper bounds

		Direct impacts		CGE driver impact		
Consequence type	Units	2001 Nisqually Earthquake (lower-bound)	ShakeOut scenario (upper-bound)	Model variable	2001 Nisqually Earthquake (lower-bound)	ShakeOut scenario (upper-bound)
Deaths	no.	28	1800	Labor force	0.00001 %	0.0007 %
Injuries	no.	11,000	53,000	Labor force	0.0023 %	0.0106 %
Medical treatment cost	2012$	$82.2M	$380.7M	Household spending	0.0047 %	0.0220 %
Evacuation cost (residential)	2012$	$0.06B	$3.3B	Household spending on transport	0.0028 %	0.1620 %
Decontamination cost	2012$	n.a.	n.a.	Household tax Waste management sector	n.a.	n.a.
Property damage cost	2012$	$1.1B	$114.9B	Capital stock	0.0166 %	1.7376 %
Infrastructure interruption	Critical infra-structure outage % annual	0.012 % (electricity)	0.7 % (water)	Side calculation		

Table 3.3 Earthquake magnitude, distance to property damage scaling factors[a]

Location[b]	Average property damage		Implied scaling factor (from baseline of urban, large earthquake)	
	Small	Large	Small	Large‘
Urban	$1.1B	$67.8B	0.017	1
Rural	$23.5M	$412.4M	0.0003	0.006

[a]These scaling factors are based on the property damage values, under the assumption that an earthquake covers a large enough area to impact CBD, Urban and Suburban equally, regardless of where the epicenter is
[b]*Urban* and *Rural* categories are based upon the population affected by the earthquake. Rural is classified as earthquakes impacting under 50,000 people

Table 3.4 E-CAT enumeration table for earthquake

Direct impact category[a]	Letter scale		Scenarios	
	Lower-bound	Upper-bound	2001 Nisqually earthquake (lower-bound)	ShakeOut scenario (upper-bound)
1. Vaccination/inoculation	n.a.	n.a.		
2. Evacuation and/or quarantine	+/−L	+/−M		−$3.3B
3. Clean-up/decontamination	n.a	n.a		
4. Medical expenditures	+/−L	+/−M/L		+/−$380.7M
5. Mortality/morbidity (humans)				
(a) Deaths	−L	−M	1	1800
(b) Injuries/infected	−L	−M	400	53,000
(c) Other (caregivers)	−L	−L		
6. Risk management				
(a) Information gathering	−L	−L		
(b) Administration	−L	−L		
7. Behavioral effects: avoidance				
(a) International travel—foreign visitors	n.a.	n.a.		
(b) International travel—residents abroad	n.a.	n.a.		
(c) Domestic tourism	n.a.	n.a.		
(d) Public gatherings/places[b]	n.a.	n.a.		
8. Behavioral effects: aversion				
(a) Public anxiety[c]	−L	−L		
(b) Wage premiums	n.a.	n.a.		
(c) Rate of return premiums	n.a.	n.a.		
(d) Other (customer discounts)	n.a.	n.a.		

(continued)

Table 3.4 (continued)

Direct impact category[a]	Letter scale		Scenarios	
	Lower-bound	Upper-bound	2001 Nisqually earthquake (lower-bound)	ShakeOut scenario (upper-bound)
9. Infrastructure interruption/ avoidance				
(a) Transportation	−L	−L		
(b) Water	−L	−L		\$21.9M (7.0 %)[d]
(c) Natural gas	−L	−L		\$184.0M (1.1 %)[d]
(d) Electricity	−L	−L	0.044%[e]	\$76.5M (0.7 %)[d]
(e) Education	n.a.	n.a.		
(f) Agriculture	n.a.	n.a.		
10. International trade impacts				
(a) Import (e.g., reductions, bans)	n.a.	n.a.		
(b) Export (e.g., reductions, bans)	n.a.	n.a.		
11. Social disruption (non-economic)	−L	−M/L		
12. Irreversibilities				
(a) Iconic structures and resources	L	L		
(b) Eco-systems	n.a.	n.a.		
13. Complex effects				
(a) Compound events	n.a.	n.a.		
(b) Cascading events	n.a.	n.a.		
14. International linkages				
(a) Foreign impacts on the U.S.	n.a.	n.a.		
(b) U.S. impacts abroad	n.a.	n.a.		
15. Resilience[f]				
(a) Conservation	+L	+L		
(b) Substitution	+L	+L		
(c) Inventories	+L	+L		
(d) Relocation or excess capacity	+L	+L		
(e) Production separation	+L	+L		
(f) Production recapture	+M	+M	Reduces losses by 80 %	Reduces losses by 66 %
(g) Other (ship diversion, export diversion)	n.a.	n.a.		

(continued)

Table 3.4 (continued)

Direct impact category[a]	Letter scale: Lower-bound	Upper-bound	Scenarios: 2001 Nisqually earthquake (lower-bound)	ShakeOut scenario (upper-bound)
16a. Negative general direct economic disruption[g]	M	M/H	$3B[h]	$216.2B
16b. Net general direct economic disruption[i]	M	M/H	1.8B	$144.9B
17. Property damage	M	M/H	$2.95B	$114.9B

[a]All impacts have indirect or general equilibrium effects. The multiplier to translate direct impacts to total impacts at the national level is approximately 2.5

[b]Includes leisure (public gatherings)

[c]Refers to either: (i) public anxiety exemplified by panic buying/hoarding and is indicated by a plus sign, or (ii) general public fear, which is not quantified. Public anxiety in the form of aversion behavior is listed under Row 7

[d]Dollar values represent direct output losses in the utility sectors. The percentages in parentheses represent percentage output reduction of the utility sectors on an annual basis

[e]Meszaros and Fiegener (2002) estimated that 11.6 % of the firms experienced electricity disruption for less than 1 day. The survey results in Chang and Falit-Baiamonte (2002) indicated that 21 % of the businesses experienced losses due to lifeline disruption. Based on the average of the estimates reported in these two studies, we assume that 16 % of the businesses in the earthquake affected area experienced electricity disruption for 1 day. This translates to a 0.05 % reduction of the electricity sector output on an annual basis

[f]Resilience refers to the ability to mute economic losses by using remaining resources more efficiently and recovering more quickly, and is bounded by the maximum level of economic disruption

[g]Does not include offsetting effects (such as medical expenditure and resilience)

[h]We assume the business interruption losses are comparable to property damage

[i]Summation of all of the above quantifiable impacts (positive and negative) on GDP. Indirect impacts will be calculated in the CGE Model

some, such as Public Anxiety, are non-quantifiable and are thus not included in the simulations. Also, those estimated to have low (L) values are not included in the simulations because they are assumed to not significantly affect the results. However, in the earthquake scenarios, we include the direct loss estimates for lifeline disruptions even when the direct output losses in the utility sectors fall into the low (L) category. This is because, as critical production inputs in most producing sectors, lifeline service disruptions would result in significant losses throughout the entire economy. The +/- designation associated with Medical Expenditures indicates they could have either a positive or negative impact on the economy depending on background conditions, such as the unemployment level, and linkages with other drivers.

Key for enumeration letter values*

Letter	Description	Dollar value range	Deaths	Illness/injuries
L	Low	<$100M	<100	<1000
M/L	Medium/Low	$100M–1B	100–1,000	1000–10,000
M	Medium	$1–10B	1000–10,000	10,000–100,000
M/H	Medium/High	$10–100B	10,000–100,000	100,000–1,000,000
H	High	>$100B	>100,000	>1,000,000

*These values pertain to both lower and upper bounds

3.3 Human Pandemic

3.3.1 Scenario

This analysis explores the economic impacts of a Human Pandemic Outbreak. We have selected as a lower-bound scenario a human influenza outbreak, similar to the 2009 H1N1 influenza (swine flu) epidemic. For this scenario, we assume a 10 % "attack (infection) rate", a 3 % outpatient medical treatment rate, a 0.10 % hospitalization rate, and a 0.01 % death rate. This scenario results in 318,000 hospitalizations and 31,000 deaths. For the upper-bound scenario, we assume a 25 % "attack rate", a 10 % outpatient medical treatment rate, a 1.50 % hospitalization rate, and a 0.50 % death rate. This scenario results in 4.7 million hospitalizations and 1.6 million deaths.

3.3.2 Conversion to CGE Drivers

Direct Impact values calculated above are then converted into "CGE Drivers", i.e. values that can be input into the CGE model, as shown in the final column of Table 3.5.

3.3.2.1 Additional Modeling Elements

Table 3.6 presents additional modeling elements that were not presented in the article by Prager et al. (2016).

Table 3.5 ECA of a Human Pandemic Outbreak: Direct Impacts Summary (2012 dollars)

Impact	USCGE modeling approach	Scenarios		
		Case	Level impact	% impact
Workforce participation	Reduction in labor workforce participation	Lower	−19.7M	−0.055 %
		Upper	−95.1M	−0.264 %
Medical expenditures	Increase household spending on medical services	Lower	$10.45B	0.604 %
		Upper	$161.79B	9.351 %
Aversion behavior	Reduction in Inbound International Travel (via exports)	Lower	−$1.95B	−2.430 %
		Upper	−$15.93B	−19.830 %
	Reduction in outbound international travel	Lower	−$0.96B	−2.430 %
		Upper	−$7.89B	−19.830 %
	Reduction in domestic travel/leisure activities	Lower	−$66.30B	−10.000 %
		Upper	−$66.30B	−10.000 %

Further details are provided in Prager et al. (2016)

Table 3.6 Additional modeling elements

Driver	Description	Calculation
Infrastructure interruption/ aversion: transportation.	Reduction in public transportation use due to fear of infection in public spaces. Can be modeled as a reduction in household demand for public transport, or as a reduction in output for public transport.	We assume 10 % reduction in public transport use. Evidence from Taipei (Wang 2014) suggests that SARS induced reductions of 50 % for less than 3 months, which equates to roughly 10 % over the course of the year.
Infrastructure interruption/ aversion: education.	Reduction in attendance of educational facilities due to fear of infection. Can be modeled as a reduction in output for education sector.	Average Daily Attendance value for US schools is around $40 per day. For the severe scenario, a total of 15.8M would be infected (or worse), and 34.7M school days would be lost. This alone would cost schools $1.39B. If we assume a further 15.8M days are lost due to children being kept home, this would cost $0.63B or $2.01B in total.
Resilience: production recapture.	Lost labor due to illness could be recaptured later in the year. We would have to assume an accepted recapture coefficient.	Production recapture can reduce 80–90 % of the BI losses if the disruption occurs within 3 months. The production recapture potentials decline as time passes. We assume that the recapture factors are reduced by 25 percentage points for each of the subsequent 3-month periods. A Severe Influenza Outbreak could last for over 6 months, implying that 30 % reduction of BI losses could be offset with production recapture. These can be applied to total impacts.

3.3.3 *Enumeration of Impact Categories*

Table 3.7 identifies categories of impacts considered in the Influenza simulations. The qualitative and quantitative values pertain to direct impacts ("CGE drivers") only, with the total impacts being determined by the CGE simulations. Note that some, such as Public Anxiety, are non-quantifiable and are thus not included in the simulations. Also, those estimated to have low (L) values are not included in the simulations because they will not significantly affect the results. The +/− designation associated with Medical Expenditures indicate they could have either a positive or negative impact on the economy depending on background conditions, such as the unemployment level, and linkages with other drivers.

Table 3.7 Categories of Direct Economic Impacts for an Influenza Outbreak

Direct impact category[a]	Domestic influenza (mid-range)	
1. Vaccination	+/−M	$5B
2. Quarantine and/or evacuation	−L	
3. Decontamination	n.a.	
4. Medical expenditures	+/−H	$162B
5. Mortality/morbidity (humans)		
(a) Deaths	−H	1.6M
(b) Infected/injuries	−H	78M
(c) Other (caregivers)	−M/H	[b]
6. Risk management		
(a) Information gathering	−L	
(b) Administration	−L	
7. Behavioral effects: avoidance		
(a) International travel— foreign visitors	−M/H	$16B
(b) International travel— residents abroad	+M	$8B
(c) Domestic tourism	−M/H	$66B[c]
(d) Public gatherings/places	−M	[c]
8. Behavioral effects: aversion		
(a) Public anxiety[d]	−L	
(b) Wage premiums	n.a.	
(c) Rate of return premiums	n.a.	
(d) Other (customer discounts)	n.a.	
9. Infrastructure interruption/avoidance		
(a) Transportation	−M	$8B
(b) Water	n.a.	
(c) Natural Gas	n.a.	
(d) Electricity	n.a.	
(e) Education	−M	$2B
(f) Agriculture	n.a.	

(continued)

Table 3.7 (continued)

Direct impact category[a]	Domestic influenza (mid-range)	
10. International Trade Impacts		
(a) Import bans—products to the U.S.	n.a.	
(b) Export bans—U.S. products abroad	n.a.	
11. Social disruption (non-economic)	−M/L	
12. Irreversibilities		
(a) Iconic structures and resources	n.a.	
(b) Eco-systems	n.a.	
13. Complex effects		
(a) Compound events	n.a.	
(b) Cascading events	n.a.	
14. International linkages		
(a) Foreign impacts on the U.S.	−L	
(b) U.S. impacts abroad	−L	
15. Resilience[e]		
(a) Conservation	n.a.	
(b) Substitution	+L	
(c) Inventories	L	
(d) Relocation	n.a.	
(e) Production separation	n.a.	
(f) Production recapture	+M	$7B
16. General economic disruption	−M/H	$80B

[a]All impacts have indirect or general equilibrium effects. The multiplier to translate direct impacts to total impacts at the national level is approximately 2.5

[b]Included in injuries and illnesses calculations

[c]Includes leisure (public gatherings)

[d]Refers to either: (i) public anxiety exemplified by panic buying/hoarding and is indicated by a plus sign, or (ii) general public fear, which is not quantified. Public anxiety in the form of aversion behavior is listed under Row 7

[e]Resilience refers to the ability to mute economic losses by using remaining resources more efficiently and recovering more quickly, and is bounded by the maximum level of economic disruption

Key for enumeration letter values*

Letter	Description	Dollar value range	Deaths	Illness/injuries
L	Low	<$100M	<100	<1,000
M/L	Medium/Low	$100M–1B	100–1,000	1000–10,000
M	Medium	$1–10B	1000–10,000	10,000–100,000
M/H	Medium/High	$10–100B	10,000–100,000	100,000–1,000,000
H	High	>$100B	>100,000	>1,000,000

*These values pertain to both upper and lower bounds

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Chapter 4
Computable General Equilibrium Modeling and Its Application

4.1 Summary

This chapter details Step 4 of the research framework: CGE modeling. CGE model simulations are run for each of the multiple random draws for each different hazard scenario. Relevant Direct Impact values are input into the USCGE model of the US economy, which captures the combined and interactive effects of these impacts through price changes and substitution effects across multiple economic institutions – 58 sectors, 9 household groups, government institutions, and international traders. GDP and employment impacts are generated for each of these multiple scenarios, and, where relevant, the economic structure of the impacted region is also factored in by scaling the national average results across three different example regional economy types to render four times the number of original unique GDP and employment combination results.

This chapter first presents a brief overview CGE modeling and the USCGE model, before discussing the range of simulation approaches that are used to model the E-CAT Tool threats. Sections 4.5.1 and 4.5.2 present a detailed discussion of the Human Pandemic case.

4.2 CGE Modeling

CGE models are able to link the impact of changes in one area of the economy (e.g. a tsunami disrupting operations at a single port) across multiple sectors and institutions within the economy, while accounting for price changes and substitution effects. CGE modeling has three distinguishing characteristics (Dixon 2006):

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9_4

- CGE models are *computable*. They represent the economy numerically. A numerical database – usually a Social Accounting Matrix[1] and substitution elasticity values – is used to calculate model coefficients and parameters, and provides data for base year calibration. Further data add policy-relevant detail.
- CGE models are *general*. They model the behavior of numerous, inter-dependent economic actors. Households maximize utility while firms maximize profits and minimize costs; other institutions such as governments, unions, imports and exporters can also be included. CGE models highlight prices of goods, services, or factors (e.g. labor and capital) and their influence on consumption and production decision-making.
- CGE models typically assume competitive market *equilibrium* conditions. The influence of demand and supply decisions on commodity and factor prices. Equations for commodity and factor prices are adjusted to ensure that aggregate demands do not exceed total supplies.

As with any economic modeling approach, CGE models have limitations. While many CGE modeling features are consistent across the literature, tailoring of models to reflect specific contexts can limit the potential for results to be replicated. There is also concern that variable uncertainty might be compounded as it passes through the model. Hence the validity of results depends on researchers running sensitivity tests on key variables and assumptions, and presenting core mechanisms (Sue Wing 2004).

4.3 USCGE Model

The USCGE model was first developed by Adam Rose and Gbadebo Oladosu for environmental policy analysis (Rose and Oladosu, 2002; Oladosu and Rose 2007) and for terrorism analysis (Rose et al. 2009). The model has been updated to 2012 data for this project. Data from Impact Analysis for Planning (IMPLAN) (MIG 2012) form the core Social Accounting Matrix in the model, and the version of the model used in this analysis is based on 2012 data for the US economy. The USCGE model consists of 58 producing sectors, along with multiple institutions: nine household income groups, three government actors (two federal and one state and local), and external agents (i.e. foreign producers). The USCGE model represents production activities as a series of nested constant elasticity of substitution (CES) functions. An Armington substitution

[1]This represents the transactions between economic sectors, households, government, and foreign entities.

function between imports and domestic production represents international trade. A constant elasticity of transformation function represents the substitution between exports and domestic sales. Substitution elasticity parameter values have been sourced and checked against the literature on CGE modeling. Household consumption is represented with a Linear Expenditure System of aggregate commodities such as Food, Housing, and Gasoline.

The USCGE model is subject to the standard limitations of most CGE models. First, for the most part it assumes the economy is in equilibrium, though we do incorporate disequilibria in the labor market (unemployment equilibrium) and in the markets for critical inputs (such as electricity and water). Second, the model is static, so E-CAT only calculates first-year impacts (which covers the majority of them for all but the largest disasters). Third, the model is constructed through a deterministic approach based on single-year data (in contrast to the superior approach of econometric models that use time series and have goodness of fit measures).

4.4 CGE Drivers Used to Simulate E-CAT Threats

For most simulations, the starting point for analysis is a short-run closure rule. This reflects the short term, usually a 1-year time frame, that is used for most of the threat cases. This closure rule assumes that capital is fixed (after the destructive force of the threat has been factored in, where relevant), while the capital rate of return is variable. In contrast, wages are fixed – reflecting the notion of sticky wages – and labor is variable. Table 4.1 provides details of the model variables and simulation approaches used for each direct impact category for the case of a nuclear attack as an example. As highlighted for the "General economic impact" category, the overall impact of each threat is the aggregate impact of simultaneously simulated combinations of direct impacts. An example of specific simulations and "shock" values for key variables is provided in Table 4.2. Because the basic input data such as these are classified information for the case of a Nuclear Terrorist Attack, we present an example of the next stage in the analysis – "Summary of Consequences" – for the Earthquake threat instead as an example (the reader is referred to Chap. 3 for more details).

Table 4.1 CGE drivers used to simulate E-CAT threats

Direct impact category	Model variables and simulation approach
1. Vaccination	Increase in household spending on health
2. Quarantine and/or evacuation	Increase in household spending on transport
3. Decontamination	Stimulus to waste management sector; Increases in government tax on households to pay for decontamination
4. Medical expenditures	Increase in household spending on health
5. Mortality/morbidity (humans)	
(a) Deaths	Permanent reduction in total labor force
(b) Infected/injuries	Temporary reduction in total labor force
(c) Other (caregivers)	Temporary reduction in total labor force
6. Risk management	
(a) Information gathering	n.a.
(b) Administration	n.a.
7. Behavioral effects: avoidance	
(a) International travel—foreign visitors	Reduction in exports for goods foreign visitors purchase in the U.S.
(b) International travel—residents abroad	Reduction in household spending on foreign air travel; Increase in budget available to households for spending on domestic travel or other goods and services
(c) Domestic tourism	Reduction in household spending on domestic tourist activities
(d) Public gatherings/places	Reduction in household spending on domestic entertainment activities
8. Behavioral effects: aversion	
(a) Public anxiety	n.a.
(b) Wage premiums	Increase in wage rate to entice individuals to work in areas perceived as risky after a hazardous incident
(c) Rate of return premiums	Increase in capital rate of return to entice individuals and corporations to invest in areas perceived as risky after a hazardous incident
(d) Other (customer discounts)	Reduction in prices to entice individuals to purchase goods and services from businesses in areas perceived as risky after a hazardous incident
9. Infrastructure interruption/avoidance	
(a) Transportation	Reduction in transportation productivity
(b) Water	Major disruption to entire regional economy proportional to size of water services outage
(c) Natural gas	Reduction in natural gas productivity
(d) Electricity	Major disruption to entire regional economy proportional to size of electricity outage
(e) Education	Reduction in productivity of education sector
(f) Agriculture	Reduction in agricultural sector productivity

(continued)

Table 4.1 (continued)

Direct impact category	Model variables and simulation approach
10. International trade impacts	
(a) Import bans—products to the U.S.	Reduction in imports
(b) Export bans—U.S. products abroad	Reduction in exports
11. Social disruption (non-economic)	n.a.
12. Irreversibilities	
(a) Iconic structures and resources	n.a.
(b) Eco-systems	n.a.
13. Complex effects	
(a) Compound events	n.a.
(b) Cascading events	n.a.
14. International linkages	
(a) Foreign impacts on the U.S.	Reduction in exports
(b) U.S. impacts abroad	n.a.
15. Resilience	
(a) Conservation	Productivity factor adjustment reflecting capacity of businesses to conserve inputs
(b) Substitution	Inherent substitution is a standard feature of CGE modeling; adaptive substitution can be modeled by adjusting substitution elasticities in the CGE model
(c) Inventories	Productivity factor adjustment reflecting capacity of businesses to use inventories to offset output losses
(d) Relocation	Adjustment to initial shock to capital stock (see Property Damage below)[a]
(e) Production separation	n.a.
(f) Production recapture	Adjustment to initial shock to productivity or labor[b]
16. General economic disruption	Aggregate impact of simultaneously simulated combinations of direct impacts
17. Property damage	Reduction in capital stock

Table 4.2 Summary of consequences for earthquakes (lower and upper bounds)

		Direct impacts		CGE driver impact		
Consequence type	Units	2001 Nisqually earthquake (lower-bound)	ShakeOut scenario (upper-bound)	Model variable	2001 Nisqually earthquake (lower-bound)	ShakeOut scenario (upper-bound)
Deaths	no.	1	1800	Labor force	0.0000%	0.0007%
Injuries	no.	400	53,000	Labor force	0.0001%	0.0106%
Medical treatment cost	2012$	$2.9M	$380.7M	Household spending	0.0002%	0.0220%
Evacuation cost (residential)	2012$	0	$3.801B	Household spending on GASO, LTRN, OTRA	0	0.1866%
Decontamination cost	2012$	n.a.	n.a.	Household tax	n.a.	n.a.
				Waste management sector		
Property damage cost	2012$	$2.95B	$114.9B	Capital stock	0.0446%	1.7376%
Infrastructure Interruption	Critical infra-structure outage % annual	0.044% (electricity)	0.7% (water)	Side calculation	$0.34B (0.002%)	$5.43B (0.033%)

4.5 Detailed CGE Analysis of the Human Pandemic Case

We analyze the economic impacts of two influenza outbreak scenarios: (1) a Mild Outbreak scenario and (2) a Severe Outbreak scenario. Section 4.5.2 presents the health outcome parameters for the two scenarios. For both the Mild and Severe Outbreak scenarios, vaccinations reduce the overall spread of the virus, and hence are expected to reduce the magnitude of overall economic impacts. This study, therefore, simulates four broad scenarios, as shown in Table 4.3, based on distinctions between disease severity and the presence/absence of vaccinations. In terms of Workforce Participation and Medical Expenditures, fewer initial cases of infection would consequentially reduce illnesses and death, and thus lead to reduced absenteeism and medical expenditures. On the other hand, vaccination would incur medical costs associated with the production and administering of the vaccination, and will result in some lost work-hours due to the time people spend on travel, waiting, and receiving a vaccination dose. Moreover, the impacts of vaccination would not be proportional (e.g. half the number of infections would not lead to half the medical expenditures) for the following reasons:

- Models of flu outbreaks are non-linear, such that more severe outbreaks would lead to a higher proportion of hospitalizations and deaths.
- Vaccinations will have economic impacts, in terms of increased Medical Expenditures and the reduced Workforce Participation for workers to have the vaccination dose.
- Aversion Behavior is unlikely to be linearly correlated with the outbreak severity.

Table 4.3 Relative impacts of the four influenza scenarios

Modeling element	Mild outbreak		Severe outbreak	
	Vaccination	Non-vaccination	Vaccination	Non-vaccination
Workforce participation	Minor reduction due to illness and death. Small additional reduction from vaccination.	Mild impact due to illness and death.	Notable reduction due to illness and death. Small additional reduction from vaccination.	Major reduction due to illness and death.
Medical expenditures	Minor increase from outbreak. Small additional increase from vaccination.	Mild increase from outbreak.	Notable increase from outbreak. Small increase from vaccination.	Major impact from outbreak.
Aversion behavior	Minor increase from outbreak.	Mild increase from outbreak.	Notable increase from outbreak.	Major impact from outbreak.

4.5.1 Modeling Approaches and Results for Individual Impact Categories

In the case of human pandemic, the economic consequences were measured through a negative shock on labor force, which is essentially a shock on the supply side. This case also involves demand side shocks through changes in household expenditure on various related sectors as described in detail in Table 4.8 below.

4.5.1.1 Workforce Participation

Labor supply decreases following an influenza outbreak. Reduced workforce participation is estimated on the basis of disease-spread scenarios and the associated absenteeism due to personal and familial illness. Although not captured here, absenteeism simulations would also include the influence of school closures and so-called "prophylaxis absenteeism" (another form of aversion behavior), whereby individuals stay at home to avoid catching or transmitting the virus.

Direct impact estimates are drawn from calculations of various parameters presented in Section 4.5.2. Following the Dixon et al. (2010) calculation approach, the 150 million workers in the U.S. contribute 240 days in each year period. For example, this implies a 19.7*100/(150*240) = 0.055 % reduction in labor inputs for the 12-month period of Case M1 (No Vaccination, Mild Outbreak; see Table 4.5). Table 4.4 provides a comparison of direct impact estimates between the No Vaccination and Vaccination scenarios.

Labor supply is represented in the USCGE model as a factor input to the production function for each sector. One challenge here is that the labor and capital factor supply elements are related to the closure conditions. In this case, we are interested in a "short-run" closure rule, whereby wages are fixed (or "sticky") yet labor supply is variable. In parallel, capital supply is fixed while the price of capital is variable. This implies that any external shock to the labor supply – such as the reduction in labor supply due to death, illness, or other forms of workplace absenteeism – will imbalance the short-run closure rule. Simulations in Table 4.5 (Cases W1-4) are run allowing the labor wage rate to vary.

4.5.1.2 Medical Expenditures

Medical expenditures increase following an influenza outbreak. Direct impact levels presented in Table 4.5 are drawn from calculations of Mild and Severe Outbreak parameters presented in Section 4.5.2. In the USCGE model, household expenditures on Medical Services sector are increased, or "shocked". The Medical Services sector is one of the largest of the 57 sectors in the model. Total baseline expenditures on Medical Services are $1,772 billion, the majority of which ($1,730 billion) are from households. As shown in Table 4.5, Case M1 (No Vaccination,

Table 4.4 Summary of direct impacts of no vaccination vs. vaccination scenarios

Scenarios			Medical expenditure (B $)	Workday losses	Aversion behavior (reduction in outbound international travel)	Aversion behavior (reduction in domestic travel/leisure activities)
No vaccination	Mild	Virus	10.45	19,716,605	2.43 %	10 %
	Severe	Virus	161.79	95,059,158	19.83 %	10 %
Vaccination	Mild	Virus	8.01	14,721,873	2.43 %	10 %
		Vaccine	4.46	6,723,048		
		Total	12.47	21,444,922		
	Severe	Virus	121.85	70,044,405	19.83 %	10 %
		Vaccine	4.89	7,441,847		
		Total	126.74	77,486,252		
Difference between vaccination and no vaccination	Mild	Virus	−2.44	−4,994,732	0 %	0 %
		Vaccine	4.46	6,723,048		
		Net change	2.02	1,728,316		
	Severe	Virus	−39.94	−25,014,754	0 %	0 %
		Vaccine	4.89	7,441,847		
		Net change	−35.05	−17,572,907		

Mild Outbreak) simulation increases household spending on Medical Services by \$10.45 billion, or 0.604 %. These simulations currently assume that households are subject to a budget constraint, and hence substitute between medical services and other consumption.

4.5.1.3 Aversion Behavior

International and domestic tourism and leisure activities are anticipated to decrease as individuals from the U.S. and abroad engage in avoidance behavior. These include reductions in foreign tourism to the U.S., reductions in U.S. resident travel abroad, and reductions in U.S. domestic tourism and leisure activity spending.

Reductions in International Travel – Inbound and Outbound

Direct impacts for these cases reflect similar scenarios developed in the Dixon et al. (2010) and Verikios et al. (2010a, b) studies of the Australian H1N1 outbreak. While those two studies used a dynamic CGE model, the USCGE is comparative static; hence, Table 4.6 presents the conversion of Verikios et al. (2010a, b) dynamic aversion behavior impacts to static parameter estimates applied in the

Table 4.5 Total direct impacts summary (2012 dollars)

Impact	USCGE modeling approach	Scenarios		
		Case	Level impact	% impact
Workforce participation	Reduction in labor workforce participation	W1	−19.7m	−0.055 %
		W2	−95.1m	−0.264 %
		W3	−21.4m	−0.060 %
		W4	−77.5m	−0.215 %
Medical expenditures	Increase household spending on medical services	M1	$10.45b	0.604 %
		M2	$161.79b	9.351 %
		M3	$12.47b	0.721 %
		M4	$126.74b	7.325 %
Behavioral considerations	Reduction in inbound international travel (via exports)	BII1	−$1.95b	−2.430 %
		BII2	−$15.93b	−19.830 %
		BII3	−$1.95b	−2.430 %
		BII4	−$15.93b	−19.830 %
	Reduction in outbound international travel	BOI1	−$0.96b	−2.430 %
		BOI2	−$7.89b	−19.830 %
		BOI3	−$0.96b	−2.430 %
		BOI4	−$7.89b	−19.830 %
	Reduction in domestic travel/leisure activities	BD1	−$66.30b	−10.000 %
		BD2	−$66.30b	−10.000 %
		BD3	−$66.30b	−10.000 %
		BD4	−$66.30b	−10.000 %

Note: Further details are provided in Prager et al. (2016)

Table 4.6 Translation of dynamic aversion behavior. Impacts to static parameter estimates

Time Period	Mild influenza outbreak	Severe influenza outbreak
Q1	−7.90 %	−34.00 %
Q2	−1.20 %	−34.00 %
Q3	−0.60 %	−25.50 %
Q4	0.00 %	−17.00 %
Q5	N/A	−8.50 %
Q6	N/A	0.00 %
Average for stated periods	−2.43 %	−19.83 %

USCGE model. Verikios et al. (2010a, b) assume that a "mild" influenza outbreak would reduce inbound and outbound international tourism by 7.9 % in the first quarter, 1.2 % in the second quarter, and would steadily return to baseline over the next two periods. We have assumed that the baseline level is achieved in the fourth quarter. Verikios et al. (2010a, b) take a similar approach in the Severe Influenza Outbreak equivalent (see Table 4.6), with the return to baseline at an even rate over four quarters. I have assumed that the baseline level is reached in the sixth quarter.

We have adjusted the impacts in Q1 and Q2 assumed by Verikios et al. (2010a, b) −65 % reductions in international tourism – down to the 34 % level assumed by Dixon et al. (2010).

Inbound International Travel

Reductions in international travel estimated in Table 4.6 are converted to sector impacts using calculations from the Customs and Border Protection (CBP)'s Office of Field Operations (OFO) study (Prager et al. 2015). In 2012, there was an estimated total of $80.3 billion spent by foreign tourists in the US (U.S. Department of Commerce, 2013). Therefore, the Mild (Cases BII1, 3) and Severe Outbreaks (Cases BII2, 4) would result in reductions in foreign tourist spending of $1.9 billion and $15.9 billion, respectively.

This element of aversion behavior is simulated through reducing exports for sectors in which foreign tourists spend money. A problem arises when applying these values to the USCGE model as reductions in sector-specific reductions in exports – based on OFO study shares presented in Table 4.7 – since some of the desired sector reduction parameters are greater than the exports for that sector. As

Table 4.7 Foreign visitor spending changes

		Desired parameters		
USCGE sectors	Tourism spend ratios	Mild outbreak ($B)	Severe outbreak ($B)	Total exports from each sector ($B)
Other food mfg	0.0434	−0.085	−0.691	44.41
Petroleum refining	0.0145	−0.028	−0.231	301.96
Other non-durable mfg	0.2218	−0.432	−3.532	56.17
Air transport	0.2689	−0.524	−4.283	21.77
Rail transport	0.0017	−0.003	−0.027	0.47
Other transport	0.0088	−0.017	−0.140	13.24
Hotels and restaurants	0.3062	−0.596	−4.877	26.83
Other business services	0.0292	−0.057	−0.465	260.71
Entertainment	0.1037	−0.202	−1.652	6.98
Medical services	0.0018	−0.004	−0.029	61.76
Total		−1.95	−15.93	794.30

[a]These values are taken from the Prager et al. (2015) study on Airport Wait Time Reduction estimates

such, we adjusted these values down to the overall spending percentage reduction level for the Mild and Severe Outbreaks (2.43 % and 19.83 % respectively). This implies that the total shock to spending is less than initially desired, as shown in Table 4.7. For the Mild Outbreak, the desired shock to tourism expenditure is −$1.95 billion, but the actual shock is −$1.16 billion. For the Severe Outbreak, the desired shock to tourism expenditure is −$15.93 billion, while the actual shock is −$9.45 billion.

Outbound International Travel

It is assumed that the only domestic sector negatively impacted by reductions in outbound international travel is the U.S. airline travel industry. While there would be other sectors negatively impacted by U.S. resident travel abroad (for business or leisure purposes), such as travel agents, local private and public transit, parking, and hotels, the proportions of these sectors impacted is likely to be minimal compared with the impact to the Air Transport sector. In 2012, U.S. residents traveling abroad for leisure and business spent $39.8 billion on airfares. For the Mild Outbreak (Cases BOI1,3), −2.43 % equates to a −$1.95 billion "shock" to Air Transport output, while for the Severe Outbreak (Cases BOI2,4), −$1.95 billion "shock" to Air Transport output, while for the Severe Outbreak (Cases BOI2,4), −19.83 % equates to −$7.89 billion to Air Transport output. This is simulated through adjusting the productivity factor of the Air Transport (TAIR) sector to capture a reduction in output.

Domestic Tourism and Leisure Spending

Domestic tourism and leisure spending is broken into three components: (1) Resident Households, (2) Business, and (3) Government. The reduction of Resident Household spending on domestic tourism and leisure is simulated through the household expenditure function, as it is with the Medical Expenditure simulations above. These shocks are grouped together for the sector commodities presented in Table 4.8, according to their respective household commodity groupings, i.e. Food (−0.60 %), Gasoline (−3.21 %), Other Household Services (−0.51 %), Other Transport (−5.08 %), and Light Transit (−5.57 %). The reduction in Business spending on domestic tourism and leisure is implemented by shocking the level of sales of the relevant sector commodities to all sector purchasers, by the values presented in Table 4.8. The reduction in Government spending on domestic tourism and leisure is implemented by shocking the government expenditures variable in the model according to the levels stated in Table 4.8.

Table 4.8 Aversion behavior, domestic tourism and leisure spending simulation ($m)

	Domestic tourism and leisure spending				Simulation input values[a]		
Sector	Resident households	Business	Gov't	Total	Resident households	Business	Gov't
Other food mfg	28,577	7685	909	37,171	−0.60 %	−2.92 %	−0.39 %
Petroleum refining	69,832	24,591	1763	96,186	−3.21 %	−0.37 %	−0.68 %
Other non-durable mfg	45,163	12,145	1437	58,745	−0.09 %	−0.42 %	−0.32 %
Air transport	40,042	17,289	7871	65,202	−5.00 %	−7.72 %	−5.43 %
Rail transport	647	408	279	1334	−0.08 %	−0.95 %	−0.08 %
Other transport	1688	2173	390	4251	0.00 %	−0.46 %	−0.13 %
Private transit	14,269	420	465	15,154	−5.57 %	−0.59 %	−0.43 %
Hotels and restaurants	119,877	94,437	16,492	230,806	−0.24 %	−4.98 %	−6.05 %
Personal services	1360	397	270	2027	0.00 %	−0.40 %	−0.25 %
Other business services	29,922	47,347	2462	79,731	−0.06 %	−0.05 %	−0.20 %
Entertainment	59,428	12,963	0	72,391	−0.12 %	0.00 %	−1.76 %
Total	410,805	219,855	32,338	662,998			

[a]Simulation input values are applied to Household Expenditures (HSVE) for Resident Households, Government Expenditures (GVEXP) for Government, and Business sales (SAL) for Business

Other Avoidance Behaviors

Other types of avoidance behaviors included in our analysis are: reductions in public transportation use and reductions in attendance of educational facilities. The major assumptions for these avoidance behaviors and the approaches we used to model their impacts in the CGE model are presented in Table 3.6.[2]

4.5.2 Discussion of National Results

4.5.2.1 Direct Impacts and the Cost-Effectiveness of Vaccination

In this section, we examine the cost-effectiveness of vaccination in terms of direct impacts. Table 4.4 compares the direct impacts of the No Vaccination and Vaccination scenarios for both the Mild Outbreak and Severe Outbreak scenarios. Note that for now, we assume the same percentage of reduction in international and domestic travel/leisure activities in the No Vaccination and Vaccination scenarios.

Major direct impact findings from Table 4.4 can be summarized as follows. For the Mild Outbreak Scenario, vaccination is cost-effective from the direct impact perspective:

- Vaccination reduces medical treatment expenditures from \$10.45 billion to \$8.01 billion (a \$2.44 billion reduction); however, vaccination itself incurs a medical cost of \$4.46 billion.
- Vaccination reduces illness related workday losses from 19.7 million days to 14.7 million days (a reduction of 5 million days); however, 6.7 million days of workdays are lost due to the time that people spend on getting the vaccination doses.
- It is unclear how vaccination and the reduced outbreak magnitude will affect the aversion behavior for the Mild Outbreak. Currently, we are assuming the same percentage reduction in international and domestic travel/leisure activities in the No Vaccination and Vaccination scenarios. If vaccination can reduce aversion behavior, and hence mute the reduction in travel activity, it is still possible that the Vaccination scenario for the Mild Outbreak can be cost-effective.

For the Severe Outbreak Scenario, vaccination is cost-effective from the direct impact perspective:

- Vaccination reduces medical treatment expenditures from \$161.8 billion to \$121.9 billion (a \$39.9 billion reduction); vaccination itself only incurs a medical cost of \$4.89 billion.

[2]In a subsequent study, we further expanded the analysis of the avoidance behavior to account for the workforce participation reduction due to people staying home from work and for caregivers taking care of children who avoid school attendance (Prager et al. 2016).

- Vaccination reduces illness related workday losses from 95.1 million days to 70.0 million days (a reduction of 25.1 million days); vaccination only causes 7.4 million days of workday losses due to the time that people spend on getting the vaccination doses.
- We are currently assuming the same percentage reduction on travel in the No Vaccination and Vaccination scenarios. If vaccination can reduce aversion behavior, and hence mute the reduction in travel activity, then the vaccination scenario can be more cost-effective than the current Severe Outbreak case results indicate.

We note that vaccines may be in limited supply for a Severe Outbreak (pandemic flu) compared with a Mild Outbreak (CDC 2010). As such, our estimates present a lower-bound of possible Severe Outbreak impacts. If we reduce the vaccination coverage of the Severe Outbreak scenario by 50 %, medical expenditures (including vaccination cost) will increase by about 12 %, while workday losses will increase by about 11 %. However, as we will see from the CGE analysis in the next section, since the medical expenditures incur overall positive impacts while workday losses incur negative impact at the macro level, the changes stemming from the direct impacts of these two effects would offset each other to some extent. at the macro level.

Another uncertainty is the vaccination effectiveness. In the base case, we used an average of the vaccination effectiveness of 2005–2006 season to 2012–2013 season for both of the two influenza outbreak scenarios. If we use the vaccination effectiveness of the 2009–2010 (H1N1) season for the Severe Outbreak scenario, and the average of the vaccination effectiveness of the other seasons for the Mild Outbreak scenario, the vaccination effectiveness will increase by about 20 % for the Severe Outbreak scenario and decrease by less than 4 % for the Mild Outbreak scenario compared to the base case. The corresponding effects to the direct impacts are small: for the Severe Outbreak scenario, the gross medical expenditures (including vaccination costs) and the workday losses will increase by 4.7 % and 3.3 %, respectively. For Mild Outbreak scenario, the gross medical expenditures and the workday losses will increase by 0.6 % and 0.8 %, respectively.

Our findings that vaccination is cost-effective from the direct impact perspective for the Severe Outbreak scenario remain the same in both of the above sensitivity cases. In other words, vaccination reduces medical expenditures and lowers workday losses for the pandemic scenario.

4.5.2.2 Total (CGE) Impacts

Key General Equilibrium Impacts

- Mild and Severe outbreaks negative impacts: household budget constraints and substitution mitigate direct impacts
- Vaccination diffs marginal (ignoring health benefits) as behavioral factors (all international travel) assumed independent

- Other major factor in economic costs is a reduction in workforce participation – vaccination reduces costs here

CGE results in Table 4.10 indicate that the implicit CGE multiplier – the ratio of total gross output results to direct expenditure impacts – is close to 2 for all simulations. This is a reasonable multiplier value for a national model (note that CGE multipliers are lower than counterpart input-output multipliers because the latter are uni-directional and the former include offsetting price effects).

Total impact results presented in Table 4.10 follow intuition, as the Severe Outbreak scenario results (Cases 2 and 4) are more negatively impactful than the Mild Outbreak scenario results (Cases 1 and 3). For the Mild Outbreak, total impacts to GDP are −$6.45 billion and −$6.89 billion for the No Vaccination and Vaccination scenarios, respectively, which suggests that, for the Mild Scenario, a vaccination may not be cost-effective for the economy as a whole. In contrast, the Severe Outbreak total impacts are -$39.64 billion and −$35.44 billion for the No Vaccination and Vaccination scenarios, respectively.

One notable result is that the GDP multipliers for the Aggregate Simulations are negative for the Severe Scenario (Cases 2 and 4). While the Direct impacts are positive overall (due to medical spending outweighing the other negative direct impacts), the Total GDP impacts are negative. It is notable that the GDP multipliers for the simulations of increased household spending on medical services and reductions in domestic travel/leisure activities are relatively low. In other words, the Direct Impacts for these simulations are relatively large, yet the Total GDP impacts are small in comparison to the direct impact levels. The small size of the multipliers is due to offsetting positive and negative impacts. These two simulations were run by constraining household expenditures on particular goods (both medical and tourism-related). Due to household budget constraints, increased spending on medical services is offset by reduced spending on all other services, while decreased spending on tourism-related services is offset by increased spending on all other services. As such, the overall economic impact is muted.

When we decompose these results further, it is notable that the reduction in labor workforce participation (Cases W1-4) appears to have the greatest single impact on the overall results in terms of absolute magnitude, with around −$5 billion impact for the Mild Scenario, and between −$19 and −$24 billion impact for the Severe Scenario. When the behavioral considerations are combined, they induce a greater impact of around −$6 billion for the Mild Scenario and −$35 billion for the Severe Scenario. Increased household spending on medical services has a positive economic impact of around $1 billion for the Mild Scenario and between $74 and $94 billion for the Severe Scenario.

The reduction in labor workforce participation results (Cases W1-4) are both reasonable and consistent, with gross output impacts 1.66 times larger than the "direct" level shock (the implicit CGE multiplier). Given these monotonic impacts, there is little difference in terms of workforce participation impacts when

Table 4.10 Gross output impacts on the U.S. economy (billions of 2012 dollars)

Simulation	Drivers	Direct output	Direct GDP	Total GDP		Total employment[a]		GDP multiplier
				Level	%	Level	%	
W1	Reduction in labor workforce participation	−4.73	−2.74	−4.90	−0.030	−0.039	−0.055	1.66
W2		−22.71	−13.17	−23.51	−0.144	−0.187	−0.264	1.67
W3		−5.16	−2.99	−5.34	−0.033	−0.043	−0.060	1.66
W4		−18.50	−10.73	−19.15	−0.117	−0.155	−0.215	1.66
M1	Increase household spending on medical services	10.45	6.06	1.20	0.007	0.010	0.014	0.18
M2		161.79	93.84	18.53	0.114	0.152	0.210	0.17
M3		12.47	7.23	1.44	0.009	0.012	0.016	0.18
M4		126.74	73.51	14.54	0.089	0.121	0.165	0.17
BII1	Behavioral: reduction in inbound international travel (via exports)	−1.95	−1.13	−2.49	−0.015	−0.021	−0.011	2.00
BII2		−15.93	−9.24	−19.47	−0.119	−0.164	−0.087	1.94
BII3		−1.95	−1.13	−2.49	−0.015	−0.021	−0.011	2.00
BII4		−15.93	−9.24	−19.47	−0.119	−0.167	−0.087	1.94
BOI1	Behavioral: reduction in outbound international travel	−0.96	−0.56	−1.70	−0.010	−0.015	−0.008	1.68
BOI2		−7.89	−4.58	−14.19	−0.087	−0.123	−0.067	1.74
BOI3		−0.96	−0.56	−1.70	−0.010	−0.015	−0.008	1.68
BOI4		−7.89	−4.58	−14.19	−0.087	−0.125	−0.067	1.74
BD1	Behavioral: reduction in domestic travel/leisure activities	−66.30	−38.45	−1.76	−0.011	−0.018	−0.026	0.05
BD2		−66.30	−38.45	−1.76	−0.011	−0.018	−0.026	0.05
BD3		−66.30	−38.45	−1.76	−0.011	−0.018	−0.026	0.05
BD4		−66.30	−38.45	−1.76	−0.011	−0.018	−0.026	0.05
F1S	Aggregate (Summation)	−63.49	−36.83	−9.64	−0.062	−0.095	−0.086	0.23
F2S		48.96	28.40	−40.40	−0.260	−0.392	−0.234	−1.17
F3S		−61.90	−35.90	−9.85	−0.063	−0.098	−0.088	0.24
F4S		18.12	10.51	−40.03	−0.258	−0.393	−0.230	−3.11

(continued)

Table 4.10 (continued)

Simulation	Drivers	Direct output	Direct GDP	Total GDP		Total employment[a]		GDP multiplier
				Level	%	Level	%	
F1A	Aggregate (simultaneous)	−63.49	−36.83	−6.45	−0.040	−0.060	−0.055	0.15
F2A		48.96	28.40	−39.64	−0.243	−0.374	−0.264	−1.17
F3A		−61.90	−35.90	−6.89	−0.042	−0.065	−0.060	0.17
F4A		18.12	10.51	−35.44	−0.217	−0.339	−0.215	−2.76
IIT2	Reduction in public transportation use	−8.11	−4.70	−57.1	−0.351	−0.451	−0.227	12.15
IIE2	Reduction in attendance of educational facilities	−2.01	−1.17	−7.23	−0.044	−0.057	−0.033	6.21
RPR2	Resilience: labor loss recapture	−15.90	−9.22	−16.47	−0.101	−0.130	−0.185	1.79
F2S2	Aggregate (summation), with additional drivers	38.84	22.53	−105.01	−0.644	−0.829	−0.496	−4.66
F2A2	Aggregate (simultaneous), with additional drivers, no resilience	38.84	22.53	−80.06	−0.491	−0.632	−0.264	−3.55
F2A3	Aggregate (simultaneous), with additional drivers, with resilience.	45.65	26.48	−73.18	−0.449	−0.578	−0.185	−2.76

[a]Employment is presented in millions of person-years

Notes: Case 1: No Vaccination, Mild Outbreak

Case 2: No Vaccination, Severe Outbreak

Case 3: Vaccination, Mild Outbreak

Case 4: Vaccination, Severe Outbreak

Table 4.11 Top 5 sectors in terms of magnitude of impact (positive or negative), Aggregate, Case F4A (no vaccination/severe outbreak)

Negative impact			Positive impact		
Sectors	% Δ	GDP Δ ($b)	Sectors	% Δ	GDP Δ ($b)
Air transport	−7.68	−5.77	Medical services	1.85	15.82
Non-durable mfg	−0.99	−4.48	Water transport	0.58	0.09
Rail transport	−0.89	−0.39	Construction	0.18	1.37
Social services	−0.78	−1.56	Federal military	0.00	0.00
Private light transit	−0.68	−0.13	Fish mfg	0.00	0.00
Public light transit	−0.68	−0.02			
Retail trade	−0.67	−4.84			
Other transport	−0.64	−0.80			
Veterinary services	−0.56	−0.08			
Entertainment	−0.54	−0.77			

comparing the Vaccination and No Vaccination cases for the Mild Outbreak. Thus any labor supply benefits from vaccination are offset by the time it takes to vaccinate that population. However, under a Severe Outbreak, the Vaccination would significantly reduce the negative impact to the economy from workforce participation.[3]

4.5.2.3 Sector Impacts

Table 4.11 presents CGE impacts by sector for the Aggregate (Simultaneous), Case F4A (Severe Outbreak/No Vaccination) scenario. Results are presented with respect to sectors with the largest magnitude of impact (positive or negative). The sector impact results follow intuition. Medical Expenditure increases are most positively impacted, due to the substantial increase in household spending on Medical Services, and in turn also benefit major trading partners such as Construction. Similarly, each of the Aversion Behavior simulations has the greatest negative impact on the Air Transport sector. In each case, the other most impacted sectors are significantly less affected. These other impacted sectors largely follow intuition, with sectors with strong linkages to Air Transport such as Entertainment, Hotels and Restaurants, and other Transport among

[3]The labor wage rate increases at a rate similar to the reduction in labor factor supply. This is to be expected as the labor wage rate is allowed to vary and the two elements (labor factor supply and labor wage rate) are on the opposite sides of the same equation. This implies that the elasticity of labor supply is around 1.A recent Congressional Budget Office (CBO) review of empirical studies found that elasticity of labor supply "ranges from 0.27 to 0.53, with a central estimate of 0.40" (Reichling and Whalen 2012).This result conflicts with intuition about the short-run theory of labor wages, which suggests that wages will be "sticky" due to contracts and worker wage preferences. On the other hand, the wage changes are small (less than 1 percent), so this is not unrealistic.

those impacted by inbound and outbound international travel simulations. For domestic leisure and tourism, the sectors most impacted in the direct analysis are also most affected in terms of total impacts, such as Non-Durable Manufacturing.

Policy-Relevant (Actionable) Findings

- Behavior key factor – government policy and public health officials can focus on influencing behavior to reduce economic costs
- Business (labor) recapture can increase economic to human pandemics – flexible working hours can help

Appendix 4A: Calculation of Input Data for Mild and Severe Influenza Outbreaks

We collected epidemiological data on pandemic influenza from various studies in terms of total population infected, the number of people that seek medical attention (either outpatient medical treatment or hospitalization), and the number of people that die from the influenza. Table 4.12 presents the data we obtained from the literature.

To determine the parameters for the two influenza outbreak scenarios, we first convert the data in Table 4.12 into infection rates, outpatient medical treatment rates, hospitalization rates, and death rates. In Table 4.13, we compute the rates of outpatient medical treatment, hospitalization, and death with respect to the total number of people infected. However, we find that different studies use different definitions in terms of the population being "infected" or "attacked". For example, in Congressional Budget Office (CBO) (2006) and Verikios et al. (2010a, b) studies, "Attack Rate" is equivalent to "Infection Rate". However, in Center for Disease Control (CDC) studies (2006, 2010), "Attack Rate" relates to the number of clinically ill cases, which are defined as "cases in persons with illness sufficient to cause an economic impact (e.g., half-day off work)". According to the CDC definition, "infected persons who continued to work were not considered to have a clinical case of influenza." The difference in the definitions regarding population infected (or attacked) makes comparison difficult across the studies. Therefore, in Table 4.14, we computed the rates on a consistent basis with respect to the total population.

Based on the range of ratios presented in Table 4.14, we determine the parameters to be used for the two outbreak scenarios in our analysis in Table 4.15. For the Attack Rate, based on the data presented in Table 4.14, we calculate the average of the lower-end percentages and the average of the higher-end percentages, and use them as the rates for our Mild Scenario and Severe Scenario, respectively. For

Table 4.12 Population infection, medical attention, hospitalization, and death data gathered from various studies

Paper/Report	Type of influenza	Age group	Total infected (or clinically ill) (million)	Outpatient medical treatment (million)	Hospitalization (million)	Death (million)	Note
Dixon et al. (2010)	Hypothetical H1N1 epidemic	0–17 (also include 65+)	88.6	15.36	0.129	0.016	Total infected population derived from Epstein agent-based modeling; among the 88.6 M infected, 59.8 M symptomatic
		18–64		13.87	0.14		Hospitalization/symptomatic = 0.45 % (Reed et al. 2009); Outpatient Treatment/infection ratio = 33 %; Death/hospitalization ratio = 6 % (Reed et al. 2009)
CDC Report (2010)	2009 H1N1 influenza	0–17	20	N/A	0.087	0.00128	This report is the last CDC updates (released in May 2010) on hospitalization and deaths in the U.S. in the 1-year timeframe (Apr 2009–Apr 2010) of the 2009 H1N1 influenza
		18–64	35	N/A	0.16	0.00957	
		65+	6	N/A	0.027	0.00162	
		Total	61	N/A	0.274	0.01247	
Molinari et al. (2007)	Seasonal influenza	0–4	4.1	1.9	0.057	0.00016	Applying health outcome probabilities data in the paper to 2012 population by age group
		5–17	5.5	1.9	0.003	0.00005	
		18–49	9.0	3.2	0.038	0.00081	
		50–64	4.0	1.7	0.078	0.00541	
		65+	3.9	2.8	0.163	0.04543	
		Total	26.4	11.6	0.340	0.05187	
CBO (2006)	H5N1 Avian flu (severe pandemic)	Total	90.0	N/A	N/A	2.00	Severe pandemic: attack rate = 30 % (10 % for Farm sector); Death rate = 2.5 %
	H5N1 Avian flu (mild pandemic)	Total	75.0	N/A	N/A	0.10	Mild pandemic: attack rate = 25 % (5 % for Farm sector); Death rate = 1.14 %

(continued)

Table 4.12 (continued)

Paper/Report	Type of influenza	Age group	Total infected (or clinically ill) (million)	Outpatient medical treatment (million)	Hospitalization (million)	Death (million)	Note
CDC FluAid moderate scenario (Meltzer 2006)	Next influenza pandemic (1968-type)	0–18	18.4	16.16	0.051	0.00285	Applying health outcome probabilities data in Table AI.2 in the Instruction document to 2012 population by age group
		19–64	49.3	13.35	0.325	0.08685	
		65+	10.8	3.34	0.205	0.08327	
		Total	78.5	32.85	0.581	0.17297	
CDC FluAid severe scenario (Meltzer 2006)	Next influenza pandemic (1918-type)	0–18	N/A	N/A	0.420	0.02343	Applying health outcome probabilities data in Table AI.4 in the Instruction document to 2012 population by age group. A scaling factor of 8.22 is used in CDC FluAid to derive the parameters for the severe scenario from the parameters for the moderate scenario.
		19–64	N/A	N/A	2.668	0.71385	
		65+	N/A	N/A	1.685	0.68448	
		Total	N/A	N/A	4.772	1.42175	
Verikios et al. (2010a, b)	Scenario 1 (11 % infected)	Total	34.0	0.7	0.085	0.00333	Verikios et al (2010a, b)is based on an Australian context. We have translated their categories of GP and flu clinic to our Outpatient Medical Treatment, and Hospital and ICU to our Hospital. They use % as the parameter values; these are converted to US population figures for comparison purposes.
	Scenario 2 (30 % infected)	Total	92.8	8.1	3.248	0.81662	

Table 4.13 Population infection rate, and medical-treatment/infection, hospitalization/infection, death/infection ratios

Paper/Report	Type of influenza	Age group	Infection or case or attack rate	Outpatient medical treatment/infection	Hospitalization / infection	Death/infection	Note to "Infection or Case or Attack Rate" column
Dixon et al. (2010)	Hypothetical H1N1 epidemic	Total	29 %	33 %	0.30 %	0.018 %	Represent infection rate. The "symptomatic" rate, which is calculated by dividing people with symptoms by total population is 19.4 %
CDC Report (2010)	2009 H1N1 influenza	Total	20 %	N/A	0.45 %	0.020 %	Represent clinical case rate. The report estimates the prevalence of the 2009 H1N1 (the total H1N1 cases) by applying scaling factors to laboratory-confirmed cases reported to CDC
Molinari et al. (2007)	Seasonal influenza	Total	9 %	44 %	1.28 %	0.196 %	Represent gross attack rate. The paper did not provide a definition on Gross Attack Rate. However, since two Meltzer's papers were cited as the sources of the Gross Attack Rate, I assume the definition should be closer to the CDC "Gross Clinical Attack Rate" definition (see CDC FluAid row below)
CBO (2006)	H5N1 Avian flu (severe pandemic)	Total	30 %	N/A	N/A	2.222 %	Represent gross attack rate, which is same as "infection rate": the percentage of the population that is infected with a disease.
	H5N1 Avian flu (mild pandemic)	Total	25 %	N/A	N/A	0.133 %	

(continued)

Table 4.13 (continued)

Paper/Report	Type of influenza	Age group	Infection or case or attack rate	Outpatient medical treatment/ infection	Hospitalization / infection	Death/ infection	Note to "Infection or Case or Attack Rate" column
CDC FluAid moderate scenario (Meltzer 2006)	Next influenza pandemic (1968-type)	Total	25 %	42 %	0.74 %	0.220 %	Represent gross attack rate = % of population which are assumed to become clinically ill with influenza during the pandemic; clinical ill cases are defined as cases in persons with illness sufficient to cause an economic impact (e.g., half day off work). Infected persons who continued to work were not considered to have a clinical case of influenza.
CDC FluAid severe scenario (Meltzer 2006)	Next influenza pandemic (1918-type)	Total	N/A	N/A	6.08 %	1.812 %	A scaling factor of 8.22 is used in CDC FluAid to derive the parameters for the severe scenario from the parameters for the moderate scenario.
Verikios et al. (2010a, b)	Scenario 1 (11 % infected)	Total	11 %	2 %	0.25 %	0.010 %	Represent attack rate, which is same as infection rate in this study
	Scenario 2 (30 % infected)	Total	30 %	9 %	3.50 %	0.880 %	

Table 4.14 Population infection rate, and medical-treatment/population, hospitalization/population, and death/population ratios

Paper/ Report	Type of influenza	Age group	Infection rate, case rate or attack rate	Outpatient medical treatment/ population	Hospitalization/ population	Death/ population
Dixon et al. (2010)	Hypothetical H1N1 epidemic	Total	29 %	10 %	0.09 %	0.005 %
CDC report (2010)	2009 H1N1 influenza	Total	20 %	N/A	0.09 %	0.004 %
Molinari et al. (2007)	Seasonal influenza	Total	9 %	4 %	0.12 %	0.018 %
CBO (2006)	H5N1 Avian flu (severe pandemic)	Total	30 %	N/A	N/A	0.676 %
	H5N1 Avian flu (mild pandemic)	Total	25 %	N/A	N/A	0.034 %
CDC FluAid moderate Scenario (Meltzer 2006)	Next influenza pandemic (1968-type)	Total	25 %	10 %	0.18 %	0.055 %
CDC FluAid severe scenario (Meltzer 2006)	Next influenza pandemic (1918-type)	Total	N/A	N/A	1.52 %	0.453 %
Verikios et al. (2010a, b)	Scenario 1 (11 % infected)	Total	11 %	0.2 %	0.03 %	0.001 %
	Scenario 2 (30 % infected)	Total	30 %	3 %	1.05 %	0.264 %

Outpatient Medical Treatment Rate, we first eliminate the seemingly low estimate from Verikios et al. (2010a, b) as an outlier, and use the next lowest rate and the highest rate in Table 4.14 as the rates to be used for our Mild and Severe Scenarios, respectively. For the Hospitalization Rate and Death Rate, we first eliminate the outlier estimates (again from Scenario 1 of Verikios et al. 2010a, b) in Table 4.14, and then use the average of the lower-end rates and the average of the higher-end rates for our Mild and Severe Scenarios, respectively. For the Hospitalization Rate and Death Rate of the Mild Outbreak Scenario, we first eliminate the outlier estimates (again from Scenario 1 of Verikios et al 2010a, b) in Table 4.14, and then use the average of the lower-end rates. For the Hospitalization Rate and Death Rate of the Severe Outbreak Scenario, we used the rates of Class 5 pandemic influenza from Reed et al. (2013) and Meltzer et al. (2015). Since not all the studies based on which we collected data provide separate health outcome estimates by age group, in Table 4.15, we computed the rates for the entire population.

4.A.1 Without Vaccination

By applying the epidemic parameters presented in Table 4.15 to the current U.S. population, we obtain the total number of people infected with symptoms, seeking outpatient medical treatment, hospitalized, and died, respectively. We then further break down these estimates among three age groups (0–17, 18–64, and 65+) based on data from CDC (2006, 2010) and Molinari et al. (2007) with respect to the mix of people from each age group in different health outcome categories. Table 4.16 presents the health outcome results for our two scenarios.

Table 4.15 Assumptions on epidemic parameters (all percentages are calculated with respect to U.S. total population)

	Mild scenario	Severe scenario
Attack rate	10 %	25 %
Outpatient medical treatment rate	3 %	10 %
Hospitalization rate	0.10 %	1.50 %
Death rate	0.01 %	0.50 %

Table 4.16 Health estimates (number of people)

Category	Age group	Mild scenario	Severe scenario
Symptoms, no medical treatment	0–17	8,507,754	16,052,367
	18–64	12,103,369	22,836,545
	65+	1,318,093	2,486,969
	Total	21,929,216	41,375,880
Outpatient medical treatment	0–17	3,944,558	13,148,526
	18–64	3,961,174	13,203,914
	65+	1,642,548	5,475,161
	Total	9,548,280	31,827,600
Hospitalization	0–17	61,923	928,848
	18–64	157,376	2,360,635
	65+	98,977	1,484,658
	Total	318,276	4,774,140
Death	0–17	1308	65,422
	18–64	14,740	737,015
	65+	15,779	788,943
	Total	31,828	1,591,380

Table 4.17 Per person lost productivity (days)

	Symptoms, no medical	Medical attention	Hospitalized
0–17	0.7	1.5	9.3
18–64	0.5	1.9	15.6
65+	1.0	5.3	14.4

Table 4.18 Workday losses due to own illness (days)

	Age group	Mild scenario	Severe scenario
Symptoms, no medical treatment	18–64	3,800,458	7,170,675
Outpatient medical treatment	18–64	4,608,181	24,459,558
Hospitalization	18–64	1,537,644	23,064,657
Total		9,946,282	54,694,890

Table 4.17 presents the per-person lost productivity in days calculated based on the data from Molinari et al. (2007). Note that the analysis in Molinari et al. (2007) was primarily focused on seasonal influenza. We also compare the assumptions of per-person productivity loss in Molinari et al. (2007) with those in Meltzer et al. (1999), which focused on more severe outbreaks (e.g., influenza pandemic). The only notable difference is in the assumption of lost productivity for self-cured people between the two studies. Meltzer et al. (1999) assumed that the number of working-days lost for self-cured people is the same as working-days lost for people that received medical treatment (but no hospital stay). In this study, we decided to adopt the assumptions in Molinari et al. (2007), i.e., lost productivity for self-cured people is lower than people receiving medical treatment in both influenza outbreak scenarios. However, we note that as a sensitivity test, if we increase the productivity loss for the self-cured people by 100% for the Severe Outbreak scenario, the reduction in labor workforce participation will increase by only about 15% for the Severe Outbreak scenario.

The workday losses due to own illness for the 18–64 age group for the two pandemic influenza scenarios are presented in Table 4.18. For each health outcome category, we multiply the number of patients in Table 4.16 by the corresponding number of lost working days per person, and adjust for the labor force participation rate of 62.8 % (BLS, 2014).

Table 4.19 presents the workday losses due to caring of sick family members. These include caring for sick children in the 0–17 age group, sick spouse in the 18–64 age group, and sick elderly family members in the 65+ age group. When we calculate the workday losses due to the care of sick children, we adopt similar assumptions used in Dixon et al. (2010): (1) for any day that the children are sick at home, one full workday is lost for the caring parent; and (2) for any day that the children are hospitalized, half workday of the caring parent is lost. We also adjust the workday losses down according to the percentage of families with children that have no non-working parent. Based on the U.S. Census Bureau data, this percentage is 63 % in 2013 (U.S. Census Bureau 2014a). When we calculate the workday losses due to the care of sick spouses, we first apply the percentage of total population married with spouse present. This percentage is 50.7 % in 2013 (U.S. Census Bureau, 2014b). We next assume that 50 % of working

Table 4.19 Workday losses due to caring of sick family members (days)

	Age group of care recipients	Mild scenario	Severe scenario
Symptoms, no medical treatment	0–17	3,664,982	6,915,061
	18–64	0	0
	65+	0	0
Outpatient medical treatment	0–17	3,813,676	12,712,252
	18–64	583,719	1,945,731
	65+	1,145,256	10,350,871
Hospitalization	0–17	180,799	2,711,982
	18–64	194,774	2,921,605
	65+	187,118	2,806,767
Total		9,770,323	40,364,269

people with spouses will decide to take sick days to care for their sick spouses during the outbreaks of the influenza. We further assume that: (1) if people in the 18–64 age group only experience flu symptoms, but do not seek medical treatment, no caring from their spouses is needed; (2) for any sick day due to outpatient medical treatment, half workday of the caring spouse is lost; (3) for any day that is lost because of hospitalization, half workday of the caring spouse is lost. When we calculate the workday losses due to the care of sick elderly family members, we first assume that 41.7 % of the sick old people will receive cares from their family members. This is based on the data presented in the National Alliance for Caregiving (2009) report, which indicated that about 43.5 million adult Americans provide unpaid family cares for someone 50+ years of age. This represents 41.7 % of the 50+ population. We also use the labor force participation rate to get the percentage of unpaid family caregivers that are in the labor forth. We then further assume that: (1) if people in the 65+ age group only experience flu symptoms, but do not seek medical treatment, no caring from their family member is needed; (2) for any sick day due to outpatient medical treatment, half workday of the caring family member is lost; (3) for any day that is lost because of hospitalization, half workday of the caring family member is lost.

Table 4.20 presents the per-person medical expenditure for the three age groups calculated based on the data presented in Molinari et al. (2007). Because of lack of better data, we assume the per-person medical expenditures are same for the two scenarios. We believe the difference in the severity of the two influenza outbreak scenarios are mostly captured by the difference in the number of people received outpatient medical treatment, hospitalized, and died.[4]

[4]If we assume a slightly higher per person medical expenditure in the Severe Outbreak scenario, it will lead to slightly higher positive impacts to the economy stemming from the higher total medical expenditure. If at the same time we assume the per person lost productivity for the Severe Outbreak scenario is also slightly higher than the Mild Outbreak scenario as discussed in the sensitivity case above, the macro effect of the two will offset each other to some extent, since increased medical expenditure results in overall positive impact to the economy while reduction in workforce participation results in negative impact to the economy.

Table 4.20 Per person medical expenditure (in 2003$)

Category	Age group	Per person cost
Symptoms, no medical treatment	0–17	3.0
	18–64	3.0
	65+	3.0
Outpatient medical attention	0–17	204.2
	18–64	334.8
	65+	378.0
Hospitalized & survived	0–17	14,737.0
	18–64	26,853.1
	65+	14,164.1
Hospitalized & died	0–17	44,511.4
	18–64	113,159.1
	65+	37,372.3

Table 4.21 Medical expenditures (in billion 2003$)

	Age group	Mild scenario	Severe scenario
Symptoms, no medical treatment	0–17	0.03	0.05
	18–64	0.04	0.07
	65+	0.00	0.01
Outpatient medical treatment	0–17	0.81	2.68
	18–64	1.33	4.42
	65+	0.62	2.07
Hospitalized and survived	0–17	0.89	12.72
	18–64	3.83	43.60
	65+	1.18	9.85
Hospitalized and died	0–17	0.06	2.91
	18–64	1.67	83.40
	65+	0.59	29.48
Total		10.45	161.79

In Table 4.21, we compute the total medical expenditures for the two pandemic influenza scenarios by multiplying the per person medical costs by the number of people seeking medical attention presented in Table 4.16. Note that in the mild scenario, the largest expenditures are for those who were hospitalized, while, in the severe scenario, those who were hospitalized and died incur the largest expenditures.

4.A.2 With Vaccination

In the following analysis, we incorporate into consideration the effects of one mitigation strategy, vaccination, on the economic impacts of the two major influenza outbreak scenarios. We make the assumptions on the vaccination coverage based on the

Table 4.22 Vaccination coverage

Age group	2012–2013 season flu vaccination coverage	Assumed vaccination coverage for influenza outbreak scenarios	
		Mild scenario	Severe scenario
0–17	56.6 %	61.6 %	66.6 %
18–64	35.7 %	40.7 %	45.7 %
65+	66.2 %	71.2 %	76.2 %
All	45 %	50.0 %	55.0 %

Source: CDC (2014) for 2012–2013 season flu vaccination coverage

Table 4.23 Vaccination effectiveness

Flu season	Age group			
	0–4	5–19	20–64	65+
05–06	42.1	42.1	42.1	29.5
06–07	50.5	50.5	50.5	35.4
07–08	47.3	47.3	47.3	33.1
08–09	50.5	50.5	50.5	35.4
09–10	61.7	61.7	61.7	43.2
10–11	68.0	61.0	50.0	36.0
12–13	58.0	46.0	52.0	32.0
Average	54.0	51.3	50.6	34.9

Sources: Kostova et al. (2013) for 2005–2011 data. Bresee et al. (2013) for 2012–2013 flu season data

vaccination coverage rate in the 2012–2013 flu season. We assume that compared with a regular flu season, the vaccination coverage rate for each age group will be 5 % higher in the mild influenza outbreak scenario and 10 % higher in the severe influenza outbreak scenario. The vaccination coverage assumptions are presented in Table 4.22.

The effectiveness of vaccination, which is defined as the percentage reduction in the number of illness cases in each age group, is calculated as the average of the influenza vaccination effectiveness in the U.S. from 2005 to 2013 (see Table 4.23), which include both non-pandemic and pandemic (H1N1) flu seasons. Since the age group designation in Table 4.20 is slightly different from the one we used in our analysis, we computed the population weighted average vaccination effectiveness rate for age groups 0–4 and 5–19 in Table 4.23 to be used for the age group 0–17 in our scenarios. The effectiveness rate for the age groups 20–64 in Table 4.23 is used for the age group 18–64 in our scenarios. The final vaccination effectiveness rates we used in our analysis are: 0–17 (52 %), 18–64 (50.6 %), and 65+ (34.9 %). In addition, we assume the same vaccination effectiveness rate across different categories of health outcome (i.e., outpatient visits, hospitalization, and death) within each age group.

The costs associated with vaccination are calculated mainly based on the data from Prosser et al. (2011). Table 4.24 presents the vaccination-associated costs by cost category and by age group. In Prosser et al. (2011), the authors assumed that two doses of vaccination for children aged 6 months to 10 years and one dose for individuals in other age groups are required for a full vaccination. The authors also made detailed assumptions regarding the variation in costs associated with the vaccination settings

Table 4.24 Vaccination cost data

Age group	Mass vaccination setting (2009$/person)				Physician office setting (2009$/person)				Proportion of people using different vaccination settings		For physician office setting	
	Vaccine dose	Administration	Travel, waiting, vaccination time	Total	Vaccine dose	Administration	Travel, waiting, vaccination time	Total	Mass	Physician	Existing visit	Vaccination-specific visit
6–23 months	17.2	22.6	28.9	68.7	17.2	40.0	36.1	93.3	0	100 %	12.5 %	87.5 %
2 year	17.2	22.6	28.9	68.7	17.2	40.0	36.1	93.3	0	100 %	12.5 %	87.5 %
3–4 year	17.2	22.6	28.9	68.7	17.2	40.0	36.1	93.3	0	100 %	12.5 %	87.5 %
5–11 year	17.2	22.6	0.0	39.8	17.2	40.0	36.1	93.3	75 %	25 %	12.5 %	87.5 %
12–17 year	8.6	11.3	0.0	19.9	8.6	19.1	15.5	43.2	75 %	25 %	25.0 %	75.0 %
18–49 year, LR	8.6	11.3	14.4	34.3	8.6	17.7	11.5	37.9	73 %	27 %	44.0 %	56.0 %
50–64, LR	8.6	11.3	14.4	34.3	8.6	17.5	10.9	37.1	73 %	27 %	47.0 %	53.0 %
18–49 year, HR	8.6	11.3	14.4	34.3	8.6	17.7	11.5	37.9	50 %	50 %	44.0 %	56.0 %
50–64, HR	8.6	11.3	14.4	34.3	8.6	17.5	10.9	37.1	40 %	60 %	47.0 %	53.0 %
65+ year, all	8.6	11.3	14.4	34.3	8.6	16.2	7.0	31.8	50 %	50 %	66.0 %	34.0 %

Source: Calculated based on Prosser et al. (2011)

Table 4.25 Per person vaccination costs and associated lost work hours

Age group	Vaccine dose (2009$)	Admi-nistration (2009$)	Travel, waiting, vaccination time (2009$)	Side effects (2009 $)	Total (2009 $)	Total (2009$) (excluding cost of time)	Lost work hours
0–17	14.28	25.85	14.61	0.59	55.33	40.72	0.71
18–64	8.60	13.39	13.42	0.92	36.33	22.91	0.65
65+	8.60	13.73	10.72	0.92	33.98	23.25	0.52

Table 4.26 Health outcome estimates with vaccination (number of people)

	Age Group	Mild Scenario	Severe Scenario
Symptoms, no medical treatment	0–17	5,780,650	10,489,233
	18–64	9,611,480	17,557,267
	65+	990,161	1,824,777
	Total	16,382,291	29,871,278
Outpatient medical treatment	0–17	2,680,156	8,591,752
	18–64	3,145,632	10,151,476
	65+	1,233,893	4,017,319
	Total	7,059,681	22,760,548
Hospitalization	0–17	42,074	606,945
	18–64	124,975	1,814,911
	65+	74,352	1,089,346
	Total	241,401	3,511,202
Death	0–17	889	42,749
	18–64	11,706	566,634
	65+	11,853	578,876
	Total	24,448	1,188,259

(mass vaccination setting, such as schools or physician office setting, vs. physician office setting) for different age groups. For the physician office setting, the authors also made the distinction between vaccination at an existing visit and vaccination-initiated visit. The cost associated with vaccination administration and the amount of time people spend on travel, waiting, and vaccination vary by vaccination setting and whether or not the physician office visit is vaccination-specific.

In Table 4.25, we computed the vaccination costs for the three age groups used in our analysis based on the data presented in Table 4.24. We use population in each sub age group in Table 4.24 as weights to calculate the costs for the broader age groups. The high-risk ratios for age groups 18–49 and 50–64 from Molinari et al. (2007) are used to aggregate the costs of high-risk and non-high risk sub groups within the same age group of these two age groups. The costs associated with any potential vaccination side effects are also computed based on the data from Prosser et al. (2011). In the last column of Table 4.25, we translated the costs associated with travel, waiting and vaccination time into the number of lost work hours using the hourly wage rate, $20.62, used in Prosser et al. (2011).

Table 4.26 presents the health outcome results with vaccination. The workday losses associated with own illness for the 18–64 age group, caring for

Table 4.27 Workday losses (days) for own illness (with vaccination)

	Age group	Mild scenario	Severe scenario
Symptoms, no medical treatment	18–64	3,018,005	5,512,982
Outpatient medical treatment	18–64	3,659,431	18,805,078
Hospitalization	18–64	1,221,068	17,732,645
Total		7,898,503	42,050,705

Table 4.28 Workday losses (days) for caring sick family members (with vaccination)

	Age group	Mild scenario	Severe scenario
Symptoms, no medical treatment	0–17	2,490,196	4,518,567
	18–64	0	0
	65+	0	0
Outpatient medical treatment	0–17	2,591,227	8,306,674
	18–64	463,541	1,495,923
	65+	860,324	7,594,801
Hospitalization	0–17	122,845	1,772,113
	18–64	154,673	2,246,198
	65+	140,564	2,059,425
Total		6,823,370	27,993,700

Table 4.29 Workday losses (days) due to vaccination

	Mild scenario	Severe scenario
Working parents of 0–17 age group	2,570,189	2,778,808
18–64	4,152,859	4,663,039

sick family members, and receiving vaccination are presented in Tables 4.27, 4.28, and 4.29, respectively. The incremental medical expenditures due to the treatments of illness and vaccination (including costs of vaccine dose, administration, and side effects) are presented in Tables 4.30 and 4.31, respectively.

Table 4.30 Medical expenditures (with vaccination) (in billion 2003$)

	Age group	Mild scenario	Severe scenario
Symptoms, no medical treatment	0–17	0.02	0.03
	18–64	0.03	0.05
	65+	0.00	0.01
Outpatient medical treatment	0–17	0.55	1.75
	18–64	1.05	3.40
	65+	0.47	1.52
Hospitalized and survived	0–17	0.61	8.31
	18–64	3.04	33.52
	65+	0.89	7.23
Hospitalized and died	0–17	0.04	1.90
	18–64	1.32	64.12
	65+	0.44	21.63
Total		8.01	121.85

Table 4.31 Medical expenditures associated with vaccination (in billion 2009$)

	Mild scenario	Severe scenario
0–17	1.88	2.03
18–64	1.86	2.09
65+	0.72	0.78
Total	4.46	4.89

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Chapter 5
User Interface Variables

5.1 Summary

This chapter details Step 4 of the E-CAT research framework. This Step plays a key role in linking CGE analysis results to the reduced-form model. The CGE output and employment results serve as the set of dependent variables against which the independent variables are regressed. We refer to the independent variables as User Interface Variables. The resulting regression coefficients for each User Interface Variable in the reduced-form model are plugged into the E-CAT User Interface. Step 4 is presented in three parts. First is the identification of unique sets of User Interface Variables for each threat. Second is the randomized draw of 100 or more combinations of these variables using Latin Hypercube Sampling. Third, the 100 plus random draws are then converted to CGE inputs ("drivers") via a series of linkages. Detailed explanation of the reduced-from regression analysis is presented in the next chapter.

5.2 User Interface Variable Identification

Sets of User Interface Variables are first identified for each threat. As shown in Table 5.1, the User Interface Variables are grouped under the following categories: Magnitude, Time of Day, Duration, Economic Structure, Location, Other, Behavioral Avoidance, Behavioral Aversion, Resilience Recapture, and Resilience Relocation. As also shown in Table 5.1, each threat has a unique set of these variables. Not all of the User Interface Variables are relevant to each threat, or their effect on the dependent variables is judged to be too small to warrant inclusion in the regression analysis.

The *Magnitude* variable represents the size of each threat. The range and units or categories vary depending on the type of threat. For instance, if influenza is

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Table 5.1 User interface variables for E-CAT threats

Threat	Magnitude	Location	Time of day	Economic structure	Duration	Other	Resilience recapture	Resilience relocation	Behavioral avoidance	Behavioral aversion
Human pandemic	Infection rate	n.a.	n.a.	n.a.	Duration of outbreak	n.a.	Labor	n.a.	Tourism	Labor
Nuclear attack	Bomb size	Point of attack	Night /day	Attacked region structure[a]	n.a.	n.a.	n.a.	Business relocation	Tourism	Labor
Earthquake	Richter scale	Epicenter	Night /day	Impacted region structure[b]	n.a.	n.a.	Labor	Business relocation	n.a.	n.a.
Explosive terror attack	Bomb size	Point of attack	Night /day	Attacked region structure[a]	n.a.	n.a.	n.a.	Relocation	Tourism	Labor
Chem-bio food terror attack	Infection rate	n.a.	n.a.	Attacked region structure[a]	n.a.	n.a.	Labor	n.a.	Tourism	Product
Power grid failure	Extent of outage	Regional	n.a.	Impacted region structure[b]	Duration of outage	n.a.	Business recapture	n.a.	n.a.	n.a.
Transport system failure	Disruption level	Local to national	n.a.	n.a.	Duration of failure	n.a.	Business recapture	n.a.	Public place	n.a.
Animal disease outbreak	Animal infection rate	n.a.	n.a.	n.a.	Duration of outbreak	n.a.	Business recapture	n.a.	n.a.	Product
Aircraft as a weapon	Explosion equivalent	n.a.	Night /day	n.a.	n.a.	n.a.	n.a.	n.a.	Tourism	n.a.
Strike/industrial action	Number of sites	Local to national	n.a.	Imapacted region structure[b]	Duration of strike/action	Industry	Business recapture	n.a.	n.a.	n.a.
Cyber attack	Size of service attack	Regional	n.a.	n.a.	n.a.	Industry	Business recapture	n.a.	n.a.	n.a.
Large oil spills	Size of spills	n.a.	n.a.	n.a.	Duration of spill	n.a.	Business recapture	n.a.	Tourism	n.a.

[a]"Attacked" refers to human-related threat
[b]"Impacted" refers to natural hazard-related threat

Table 5.2 Day and night populations for location categories (people per square mile)

Location	Day time population			Night time population		
	Range	Mid-point	Implied scaling factor (from baseline of CBD, Day)	Range	Mid-point	Implied scaling factor (from baseline of CBD, night)[a,b]
CBD	>30,000	100,000	1	>10,000	10,000	0.07–0.36
Urban	2000–30,000	10,000	0.10	5000–10,000	7000	0.049–0.252
Suburban	500–2000	1000	0.01	1000–5000	2000	0.014–0.072
Rural	0–500	250	0.0025	0–1000	500	0.0035–0.018

[a]The range reflects the variation among different economic structures
[b]Any business-related initial shocks are Day Population only

selected, the magnitude is measured in numbers of people being affected, ranging from 30 to 75 million, whereas if the nuclear bomb attack is selected, the magnitude is measured in by size of the bomb, with a range between 1 KT and 25 KTs.[1]

The *Location* variable represents the location of the threat occurrence with respect to economic regions. For most of the threat types that involve a location variable, the following four categories are available for the user to specify: CBD, urban, suburban and rural. The economic consequences of threats occurring at different locations would vary substantially given the differences in impacted economic activities and population densities at those locations. For example, a daytime Nuclear Attack in the CBD/downtown area would kill far more people than an equivalent attack occurring in a suburban area, thereby causing greater impacts on the labor supply.

To determine the appropriate scaling factor for the magnitude of each threat with respect to location, we focus on population density as an indicator of economic impacts within each location class. Since there are no population density standards that relate directly to the classifications we are using, we construct a location impact scaling scheme based on the U.S. Census Data (2015) and expert judgment. The U.S. Census Bureau broadly defines an urban area as a region with population density greater than 1000 people per square mile (i.e. within 1.5 miles of the "Central Area"). However, analysis of Census data suggests that the population densities are more appropriately scaled as CBD (+30,000/sq. mile [employment]; midpoint 100,000/sq. mile), Urban (+10,000/sq. mile; midpoint 20,000/sq. mile), Suburban (+1000/sq. mile; midpoint 2000/sq. mile), and Rural (<1000/sq. mile; midpoint 500/sq. mile).

These values are in some cases integrated with the Time of Day considerations to produce the values in Table 5.2 above. These apply to incidents of short duration such as earthquakes, flash floods, and nuclear and radiologic devices. Values for

[1]Magnitudes below the lower end of the range are considered to yield relatively low levels of overall consequences.

Table 5.3 Earthquake magnitude, distance to property damage scaling[a]

Location[b]	Average property damage		Implied scaling factor (from baseline of urban, large Earthquake)	
	Small	Large	Small	Large
Urban	$1.1B	$67.8B	0.017	1
Rural	$23.5M	$412.4M	0.0003	0.006

Source: Calculations by authors, based on data from Heatwole and Rose (2013)
[a]These factors are based on the property damage values, under the assumption that an earthquake covers a large enough area to impact CBD, Urban and Suburban equally, regardless of where the epicenter is
[b]Urban and Rural categories are based upon the population affected by the earthquake. Rural is classified as earthquakes impacting under 50,000 people

Table 5.4 Calculation of nighttime and daytime population ratio for different cities

City	City			CBD/downtown		
	Nighttime population[a]	Daytime population[a]	Night/ day ratio	Nighttime population	Daytime population	Night/ day ratio
Miami	173,211	605,034	0.29	71,600[b]	200,000[b]	0.36
Denver	228,015	808,908	0.28	35,037[c]	136,401[c]	0.26
Des Moines	101,334	238,748	0.42	5431[d]	75,000[e]	0.07
National avg	93,306,969	217,803,860	0.43	30,915[f]	104,476[f]	0.30

[a]Nighttime population is measured by number of residents. Data are obtained from American Community Survey (2011), Table 3 Commuter-Adjusted Daytime Population: Places http://www.census.gov/hhes/commuting/data/acs2006_2010.html
[b]Miami Downtown Development Authority. Data reflect statistics for Year 2011
[c]Bell et al. (2014). Data reflects statistics for Year 2014
[d]U. S. Census Bureau (2011) https://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml
[e]Razor (2010)
[f]We use Denver as a proxy for the national average. See Denver Retail Scene (2011)

earthquakes are presented in Table 5.3 as an illustration, with our calculations using data from Heatwole and Rose (2013).

The *Time of Day* variable differentiates when the threat occurs because the economic impact of particular threats may vary substantially at different times of the day. We again focus on population density at different times of day as a primary indicator of economic impact. To continue the example from above, a daytime Nuclear Attack on a CBD area would have a greater impact than the same attack during the nighttime.

In addition, the time of day variable is also considered to vary among different types of cities with different economic structures. As illustrated in Table 5.4, we calculated the night/day population ratio for both city and CBD among four typical regions: US national average; Manufacturing-based (Detroit), Services-based (Miami); and Agricultural/Services-based (Des Moines), based on daytime and nighttime population data primarily obtained from the American Community Survey (2011).

The *Economic Structure* variable allows the user to specify the type of regional economy that the threat impacts. We adjust sectoral results following the CGE modeling simulations to account for differences between regional economic structures. As shown in Table 5.5, we use four "typical" regions on the basis of U.S. Bureau of Economic Analysis (2015) data: US national average; Manufacturing-based (Detroit), Services-based (Miami); and Agricultural/ Services-based (Des Moines).

The *Duration* variable is also threat-specific. For example, for the Human Pandemic, duration refers to the length of the outbreak, while for the Nuclear Attack this refers to the duration of contamination.

The *Other* variable is a catch-all variable that can apply to any threat-specific characteristic not included elsewhere.

The *Resilience* variables represent the resilience strategies that can be modeled with respect to each threat (recall the discussion of resilience in Chap. 1). Resilience strategies included here are Production Recapture and Relocation; other strategies such as Conservation, Substitution and Inventories are either inherently captured in the CGE (as in the case of Substitution), and hence are not included as a User Interface Variables that can be adjusted, or are not significantly distinct from the baseline (as in the case of Conservation) to be useful to decision makers in these cases.

For Relocation, we follow assumptions in terms of business continuity of operations after an improvised nuclear device (IND) attack used in the Radiological and Nuclear Terrorism Risk Assessment (RNTRA) economic model:

- 20 % of the evacuated businesses would fail because of the evacuation, resulting in output losses for one year (the duration of impact analyzed in the RNTRA model);
- 40 % of the businesses would relocate in 6 weeks and then resume the previous production level; for these businesses, the BI losses equal the total output of 6 weeks;
- The remaining 40 % businesses would relocate nearly immediately, resulting in zero BI losses.

These assumptions regarding business relocation translate to a reduction of about 75% of the BI losses from relocation in the first year (1 − 20 %–40 % * 6/52=75 %).

For Production Recapture, if the disruption caused by the threat/disaster is economy-wide, and last less than 3 months, the Recapture factor is 80 % for the upper-bound and 40 % for the lower-bound. If the total impacts are confined to any specific sector, we use the sector-specific Recapture factor from HAZUS as the upper bound, and the halved percentage as the lower bound. Note that the potential for Production Recapture diminishes as time passes. The factor decreases by 25 percentage points for every 3-month period, and, after 12 months, the recapture potential decreases to zero.

Table 5.5 Economic structure of typical regions

	Average		Manufacturing			Services			Agriculture/Manufacturing		
Industry	U.S.	Share	Detroit-Warren-Dear-born, MI	Share	Relative to US share	Miami-Fort Lauder-dale-West Palm Beach, FL	Share	Relative to US share	Des Moines-West Des Moines, IA	Share	Relative to US share
All industry total	15,079,920	100.0 %	224,726	90.7 %		281,076	100.0 %		42,654	100.0 %	
Private industries	13,245,359		206,861			252,309			39,025		
Agriculture, for-estry, fishing, and hunting	124,434	0.8 %	(D)	(D)	2.82	1858	0.7 %	0.80	576	1.4 %	1.64
Mining	328,271	2.2 %	(D)	(D)	1.07	400	0.1 %	0.07	50	0.1 %	0.05
Utilities	241,727	1.6 %	(D)	(D)	1.45	4264	1.5 %	0.95	206	0.5 %	0.30
Construction	546,816	3.6 %	6272	2.8 %	0.77	10,923	3.9 %	1.07	2034	4.8 %	1.32
Manufacturing	179,2684	11.9 %	39,869	17.7 %	1.49	9305	3.3 %	0.28	2286	5.4 %	0.45
Durable goods manufacturing	*953,678*	*6.3 %*	*33,945*	*15.1 %*	2.39	*5199*	*1.8 %*	0.29	*904*	*2.1 %*	0.34
Nondurable goods manufacturing	*839,006*	*5.6 %*	*5924*	*2.6 %*	0.47	*4106*	*1.5 %*	0.26	*1382*	*3.2 %*	0.58
Wholesale trade	929,698	6.2 %	(D)	(D)	0.38	26,337	9.4 %	1.52	3143	7.4 %	1.20
Retail trade	846,277	5.6 %	13,013	5.8 %	1.03	20,590	7.3 %	1.31	2001	4.7 %	0.84
Transportation and warehousing	431,165	2.9 %	6647	3.0 %	1.03	12,113	4.3 %	1.51	909	2.1 %	0.75
Information	776,346	5.1 %	6822	3.0 %	0.59	12,634	4.5 %	0.87	1388	3.3 %	0.63
Finance, insur-ance, real estate, rental, and leasing	3,145,102	20.9 %	43,419	19.3 %	0.93	69,225	24.6 %	1.18	17672	41.4 %	1.99
Finance and insurance	*1,065,947*	*7.1 %*	*13,332*	*5.9 %*	0.84	*15,880*	*5.6 %*	0.80	*11,021*	*25.8 %*	3.66

Real estate and rental and leasing	*2,079,155*	*13.8 %*	*30,087*	*13.4 %*	0.97	*53,345*	*19.0 %*	1.38	*6652*	*15.6 %*	1.13
Professional and business services	1,926,698	12.8 %	37,427	16.7 %	1.30	36,201	12.9 %	1.01	3786	8.9 %	0.69
Educational services, health care, and social assistance	1,269,605	8.4 %	20,177	9.0 %	1.07	25,086	8.9 %	1.06	2957	6.9 %	0.82
Arts, entertainment, recreation, accommodation, and food services	566,476	3.8 %	7541	3.4 %	0.89	15,698	5.6 %	1.49	1199	2.8 %	0.75
Other services, except government	320,060	2.1 %	4748	2.1 %	1.00	7675	2.7 %	1.29	818	1.9 %	0.90
Government	1,834,561	12.2 %	17,865	7.9 %	0.65	28767	10.2 %	0.84	3630	8.5 %	0.70

(*D*) Data are not provided by U.S. BEA (2015). In this case, average shares are used to estimate the region relative to the U.S. share value

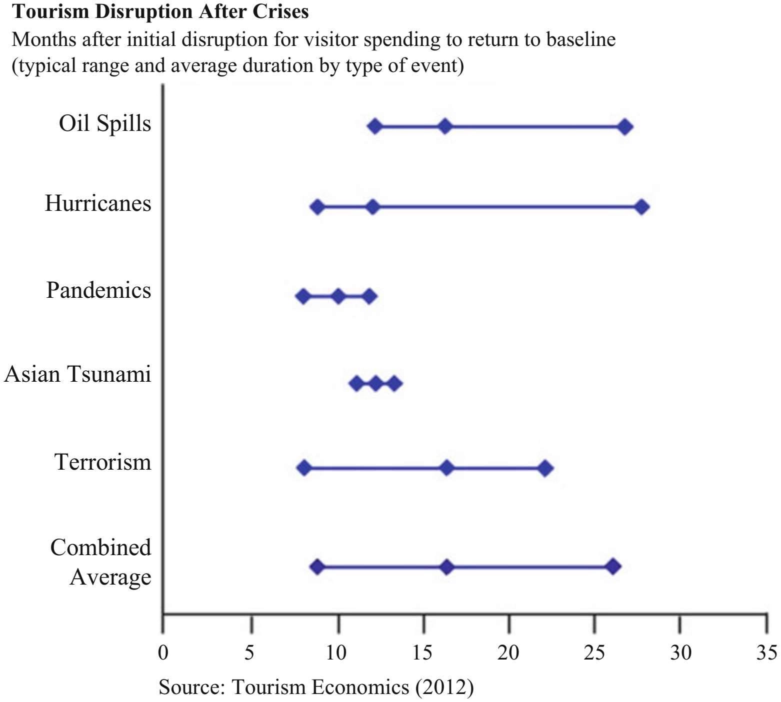

Fig. 5.1 Tourism disruption after crises

Table 5.6 Tourism disruptions by threats

Event	Tourism disruption	Relative to terrorism	Total tourism spending ($B)
Oil spills	18 months	1.125	72.27
Hurricanes	12 months	0.75	48.18
Pandemics	11 months	0.6875	44.17
Asian tsunami	12 months	0.75	48.18
Terrorism	16 months	1	64.24

Source: Oxford Economics (2009)

The *Behavioral* variables represent individual and collective behavioral responses that might on aggregate influence overall economic impacts. These include both avoidance and aversion behaviors discussed in Chap. 1. Tourism is an example of avoidance behavior with most application here. As shown in Figure 5.1, tourism has been differentially impacted across numerous types of hazardous events. Table 5.6 translates the midpoints identified in Fig. 5.1 into scaling estimates for the impact of different threats in E-CAT on tourism.

5.3 Randomized Draws of User Interface Variable Combinations

In the second part of the User Interface Variable step, randomized draws of multiple variable combinations are conducted. These randomized draws generate values between the range boundaries for the Magnitude case (e.g., 30 and 75 million people infected for the Human Pandemic threat), and different options for the other relevant User Interface Variable categories across each threat. This randomized draw is performed using Latin Hypercube Sampling, which essentially ensures that draws are spread across the entire distribution range. This approach protects against clustering of draws within particular areas of the distribution.

5.4 Conversion of Random Draw Combinations to CGE Inputs

In the third part of the User Interface Variable step, the multiple random draw combinations are converted to CGE inputs via a series of linkages. Here, for each random draw, the values for most of the User Interface Variable are converted into a single "Impact Size" variable. This process starts with the Magnitude variable, and subsequently each relevant User Interface Variable value is used to scale up or down the Magnitude value. For example, for the Human Pandemic, if the initial Magnitude value were 30 million people infected, a Duration User Interface Variable (in this case, the Length of Outbreak) value of 6 months would not change the Impact Size value because that is the default value. However, a value of 9 months would increase the Impact Size to 1.5 times the initial Magnitude, or 45 million (this stems from a linear relationship between impacts and duration—9 months is 50 % longer than the base case duration of 6 months).

This Impact Size is then converted into the CGE drivers specific to each threat, e.g., to capital stock damage, workforce participation disruption, changes in medical expenditures, and behavioral change factors such as impacts on tourism (foreign inbound, domestic outbound, and domestic internal), education, imports and exports, and transportation use. These linkages are assumed to be linear across all values between the upper- and lower-bound estimates of the Impact Size threat characteristics, except for the case of earthquakes because the Richter scale is a logarithmic, but other distributional relationships could be adopted for other threats.

There are a number of exceptions to this approach of converting the relevant variables into a single Impact Size variable. First, the Economic Structure (of the impacted region) variable does not influence the Impact Size variable, as it is not input into the CGE model, but instead is used to convert CGE model results into appropriate regional impacts (more details are provided in the following chapter). Hence, any threat for which Economic Structure is a relevant variable generates 400 result outputs instead of the minimum 100, as there are 4 different Economic Structure options.

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Chapter 6
Estimation of the Reduced Form Coefficients for the E-CAT User Interface

This chapter illustrates the modeling procedures for estimating the reduced form coefficients for the E-CAT user interface tool. The process includes the following steps: a random sampling procedure, a CGE simulation with an automatic looping function, and an econometric analysis including both ordinary least squares estimation (OLS) and quantile regression. The key purpose is to establish the linkages between the threat characteristics identified in the user interface (type of threat, magnitude of threat, time of day, location, sectors impacted, etc.) and the CGE "driver" inputs (capital stock, labor, medical expenditures, tourism, etc.). For illustration purposes, the Human Pandemic scenario is used in the discussion below.

6.1 Random Sampling Procedure

The first step is to establish the linkage between each user input variable and its associated CGE "drivers." The current version of analysis assumes a linear relationship for most of the threat types. For instance, since the range of Human Pandemic threat is between 30 million (10 % population infection rate) and 75 million (25 % infection rate), the CGE input variables such as a labor shock (deaths and injuries), the health expenditure shock and tourism shock are expected to have a linear relationship with magnitude. The specific upper- and lower-bounds of the direct impact values for each CGE driver, as illustrated in Table 6.1, are then used to calculate the parameters (alpha and beta) of the following linear Eq. (6.1) using a deterministic simultaneous equation solution:

$$Y_{i,j} = \alpha_j + \beta_j M_i \tag{6.1}$$

where M denotes the magnitude of the threat in case i, which represents a particular simulation scenario, where i = 1, 2,. . .100. $Y_{i,j}$ is the *j*th direct impact driver corresponding to the *i*th case (each case scenario involves a different value of

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Table 6.1 Summary of consequences for human pandemic lower and upper bounds

			Direct impacts		CGE driver impact		
CGE driver ID No.	Consequence type	Unit	Non-pandemic influenza (10 % infection rate)	Severe outbreak (25 % infection rate)	Model variable	Non-pandemic influenza (10 % infection rate)	Severe outbreak (25 % infection rate)
1	Deaths	no.	31,282	403,746	Labor force	−0.01 %	−0.16 %
2	Illnesses (workday losses)	million	18.7	83.3	Labor force	0.05 %	−0.23 %
3	Medical treatment cost	billions of 2012$	$5.92	$81.18	Household spending	0.34 %	4.69 %
	Avoidance behavior:						
4	Reduction in inbound international travel	billions of 2012$	−$1.95	−$15.93	Exports	−2.43 %	−19.83 %
5	Reduction in outbound international travel	billions of 2012$	−$0.96	−$7.89	Air travel	−2.43 %	−19.83 %
6	Reduction in domestic travel/leisure activities	billions of 2012$	−$33.15	−$66.30	Household, Gov't, Business spending	−5.00 %	−10.00 %
7	Reduction in public transportation use	billions of 2012$	−$4.05	−$8.11	Public transit sector productivity	−5.00 %	−10.00 %
8	Reduction in attendance of educational activities	billions of 2012$	−$1.01	−$2.01	Education sector productivity	−0.11 %	−0.22 %

Table 6.2 Linear equations between the magnitude of human pandemic and CGE drivers

Driver	Equation
Deaths (thousands of people)	$Y_1 = -216.7 + 24.8*M$
Illnesses (millions of workday losses)	$Y_2 = -24.3 + 4.3*M$
Medical treatment cost	$Y_3 = -44.1 + 5.0*M$
Avoidance behavior (Reduction in inbound international travel)	$Y_4 = 7.1 - 0.9*M$
Avoidance behavior (Reduction in outbound international travel)	$Y_5 = 4.0 - 0.5*M$
Avoidance behavior (Reduction in domestic travel/leisure activities)	$Y_6 = -11.2 - 2.2*M$
Avoidance behavior (Reduction in public transportation use)	$Y_7 = -1.1 - 0.3*M$
Avoidance behavior (Reduction in attendance of educational facilities)	$Y_8 = -0.3 - 0.1*M$

M denotes the magnitude of the threat and Y denotes the different CGE input variables such as capital, labor, medical expenditure, international tourism expenditure, etc

M). j represents the direct impact driver category and $j = 1, 2, \ldots 8$. As illustrated in Table 6.1, the direct impact drivers include death, illnesses, medical treatment cost, and avoidance behaviour in 8 travel and tourism-related sectors. For working out the size of α_j and β_j, M takes two extreme values, 55 and 75, representing millions of people being infected.

The second step is to generate synthetic data including all explanatory variables of economic consequences, which will be then converted into CGE drivers to simulate economic impact results in terms of GDP and employment. The user interface variables in the case of Human Pandemic scenario (including magnitude, duration, and avoidance behavior) are randomly generated 100 times with randomized combinations using Latin-Hypercube sampling approach. The corresponding shock values for each CGE input driver are then randomly generated 100 times as well based on the estimated linear Eq. (6.1) in the general form, as illustrated in Table 6.2.

The duration, time of day and location variables are introduced to rescale the magnitude variable to control for the variations of impacts caused by different duration of a threat, different populations affected (day-time vs. night-time), and types of geographic areas being impacted, respectively. The scaling criteria are different for each variable. For example, the direct impact drivers of a 9-month human pandemic are assumed to be 1.5 times the 6-month threat, ceteris paribus. Likewise, the direct impact of a threat occurs in an urban area is assumed to be 0.2 times of the threat that occurs in a Central Business District (CBD).

Resilience factors are considered in terms of relocation and production recapture in this threat scenario. The lower and upper bounds for relocation are assumed as 37.5 and 75 %, respectively (see Heatwole et al. 2014).

The lower – and upper – bound recapture are assumed as 40 and 80 %, respectively (see Rose and Lim 2002). The dampening effect of resilience due to relocation is applied to capital shock in the CGE analysis, whereas the resilience caused by recapture is applied to productivity shock.

The effect of avoidance behavior is modeled through the shock to tourism-related sectors, which is simulated through the change of export demand in sectors including Food Manufacturing, Petroleum Refinery, Other Non-Durable Goods, Air Transport, Rail Transport, Hotels and Restaurants, Other Business Services, Entertainment and Medical Services.[1] If the variable of avoidance behavior equals one, the tourism shock is added as an additional driver in a simulation. The benchmark of the tourism impact is based on the Human Pandemic scenario (Prager et al. 2016), and the Oxford Economics (2009) study is adopted as a reference to rescale the tourism shock for other types of threats.

The effect of aversion is modeled through a fixed shock of wage increase. If the dummy user input variable of aversion equals to one, a shock of 0.2 % increase in the national wage level is added to the CGE simulation. This is based on Giesecke et al. (2012) who find that a wage increase of 20 % at the regional level could be translated into a national level at the rate of 0.2 %.

6.2 CGE Simulation with Loop Function

After the generation of 100 different groups of CGE drivers for each threat type, CGE simulations are conducted to generate economic impact results including GDP value change, GDP percent change, employment level change, and employment percent change. To achieve efficient CGE simulations for multiple times with combinations of different CGE input variables, the input and output codes of the USCGE model were modified and a loop function for modelling execution was developed. The CGE simulations are able to be executed automatically up to a thousand times. The execution time for various threats ranges between half an hour and two hours depending on the numbers of CGE drivers and the magnitude of shock values.[2] Figure 6.1 illustrates the distribution of simulation results of the Human Pandemic scenario in terms of GDP and employment losses. The simulated results are then adopted to estimate reduced-form coefficients using both ordinary least-square (OLS) and quantile regressions.

[1] Avoidance only is applied to foreign travel. Domestic travel is offset by spending on other travel modes and other goods.

[2] Simulation with the productivity shock can take a relatively longer time to solve due to the greater requirements to achieve a feasible solution (computational convergence). Only simulation results with a feasible solution were included in the final synthetic data.

6.3 Econometric Analysis

The econometric analysis is conducted based on synthetic data generated from both the Latin-Hypercube sampling and the corresponding economic impact results from CGE simulations. Table 6.3 provides an example of the descriptive statistics of the human pandemic scenario.

The Pearson correlation test is conducted before the econometric analysis to detect whether any potential multicollinearity exists in the data. The test result for the human pandemic scenario is summarized in Table 6.4. The relatively low correlation suggests that the issue of multicollinearity does not exist in this case.

The reduced form coefficient estimation of the Human Pandemic scenario is conducted using multivariate regression analysis. For this particular threat case, the reduced form estimations are conducted using GDP and employment losses both in value terms (GDP) and percent change as the dependent variables, respectively.

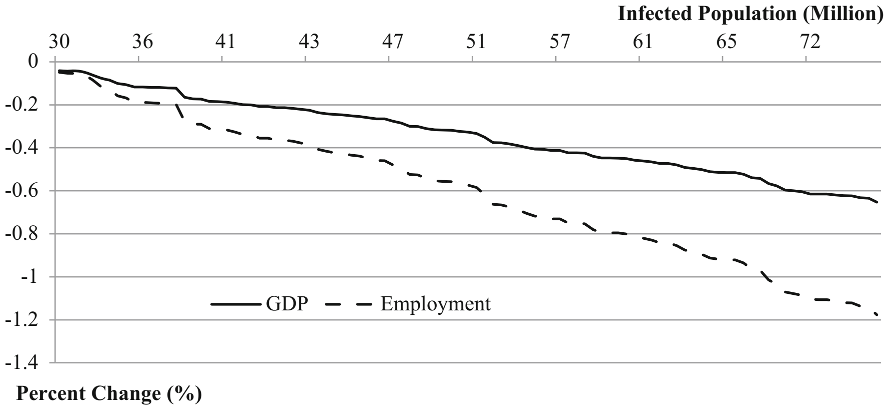

Fig. 6.1 Distribution of simulated GDP and employment losses in the human pandemic scenario

Table 6.3 Descriptive statistics of the synthetic data of the human pandemic scenario

Variable	Obs.	Mean	Std. Dev.	Min	Max
GDP	100	−45.483	30.304	−140.973	−7.634
Employment	100	−0.590	0.509	−2.084	−0.013
GDP percent	100	−0.279	0.186	−0.865	−0.047
Employment percent	100	−0.459	0.396	−1.620	−0.010
Magnitude	100	52.681	13.350	30.100	74.800
Duration (0=6 months, 1=9 months)	100	0.480	0.502	0	1
Lower_recapture	100	0.460	0.501	0	1
Upper_recapture	100	0.290	0.456	0	1
Avoidance	100	0.540	0.501	0	1
Aversion	100	0.510	0.502	0	1

Table 6.4 Pearson correlation test of the human pandemic scenario

Variable	Magnitude	Duration	Lower_ Recapture	Upper_ Recapture	Avoidance	Aversion
Magnitude	1					
Duration	0.031	1				
Lower_Recapture	−0.026	−0.043	1			
Upper_Recapture	−0.033	0.004	−0.590	1		
Avoidance	−0.046	0.003	−0.034	−0.073	1	
Aversion	0.107	−0.099	−0.059	−0.079	0.019	1

Independent variables include magnitude, duration and resilience factors of lower and upper bounds, behavioral avoidance and aversion.

The magnitude variable is measured in the numbers of people being infected with a range between 55 million (mild Pandemic) and 75 million (severe Pandemic). Duration is a dummy variable in which one indicates the 9-month duration, and zero indicates the 6-month duration. The resilience factor represents the effect of production recapture on labor force loss and household spending on medical services. The lower bound variable indicates that 40 % of the damages were recovered due to production recapture, whereas the upper bound represents an 80 % of recovery.

The econometric estimations are conducted using ordinary least square (OLS) regression and quantile regression at the 5th, 25th, 50th, 75th, and 95th quantile level using Stata, respectively. The major difference between OLS and quantile regression is that the method of OLS results in estimates that approximate the conditional mean of the response variable given certain values of the predictor variables, whereas quantile regression aims at estimating either the conditional median or other quantiles of the response variable (Davino et al. 2013). Quantile regression is expected to be more robust against outliers in the response measurements than OLS and the adoption of estimates at various quantile levels captures uncertainties in the reduced form estimates. The results of OLS and different quantile regressions in terms of factors explaining GDP and Employment losses are illustrated in Tables 6.5 and 6.6, respectively.

The results show that the quantile coefficients of magnitude, duration, resilience factors and avoidance are all statistically significantly different from the OLS estimates, indicating different effects along the distribution of the dependent variables. Overall, the results suggest that quantile regression provides more robust and comprehensive estimates of the user input variables on the dependent variables. The uncertainties of economic consequences are captured in terms of different quantile coefficient estimates.

The distribution of CGE simulation results in terms of impacts on the national GDP illustrates a clear linear influence from various user input variables. The econometric estimation results in Table 6.5 suggest that in the Human Pandemic scenario, a 100 million people being infected case is associated with a $1.475 billion (−0.01 %) loss of the national GDP and 23 thousand (−1.80 %) job losses.

Table 6.5 Regression results for the human pandemic scenario (Dependent variable: GDP, billions of dollars)

Model	(1) OLS	(2) 5 % Quantile	(3) 25 % Quantile	(4) 50 % Quantile	(5) 75 % Quantile	(6) 95 % Quantile
Magnitude	−1.475***	−1.460***	−1.490***	−1.528***	−1.514***	−1.541***
	(−18.34)	(−13.22)	(−11.03)	(−186.15)	(−11.86)	(−30.87)
Duration	−12.84***	−20.33***	−12.27***	−12.87***	−9.816***	−1.437
	(−6.02)	(−10.26)	(−3.90)	(−60.06)	(−3.34)	(−1.61)
Lower_recapture	24.55***	42.70***	32.59***	20.42***	15.09***	8.700***
	(9.18)	(−10.26)	(8.56)	(74.89)	(4.05)	(11.93)
Upper_recapture	44.12***	47.48***	48.85***	40.94***	41.49***	38.39***
	(14.99)	(19.99)	(11.44)	(135.79)	(10.42)	(32.53)
Avoidance	−13.80***	−9.840***	−14.89***	−16.00***	−16.19***	−21.99***
	(−6.44)	(−4.96)	(−4.60)	(−74.02)	(−5.89)	(−26.74)
Aversion	−1.310	2.919	−0.600	−0.0563	0.723	2.460***
	(−0.60)	(1.61)	(−0.18)	(−0.26)	(0.24)	(3.30)
Constant	22.42***	−7.051	13.71	29.15***	34.34***	47.69***
	(4.25)	(−0.95)	(1.58)	(53.76)	(4.41)	(21.02)
No. of Obs. Adj. R^2	100	100	100	100	100	100
	0.878					

t statistics in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 6.6 Regression results for the human pandemic scenario (Dependent variable: EMP, thousands of jobs)

Model	(1) OLS	(2) 5 % Quantile	(3) 25 % Quantile	(4) 50 % Quantile	(5) 75 % Quantile	(6) 95 % Quantile
Magnitude	−23.05***	−19.41***	−21.70***	−23.91***	−24.48***	−20.83***
	(−16.20)	(−28.29)	(−23.60)	(−16.20)	(−12.94)	(15.56)
Duration	−266.8***	−447.9***	−302.5***	−257.5***	−232.7***	−79.75***
	(−7.06)	(−31.49)	(−13.89)	(−6.78)	(−5.80)	(−3.32)
Lower_recapture	454.8***	792.4***	555.1***	381.0***	360.7***	121.2***
	(9.61)	(43.83)	(19.65)	(8.10)	(6.86)	(6.20)
Upper_recapture	833.0***	843.1***	863.8***	770.6***	870.0***	651.1***
	(15.99)	(49.02)	(30.05)	(14.77)	(14.98)	(20.57)
Avoidance	33.52	−0.00000123	47.04**	26.23	−1.623	−1.111
	(0.88)	(−0.00)	(2.11)	(0.69)	(−0.04)	(−0.05)
Aversion	−50.67	−0.0000162	−15.62	−14.86	−4.392	−3.994
	(−1.32)	(−0.00)	(−0.69)	(−0.38)	(−0.11)	(−0.20)
Constant	308.9***	−246.6***	60.72	403.3***	532.9***	527.9***
	(3.31)	(−7.65)	(1.04)	(4.18)	(4.03)	(8.72)
No. of Obs. Adj. R^2	100	100	100	100	100	100
	0.865					

t statistics in parentheses
*p < 0.10, **p < 0.05, ***p < 0.01

Table 6.7 OLS and quantile reduced-form equations

OLS	GDP	=	$22.42 - 1.48 \cdot Magnitude - 12.84 \cdot Duration + 22.55 \cdot Lower\ recapture + 44.12 \cdot Upper\ recapture - 13.80 \cdot Avoidance$
	Employment	=	$308.9 - 23.05 \cdot Magnitude - 266.8 \cdot Duration + 454.8 \cdot Lower\ recapture + 833 \cdot Upper\ recapture$
5 % Quantile	GDP	=	$-7.05 - 1.46 \cdot Magnitude - 20.33 \cdot Duration + 42.70 \cdot Lower\ recapture + 47.48 \cdot Upper\ recapture - 9.84 \cdot Avoidance$
	Employment	=	$-246.6 - 19.41 \cdot Magnitude - 447.9 \cdot Duration + 792.4 \cdot Lower\ recapture + 843.1 \cdot Upper\ recapture$
25 % Quantile	GDP	=	$13.71 - 1.49 \cdot Magnitude - 12.27 \cdot Duration + 32.59 \cdot Lower\ recapture + 48.85 \cdot Upper\ recapture - 14.89 \cdot Avoidance$
	Employment	=	$60.72 - 21.7 \cdot Magnitude - 302.5 \cdot Duration + 555.1 \cdot Lower\ recapture + 863.8 \cdot Upper\ recapture + 47.04 \cdot Aversion$
50 % Quantile	GDP	=	$29.15 - 1.53 \cdot Magnitude - 12.87 \cdot Duration + 20.42 \cdot Lower\ recapture + 44.94 \cdot Upper\ recapture - 16.00 \cdot Avoidance$
	Employment	=	$403.3 - 23.91 \cdot Magnitude - 257.5 \cdot Duration + 381 \cdot Lower\ recapture + 770.6 \cdot Upper\ recapture$
75 % Quantile	GDP	=	$34.34 - 1.51 \cdot Magnitude - 9.82 \cdot Duration + 15.09 \cdot Lower\ recapture + 41.49 \cdot Upper\ recapture - 16.19 \cdot Avoidance$
	Employment	=	$532.9 - 24.48 \cdot Magnitude - 232.7 \cdot Duration + 360.7 \cdot Lower\ recapture + 870 \cdot Upper\ recapture$
95 % Quantile	GDP	=	$47.69 - 1.54 \cdot Magnitude - 1.44 \cdot Duration + 8.70 \cdot Lower\ recapture + 38.39 \cdot Upper\ recapture - 21.99 \cdot Avoidance + 2.46 \cdot Aversion$
	Employment	=	$527.9 - 20.83 \cdot Magnitude - 79.75 \cdot Duration + 121.2 \cdot Lower\ recapture + 651.1 \cdot Upper\ recapture$

The reduced-form equations shown in Table 6.7 indicate the E-CAT estimations for GDP and employment by substituting the “conditioning” factors for the analysis to specify in a particular case chosen by an analyst for the right-hand side variables.

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Chapter 7
Uncertainty Analysis

7.1 Introduction

Economic consequences of natural, intentional, and accidental hazards include uncertainties. These uncertainties may arise due to variability in an event's magnitude, timing, duration, and location, as well as differing economic structures in various regions of interest. Quantification and propagation of these uncertainties result in probability distributions associated with various economic consequences. In this study, uncertainties associated with economic consequences are based on variability in stochastic regressors (predictor variables) within least squares and quantile regression models. Addressing uncertainties associated with regression model form (using linear predictor functions) was beyond the scope of this study.[1] Variability in stochastic regressors may arise due to inherent randomness *(aleatory* uncertainty) or incomplete knowledge (*epistemic* uncertainty) about underlying phenomena. *Epistemic* uncertainty may be reduced to *aleatory* uncertainty with more information, whereas *aleatory* uncertainty is not reducible. These consequence distributions, presented within a user-friendly and readily deployable tool, may be valuable for homeland security policy-makers conducting national risk assessments and for emergency management decision-making.

7.2 Overview

This chapter discusses the quantification, representation, propagation, and visualization of uncertainties in economic consequences within the E-CAT user interface. E-CAT displays inputs and outputs associated with hazardous events and their economic impacts with appropriate characterization of uncertainty. The economic

[1]Regression parameter uncertainty will result in additional uncertainty associated with economic consequences.

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9_7

consequences for each threat type are presented as probability distributions using input variables as: (1) point estimates, (2) mathematical intervals, and (3) triangular probability distributions. The uncertainty analysis is integrated with the CREATE Economic Consequence Analysis Framework (Rose 2009, 2015; Rose et al. 2014), which has expanded economic impact analysis to include resilience (actions to maintain system function and recover more rapidly), behavioral linkages (primarily fear), and remediation of consequences and spillover effects of countermeasures. Measures of uncertainty are aligned with various components of the framework and leverage prior work on quantifying uncertainties in direct hazard consequences (Chatterjee et al. 2015; Chatterjee et al. 2013a, b).

7.3 Uncertainty Quantification Tasks

The uncertainties in economic consequences may be characterized as statistical probability distributions using simulation methods. The research team implemented the following uncertainty quantification tasks:

- Monte Carlo sampling with variance reduction – This task involved Latin Hypercube sampling (Wyss and Jorgenson 1998), leading to more evenly distributed sample points across the sample space, to generate synthetic data associated with the E-CAT user interface input variables.

- Ordinary Least Squares regression (OLS) with stochastic regressors using synthetic data – This task produced estimates that approximate the conditional mean (given independent variables) of the dependent variable (i.e. economic consequences generated from CGE simulations).

- Quantile regression (QR) with stochastic regressors using synthetic data – This task produced estimates that approximate the conditional median (given independent variables) and other quantiles (i.e. 5, 25, 75, and 95 %) of the dependent variable. QR generates richer distributional data associated with the dependent variable and is more robust against outliers in the consequence estimates (Koenker and Bassett 1978; Koenker and Hallock 2001; Yu et al. 2003).

7.4 Uncertainty Representation

Uncertainties in quantitative models may emerge due to inherent randomness in samples or incomplete knowledge about fundamental phenomena (Paté-Cornell 1996). Representing these uncertainties appropriately is an important step for identifying knowns and unknowns among the modeling elements. Randomness may be addressed through the use of statistical probability distributions, whereas

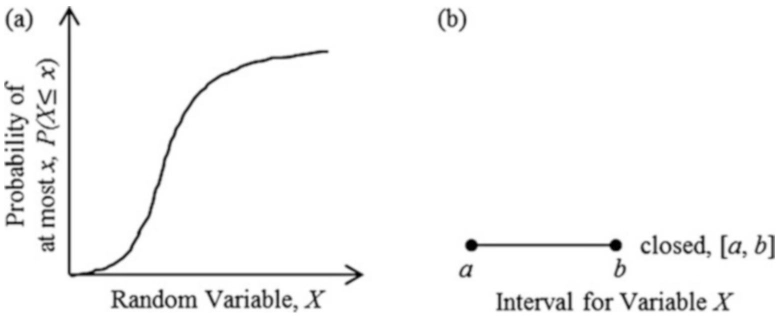

Fig. 7.1 Uncertainty representations for hypothetical variable, X. (**a**) Probability distribution. (**b**) Mathematical interval

incomplete knowledge may be represented using mathematical intervals (Abrahamsson 2002).

Figure 7.1 presents two uncertainty representations (probability distribution and mathematical interval) for a hypothetical variable, X with uncertain values. Other uncertainty representations including probability bounds, probability boxes, and fuzzy sets are beyond the scope of this study. A probability distribution (see Fig. 7.1a) contains probabilities of occurrence of outcomes from a random experiment; and may be represented as a cumulative distribution function, $F(X) = P(X \leq x)$ that is a plot of probabilities of non-exceedance at various values (or estimates) associated with a random variable, X. Random variables with uncertain values may be *discrete* (with countable number of values; described using probability mass functions) or *continuous* (all values in a given interval; described using probability density functions). A mathematical interval (see Fig. 7.1b) is a set of real numbers between lower and upper bounds, $[a, b]$. The choice of uncertainty representation depends on data and knowledge associated with the variable of interest, i.e. economic consequences as GDP or employment losses in this study. Typically, with limited historical data for catastrophic events, probability distributions associated with reduced form model variables may be defined using a Bayesian approach (i.e. as degree of belief) with expert judgments.

7.5 Uncertainty Propagation

Approaches for propagating uncertainty to the output variables (i.e. GDP or employment losses) using reduced form regression models depend on the representations associated with the uncertain input variables. Let us assume $\mathbf{x}$ representing a vector of m uncertain input variables; a single input variable is denoted as X; and the regression model output y is a function of $\mathbf{x}$: $y = g(\mathbf{x})$. In this study, the function $g(\mathbf{x})$ represents the OLS and QR models that generate output y as

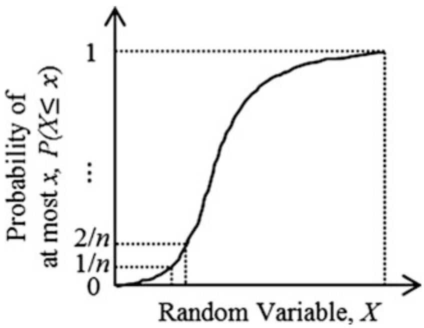

Fig. 7.2 Pictorial representation of Latin Hypercube sampling

conditional mean or quantiles (given independent variables $\mathbf{x}$) respectively. A Monte Carlo sampling approach is adopted in this study and is outlined below (for detailed discussion on additional approaches refer to: Abrahamsson 2002 and Cox 2012).

Let us assume an input random variable, X that has a cumulative distribution function $F(X) = P(X \leq x)$ and an inverse cumulative distribution function $F^{-1}(p) = x$. If $F(X)$ is strictly increasing and continuous, then $F^{-1}(p)$, where $p \in [0, 1]$, is a real number x such that $F(x) = p$. To generate a random sample value for an input random variable, X, a random number, r, is first generated between 0 and 1 (there are several random sampling schemes available in the literature (Abrahamsson 2002) including Latin hypercube sampling (a stratified sampling scheme without replacement–adopted in this study and presented in Fig. 7.2)). In the Latin Hypercube approach, $F(X)$ is segmented into n equally spaced intervals, where n represents the number of sampling iterations and a sample is drawn from each of these intervals. This sampled value, r, is then passed through the inverse cumulative distribution function $F^{-1}(r)$ to generate a random sample value, x. Similarly, random sample values for all m uncertain input variables may be generated resulting in a random sample vector, $\mathbf{x}$. The vector $\mathbf{x}$ when passed through the function $g(\mathbf{x})$ produces a random output value of y. This Monte Carlo sampling process may be repeated several times to generate an empirical (simulation data-driven) probability distribution for the output random variable, Y. In this study, a Latin Hypercube sampling technique is adopted to sample from triangular probability distributions (with parameters as the minimum, most likely or mode, and maximum values) associated with the input random variables. Selecting values at equal intervals between the minimum and maximum values does not take into account the probabilistic structure associated with the input random variables. Also, this may not result in samples that are drawn from the overall distributional spread.

Often times, an analyst may require summarizing the distribution of the output variable, Y using mathematical expectation, $E[Y]$. With the discrete variable assumption: $E[Y] = \sum_{i=1}^{\infty} y_i \cdot p_i$; and with the continuous variable assumption, $E[Y] = \int_{-\infty}^{\infty} yf(y)dy$ where $f(y)$ is the probability density function. Also, various quantile values, $Q(p)$ may be computed as $\inf\{y \in \mathbb{R} : F(y) \geq p\}$ to identify the minimum value of y that results in $F(y) \geq p$. In this study, expected means and quantiles are computed using empirical consequence distributions under the discrete assumption.

For the case with interval representation of input variables, lower and upper bound values are passed through the reduced form regression models (both OLS and QR) to generate lower and upper bound estimates for the output variables.

7.6 Uncertainty Visualization

Uncertainty analysis outputs may be visualized in various forms, given user-specified inputs as point estimates, intervals, or triangular probability distributions (represented using minimum, most likely, and maximum estimate values of a, c, and b respectively—see Fig. 7.3). Triangular distributions were chosen due to the relative ease in eliciting expert judgments for distribution parameters a, c, and b. Figure 7.3a displays a notional probability density function and Fig. 7.3b presents a notional cumulative distribution function for a random variable, X with triangular probability distribution.

The following discussion includes numerical examples to demonstrate various uncertainty visualizations based on notional input estimates. Loss variable in the charts below refers to an economic loss output type, e.g., GDP or employment loss.

- *Input Variables as Point Estimates* – Figure 7.4 presents an empirical distribution function using the QR results. This chart provides probabilities of not

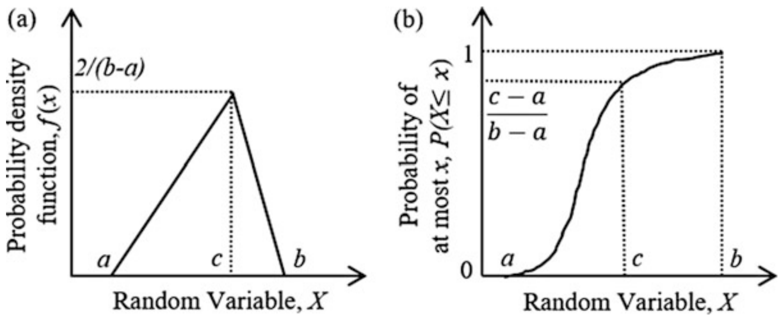

Fig. 7.3 Notional triangular probability density and cumulative distribution functions. (**a**) Triangular probability density function. (**b**) Triangular cumulative distribution function

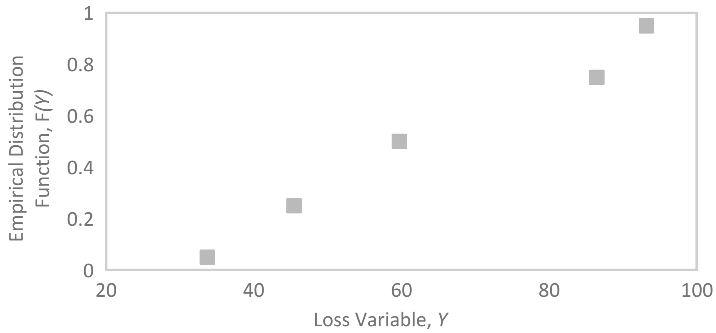

Fig. 7.4 Notional empirical distribution function

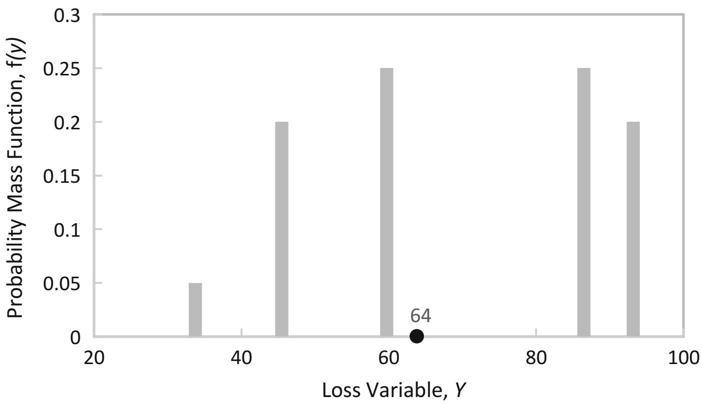

Fig. 7.5 Notional truncated probability mass function

exceeding certain levels of loss. For example, with probability of 0.5, losses will not exceed 59.74 units. Figure 7.5 presents a truncated probability mass function using the QR results and assuming economic loss as a discrete random variable. The bars in the plot represent probabilities of various levels of losses. For example, with probability of 0.05, losses will be 33.74 units. The mean loss is represented as a point value (at $y = 64$) from the OLS results. Figure 7.6 presents a box and whisker plot representing variability in the loss variable at different quantiles (5, 25, 50, 75, and 95 %) and the mean. We assume that the minimum and maximum losses correspond to the 5 and 95 % quantile losses. For example, with probability of 0.75, losses will not exceed 86.47 units.

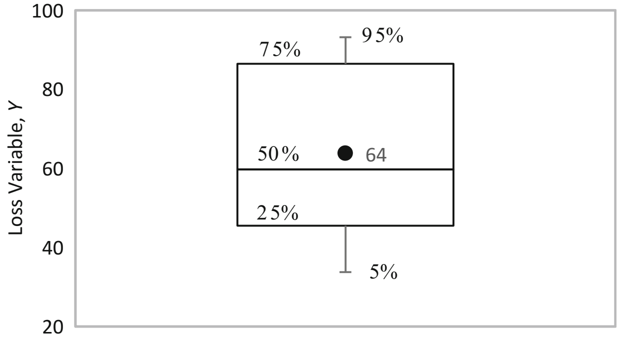

Fig. 7.6 Notional box and whisker plot

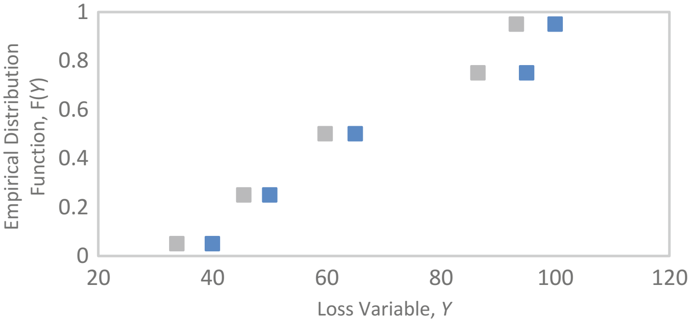

Fig. 7.7 Notional empirical distribution function with bounds (Note: *lower* bounds are in *gray* and *upper* bounds are in *blue*)

- *Input Variables as Mathematical Intervals* – Figure 7.7 presents bounds for empirical distribution functions using the QR results. This chart provides probabilities of not exceeding certain bounded levels of loss. For example, with probability of 0.5, losses will not exceed a level between [59.74, 65] units. Figure 7.8 presents truncated probability mass functions for lower and upper bounds of economic losses using the QR results. The underlying assumption here is that the lower and upper bounds of economic losses are discrete random variables (In Fig. 7.5, lower bounds are in gray and upper bounds are in blue). The bars in the plot represent probabilities of various levels of losses. For example, with probability of 0.05, losses will be between [33.74, 40] units. The bounds on the mean loss (i.e. [64, 75]) are represented as point values from the OLS results. Figure 7.9 presents box and whisker plots, at the lower and upper bounds, representing variability in the loss variable at different quantiles (5, 25, 50, 75, and 95 %) and the mean. For example, with probability of 0.75, losses will not exceed a level between [86.47, 95] units.

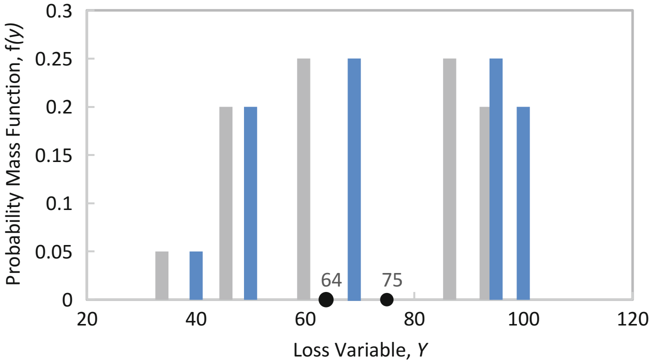

Fig. 7.8 Notional truncated probability mass function with bounds (Note: *lower* bounds are in *gray* and *upper* bounds are in *blue*)

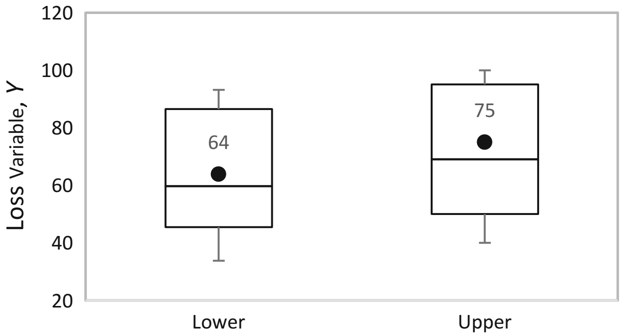

Fig. 7.9 Notional box and whisker plot with bounds

- *Input Variables as Triangular Probability Distributions* – Figure 7.10 presents empirical cumulative distribution functions (ECDF) for the mean value, 5, and 95 % quantiles of an economic loss variable, based on empirical measures from the OLS and QR results. Lower to higher quantile distributions are presented as we navigate from left to right in the figure. These curves provide cumulative probabilities of non-exceedance at different levels of loss. The expected magnitudes of mean and quantile losses are estimated by evaluating the area above these curves. Figure 7.11 presents a relative frequency distribution for the mean value of an economic loss variable. A relative frequency distribution is a summary of the frequency proportions in a group of non-overlapping data

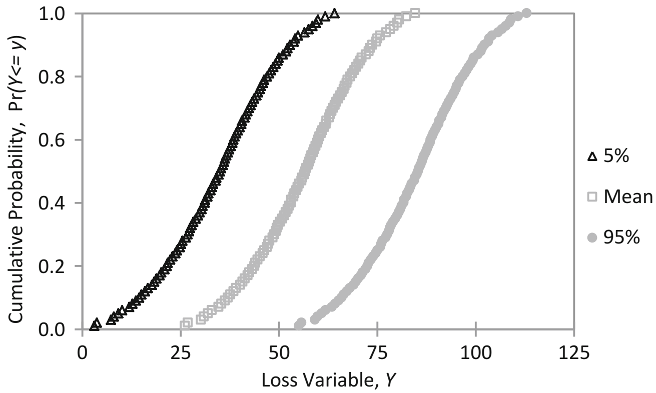

Fig. 7.10 Notional empirical cumulative distribution functions for mean and quantiles of the loss variable

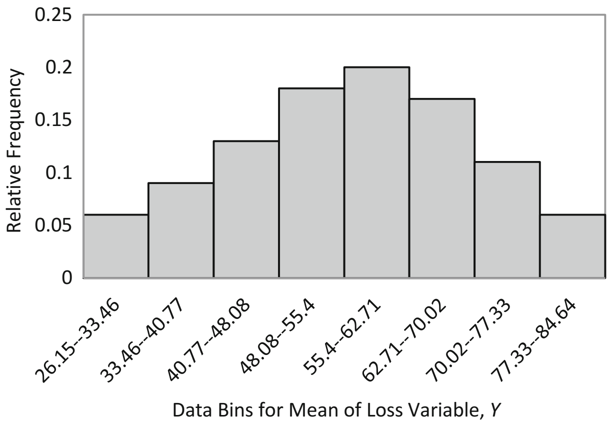

Fig. 7.11 Notional relative frequency distribution for mean of the loss variable

bins. Similar relative frequency plots were generated at other quantiles using the QR results.

As an example, based on the triangular probability distribution assumption, cumulative probability distributions at various quantiles and relative frequency plots for economic losses due to aviation system disruption are presented in Fig. 7.12.

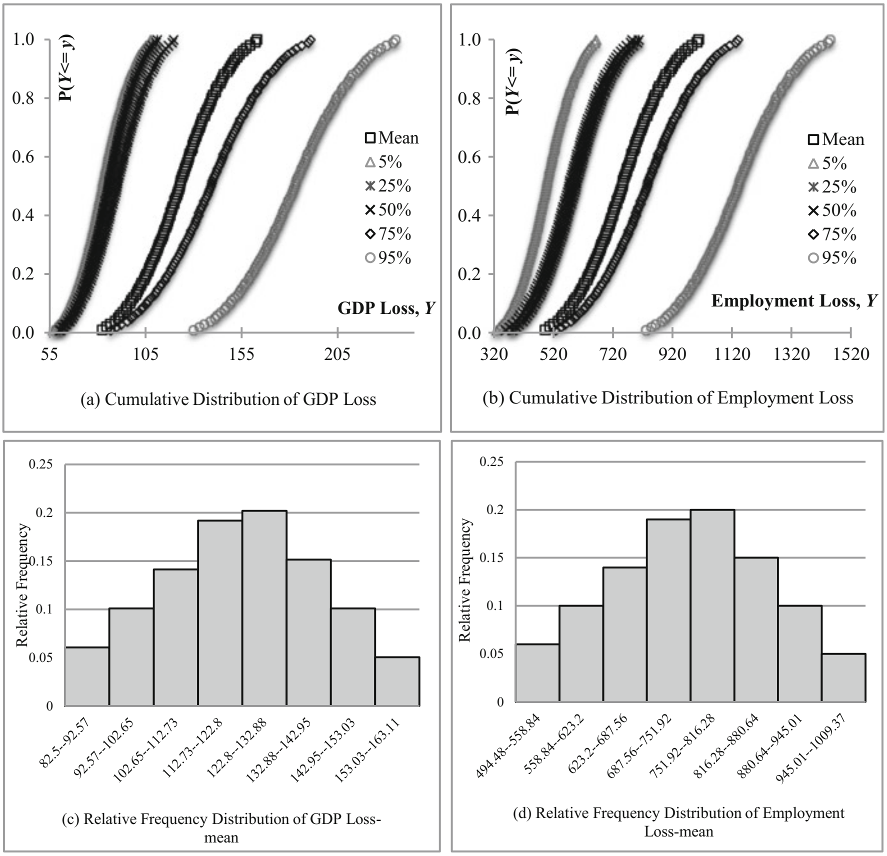

Fig. 7.12 Probability distributions of economic losses due to aviation system disruption

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Chapter 8
Validation of Computable General Equilibrium Based Models

8.1 Introduction

Model validation in economics is more difficult than in many other disciplines, especially at the macroeconomic level. Controlled experiments are often inappropriate because macroeconomic modeling involves independent individual decision-makers and their interactions in the context of background conditions, such as changes business cycles and technological change, many of which are random or otherwise difficult to predict. Economics is more of an "observational" discipline like meteorology, astronomy, or sociology, and must therefore use approaches such as statistical analysis of data or simulation approaches.

Thus, the validation of E-CAT must be accomplished through indirect methods. In this chapter, we present some of these methods, discuss their relative merits and limitations, and apply two formal methods to one of the threats—an aviation system disruption.

This report is divided into 4 Sections. In Sect. 8.2, we summarize validation approaches and their application to CGE models in general. In Sect. 8.3, we discuss various model validation procedures, and in Sect. 8.4 apply two of them to the E-CAT Model.

8.2 Validation Criteria and Their Application to CGE Models

The following criteria have been used to validate economic models in general (see, e.g., Rose 2004; Dixon and Rimmer 2013):

Conceptual Soundness Does the model have a solid conceptual base? Is it based on established theory?

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9_8

CGE models are generally considered to have a solid conceptual base because they represent an operational version of general equilibrium theory, or the interaction of individual decision-makers in multiple interconnected markets. The CGE model at the core of E-CAT is based on one major traditional approach to CGE model construction initially developed by Dervis et al. (1982) and Robinson et al. (1990) and that is closely related to another prevalent approach popular in the U.S. (Rutherford 1999).

Realism. Is the model reasonably realistic? Are its major assumptions too great a departure from reality? Of course, all models are an abstraction, but is the level of abstraction so great as to question its validity?

CGE models reflect standard behavior of representative producers and consumers in a multi-market context. The assumption of equilibrium is often criticized, but the CGE model at its core allows for disequilibria in the labor market, trade balances, fiscal balances, and, most importantly, imbalances in markets of produced goods and services due to external shocks (Rose 2015).

Applicability. Is the model appropriate to the case in point? Does it cover the requirements of the topic to be addressed?

CGE models represent the state-of-the-art approach to analyzing the economic consequences of disasters. They are especially adept at tracing economy-wide impacts of targeted shocks. More recently, they have been refined to include the 2 major categories of unconventional responses that distinguish economic consequence analysis of disasters from ordinary economic impact analysis: behavioral responses and resilience (see, e.g., Giesecke et al. 2012; Rose and Liao 2005). These 2 major categories of drivers are key components of the E-CAT analysis.

Comprehensiveness. Is the model broad enough to encompass key background conditions that could have a significant effect on the results?

CGE models are very comprehensive in several ways. They represent a full accounting of all inputs into production and all goods and services in consumption. They also include socioeconomic accounts and can include environmental variables, though there was no necessity for this to be done for E-CAT, except in limited cases such as oil spills. They also factor in many background conditions, such as unemployment rates, labor force participation rates, and factor constraints. However, most CGE models omit explicit consideration of inventories and excess capacity, as does ours, but these are relatively minor sources of resilience.

Data Quality. Are the data reasonably current? Are the data from a reliable source? Primary data are generally considered the most reliable, in part, because collection methods and assumptions are likely known, in contrast to secondary data, which refers to a compilation or aggregation of data, typically from published source, for which the origin is not as well known.

CGE models are based on a comprehensive set of input-output table accounts and their extension to social accounting matrix. Only national governments have the resources to collect the universe of data to compile these tables from primary sources. Even tables based on samples are prohibitively expensive. Hence, a number of "data-reduction", or "non-survey", methods have been devised to generate input-output (I-O) tables. Similar methods have been devised to provide reasonable model updates as well (Miller and Blair 2007). We have used the most recent I-O data available to calibrate the USCGE Model. One area in which practically all CGE models can be criticized is the fact that their other major parameters, elasticities substitution in elasticities of demand are not based on primary data or inferential statistics as for the time and place which the model conforms. Rather they are "borrowed" from the most closely related context possible. Our selection of elasticity values was made after an extensive inspection of alternative elasticity values.

Model Construction. Is the method of model construction sound?

CGE Models are constructed on the basis of model calibration fitting many of the parameters to a single year of data by using "ratio" estimators, or simply the division of data on inputs by data on the gross output they produce in each sector. This estimator is considered to have less desirable properties than, for example, OLS or maximum likelihood estimators using regression analysis. The USCGE Model is also open to this criticism.

Track Record. Has the model or similar models been validated in related contexts?

CGE models are one of the most widely used tools of economic consequence analysis. They are held to be widely superior to input-output models, especially in the more complex context of disasters (Rose 1995, 2015). They are considered to be reliable for a broad range of public and private sector decisions. They have been validated in general by several methods (Dixon and Rimmer 2013). The US CGE Model and its several regional variants have been applied in more than a dozen major studies of the economic consequences of disasters published in major peer-reviewed journals (see, e.g., Rose and Liao 2005; Rose et al. 2007; Rose et al. 2009; Oladosu et al. 2013; Rose et al. 2015).

Accuracy. Are the results of the application of the model reasonable overall, or, better yet, considered accurate according to modeling or statistical criteria?

CGE models are considered to provide reliable results in many applications, especially where omitted variables are not likely to have a major influence and where assumptions are not too great of a departure from reality. Two validation tests are applied later in this chapter and help demonstrate the accuracy of the US CGE Model.

8.3 Model Testing Procedures and CGE Models

Several methods, or procedures, have been used to test economic models. Dixon and Rimmer (2013) note that there is not necessarily a one-to-one correspondence between the purposes of model validation (which we have labeled "approaches") and procedures. The following represents a list of such procedures, following Dixon and Rimmer (2013), and general practice in economics and other fields.

- Is the model consistent with an underlying set of statistical accounts? For example, does the base year or equilibrium version of the model replicate these accounts?

CGE models are based on an underlying table of double-entry book keeping accounts for an economy in a given year stemming from both input-output tables and social accounting matrices. The model is based on a transparent conversion of these annual inter-sectoral flows to normalized parameters (initial direct input values) by dividing each element in the table by its column sum (in most cases, the gross output of the good or service produced). Key parameters allow these input values to vary under different conditions. One of the standard consistency checks in constructing an I-O model is whether the equilibrium solution replicates the base accounts. This was done for our model as well.

- Estimation of Parameters. Do superior methods other than those on which the model is based, such as econometric estimation, yield parameter estimates close to those used in the model?

It has long been observed that the accuracy of many parameters used in CGE models could be improved by econometric estimation. However, the necessary time series data are generally not available to do so. Only one major US CGE model has been completely and consistently econometrically estimated (Jorgenson and Wilcoxen 1990).

- In-sample Tests. Can the model be used to accurately reflect the data and results of some of the inputs in its construction? For example, for regression analysis of model results, will that regression equation yield a close approximation to one of the sets of variable and parameter values used to estimate the regression in the first place?

CGE models have been found to pass this most basic test, which we apply below. We also applied a more sophisticated version known as the "cross-validation" test (Armine et al. 2013).

- Out-of-sample Tests. Do the model predictions conform to observed cases not in the sample?

This is a valuable test of CGE models when it is feasible. However, due to the lack of accurate estimates of out-of-sample cases, we do not apply it to our model in this volume. Note also that CGE models, as is the case for other modeling approaches, will perform better if background conditions remain relatively constant.

- Back-casting. Can the model simulate the historical record? This overlaps with the third procedure, if the historical case is within the sample, and overlaps with the fourth procedure if it is not.

  This applies in a like manner to out-of-sample Tests.

- Sensitivity Tests. Do the predictions of the model swing wildly as a result of small changes in parameters? A more formal version of this procedure would generate confidence intervals surrounding the model outputs.

Given a large number of parameters (direct input or "technical" coefficients) in most I-O models, individual, or a small set of, parameter changes are unlikely to cause major swings in the results, except for limited cases where the parameters are a very high proportion of the sector's input requirements. Estimation of confidence intervals is not possible because CGE models lack, or have very limited, formal statistical properties.[1] We have performed several tests on the model parameters, such as input substitution elasticities and import (Armington) elasticities.

- Reduced-form Methods. The most basic version of this approach is what Dixon and Rimmer (2013) refer to as the "back-of-the-envelope" (BOTHE) approach, which translates the analysis into simple supply-demand, or equivalent "basic principles" diagrams. Another approach is regression analysis of multiple simulations from the model on the basis of the "synthetic" data generated by it. Typically ordinary least squares estimation is used, but additional insight can be developed by breaking the sample up in applying quantile regression analysis (see, e.g., Rose et al. 2011).

  This approach is at the core of the E-CAT Model.

- Consistency Checks. Is the model able to replicate outcomes for its endogenous variables given "true" values of exogenous ones?

  This represents an important step in the calibration of CGE models in general, and is satisfied in the construction of the US CGE Model. Specifically, the initial equilibrium solution of a CGE model must replicate its underlying social accounting matrix.

8.4 Model Validation Applications

We performed two formal tests of the validity of an Aviation System Disruption Scenario that is included in E-CAT. Below we present the results of both In-sample Validation and Cross-sample Tests.

8.4.1 In-Sample Validation

We first tested the reduced-form estimates from the E-CAT by subjecting them to two in-sample test cases. This involved comparing the GDP loss estimates of the Tool with the estimates from the studies by Rose et al. (2015) and Rose et al. (2009). The former was adopted as the lower-bound case, whereas the latter was adopted as the upper-bound case. Both studies were conducted independently under

[1] Econometric methods are often considered superior because they involve more extensive data (e.g., a time series, as opposed to data for a single year) and yield "goodness of fit" measures.

Table 8.1 Comparison of economic consequence estimates between E-CAT and the literature

Scenario	Reference case estimate[a]	E-CAT estimate[a] (High resilience)	Percent difference from reference case estimate	E-CAT estimate[a] (Low resilience)	Percent difference from reference case estimate
LAX bomb	23.1	16.5	−28.6	28.5	23.4
9/11 WTC	121.0	109.5[b]	−9.5	n/a	n/a

[a]Measured in billions of 2012 dollars
[b]The estimate is converted from $109 billion in 2006 dollars using the GDP deflator

somewhat different analytical frameworks, but under similar assumptions. This consistency and the broad range of outcomes make them useful benchmarks to validate E-CAT for this scenario.

The comparison of economic consequence estimates between E-CAT and the two in-sample test cases are presented in Table 8.1. For the case of a hypothetical bomb attack at the Los Angeles International Airport (LAX), the GDP loss estimates in the lower- and upper-bound resilience cases from E-CAT are $28.5 billion and $16.5 billion, respectively, and the reference case estimate of the national GDP loss is $23.1 billion (Rose et al. 2015), which falls very close to the midpoint of the range of the E-CAT estimates.

For the 9/11 World Trade Center (WTC) case, the estimate from E-CAT in the upper-bound resilience case is $109.5 billion, which is very close to the estimate of $121 billion by Rose et al. (2009). Only the E-CAT estimate with high resilience is included for the WTC attack scenario given the fact that resilience was actually found to be high in this case (Rose et al., 2009), so no bounding exercise was necessary. In the LAX Bomb Attack scenario, modeled in accordance with a TSA scenario, both low- and high-level resilience are included, as this scenario is purely hypothetical, and we have no specific knowledge of whether resilience would be closer to the lower or upper bound.

Overall, the in-sample validation tests support the contention that the E-CAT reduced-form tool is able to produce estimates of GDP losses consistent with the reference case estimates. The difference between the E-CAT estimate and the reference estimate is – 9.5 % in the case of the 9/11 WTC Attack, whereas the estimates from the E-CAT in the case of the LAX Bomb Attack range between −28.6 and +23.4 % of the reference case estimate, and the average estimate ($22.5 billion) from E-CAT deviates from the reference estimate ($23.1 billion) by only −2.5 %.

8.4.2 Cross-Validation Test

The reduced-form CGE approach is validated using the cross-validation test with holdout samples based on the aviation system disruption scenario. The purpose is to evaluate whether the synthetic data generated from Latin-hypercube sampling

Table 8.2 Mean value comparison of variables among data sets

Variable	Training set	Testing set	Raw data
GDP change in value (billions of dollars)	−51.70	−31.81	−47.45
GDP change in percent	−0.32	−0.20	−0.29
Employment change	−0.32	−0.21	−0.30
Employment change in percent (millions of jobs)	−0.25	−0.17	−0.23
Magnitude (Percent of air service being disrupted)	14.59	14.72	14.65
Resilience lower bound (1=Yes/0=No)	0.45	0.40	0.44
Resilience upper bound (1=Yes/0=No)	0.23	0.35	0.25
Behavioral effect (1=Yes/0=No)	0.56	0.30	0.50
No. of observations	80	20	100

procedure and CGE analysis has an overfitting problem.[2] This is an important task as the validation helps to justify the predictive power of the reduced form equations.

The test with holdout samples was implemented in the following six steps:

- 80 % of the raw synthetic data is selected as the "training set" and the remaining 20 % as the "testing set".
- Training set, testing set and raw dataset are compared.
- Reduced form OLS regressions were conducted based on the training set for GDP and employment.
- Comparison of regression results for GDP based on the raw dataset and the training set suggests that the reduced form estimates for GDP and employment are consistent in both cases.
- Predicted estimates based on the training set are applied for the testing set to calculate goodness of fit of sub-reduced form model.
- Validation results are compared, suggesting the training set provides very similar estimates to those based on the raw data.

The descriptive statistics of the training set, testing set and the raw dataset are compared in Table 8.2, which shows that the mean values of all the variables for the training sets are higher than that for the original data set, whereas the mean values for the testing sets are relatively lower than that for the original set. The results of the reduced-form regression analysis are compared and summarized in Table 8.3. The deviations (in percent) of the training set estimates from the original set are generally within 5 %.

To further validate the data, the predicted estimates based on the training set are compared with the raw data set. The goodness of fit is measured through the multiple correlation coefficient, R-squared, which is calculated based on the

[2]"Overfitting is an issue that exists in in statistics and machine learning. It occurs when a statistical model describes random error or noise instead of the underlying relationship. Overfitting generally occurs when a model is excessively complex, such as having too many parameters relative to the number of observations. A model that has been overfit will generally have poor predictive performance, as it can exaggerate minor fluctuations in the data."

Table 8.3 OLS regression results for the aviation system disruption scenario

	Original data		Training set		Deviation (in percent)[a]	
Dependent variable	GDP	Employment	GDP	Employment	GDP	Employment
Magnitude	−7.32***	−0.05***	−7.43***	−0.05***	1.50	0.00
	(−10.16)	(−11.14)	(−9.42)	(−10.18)		
Resilience lower bound	48.13***	0.318***	50.55***	0.329***	5.03	0.03
	(−8.47)	(−9.60)	(8.11)	(−9.02)		
Resilience upper bound	60.14***	0.392***	61.96***	0.401***	3.03	0.02
	(−9.22)	(−10.33)	(8.39)	(9.26)		
Behavior impact	−73.14***	−0.400***	−74.56***	−0.408***	1.94	0.02
	(−14.93)	(−14.03)	(−13.59)	(−12.71)		
Constant	60.15***	0.350***	61.93***	0.357***	2.96	0.02
	(−5.08)	(−5.08)	(4.88)	(4.81)		
No. of observations	100	100	80	80		
adj. R-squared	0.795	0.803	0.804	0.802		

[a]Deviation is calculated using the difference of estimates between the training set and the original data divided by the original estimates
[b]T-statistics are included in parenthesis
[c]***represents statistical significance at the 1 % level

Table 8.4 Validation test based on the comparison between predictions of testing set

Content	Training set (80 observations)	Raw data (100 observations)
Reduced form equation		
GDP	GDP=61.93−7.43*Magnitude +50.55*Lower-Bound Resilience +61.96*Upper-Bound Resilience−74.56*Behavioral Effect	GDP=60.15−7.32*Magnitude +48.13*Lower-Bound Resilience +60.14*Upper-Bound Resilience−73.14*Behavioral Effect
Employment	Employment=0.35−0.05*Magnitude +0.32*Lower-Bound Resilience +0.4*Upper-Bound Resilience−0.40*Behavioral Effect	Employment=0.36−0.05*Magnitude +0.33*Lower-Bound Resilience +0.4*Upper-Bound Resilience−0.41*Behavioral Effect
R-squared[a]		
GDP	0.749	0.756
Employment	0.784	0.782

[a]The R-squared is calculated based on comparing the variability of the estimation errors with the variability of the original values for the testing sets, and is defined as: $R^2 = 1 - \frac{SS_E}{SS_T}$ where $SS_T = \sum_i (y_i - \widetilde{y})^2$ and $SS_E = \sum_i (y_i - \widehat{y}_i)^2$. y_i and $\widehat{y}_i$ are the original data values and predicted values based on either the training set or the original data set, respectively. Hence, the SS_T measures the total sum of squares, and SS_E measures the sum of squared errors

predicted values of GDP and employment and their corresponding values in the two different data sets. The validation results in Table 8.4 suggest that the training set provides very similar estimates to the estimates based on the raw data. Hence, it shows that the synthetic data are reliable for the reduced-form analysis.

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Chapter 9
E-CAT User Interface Tool

This chapter introduces the design of the E-CAT user interface tool. The tool is based on Excel with Visual Basic for Applications (VBA). Three different economic consequence options are developed for each type of threat, including a point estimate (Option 1), interval estimate (Option 2) and uncertainty distribution (Option 3). Step-by-step instructions are presented in the User's Guide in Appendix A.

The conceptual framework of the E-CAT user interface tool is illustrated in Fig. 9.1. The analytical function of E-CAT is structured in four layers. The master user interface is designed in layer 1, which functions as the gate for various options. The different user options are designed in layer 2, which functions as the major platform for both data input and output visualization. User input information is translated from contextual format into numerical format and is then calculated based on the corresponding reduced-form coefficients stored in layer 4. User Option 3 differs from Option 1 and 2 in that an additional step for Latin-hypercube sampling (LHS) procedure is added in layer 3 to present the output uncertainty in various forms of probability distribution.

One of the fundamental objectives of E-CAT user interface development is to achieve a user-friendly design. This requires the following considerations:

1. To make the interface page as concise as possible, but to maintain its functionalities as comprehensive as possible
2. To have the internal modeling mechanism operating as smoothly as possible with minimum computational source consumption
3. To make the interface tool as compatible as possible so that users with little knowledge of software installation can operate it
4. To make the functionalities as clear as possible in providing instruction to guide operation.

The designs of the various functional pages of E-CAT are introduced as follows. The master user interface page, as illustrated in Fig. 9.2, is designed for the user to specify the types of threat and option of output estimation. The current version of E-CAT is able to conduct economic consequence analysis for the following types

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9_9

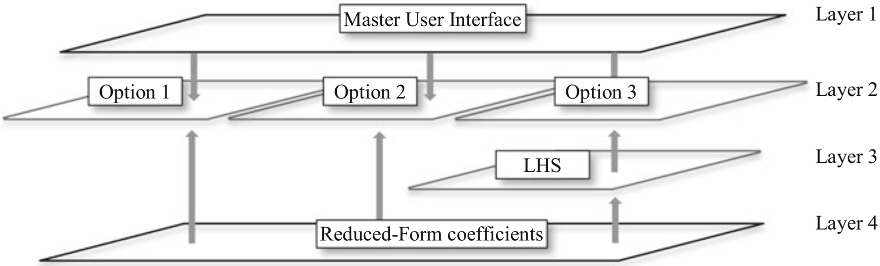


Fig. 9.1 E-CAT user interface tool structure design

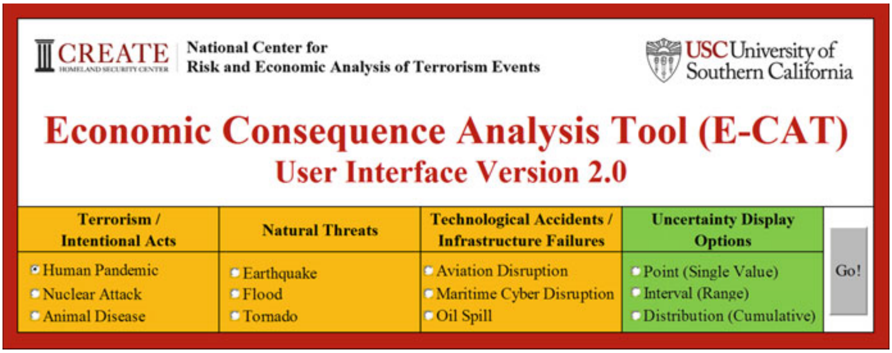


Fig. 9.2 E-CAT user interface for threat type and option selection

of threats: human pandemic, nuclear attack, animal disease, earthquake, flood, aviation system disruption, maritime cyber disruption and an oil spill. Three output estimation options are provided for each one. The Tool is designed to be user-friendly. For instance, when a user specifies the type of threat as “human pandemic” and the output option type as “point estimate”, a point estimate page as illustrated in Fig. 9.3 is presented automatically. After the consequence analysis, the user can return to the main menu to select another threat or a different estimation option by clicking the “Main Menu” button on the top right of each option page. All results can be printed automatically by clicking the “Print Results” button. In addition, a “Reset Default” button is designed for the user to reset all the settings to default values.

The point estimate results (Fig. 9.3) allow the user to calculate economic consequences of a selected threat type in terms of GDP and employment losses based on a single magnitude input variable with combinations of other user input variables, such as “time of day”, “duration”, “resilience”, “location”, and etc. The user input area is highlighted in yellow, whereas grey boxes are not applicable for the specified threat type. For instance, in the case of Option 1 for the human pandemic scenario, the user is provided with five selection options in terms of magnitude, duration, behavioral-avoidance, behavioral-aversion and resilience-recapture. The magnitude variable requires an input of numerical value within the given range as suggested, whereas other variables provide various options of

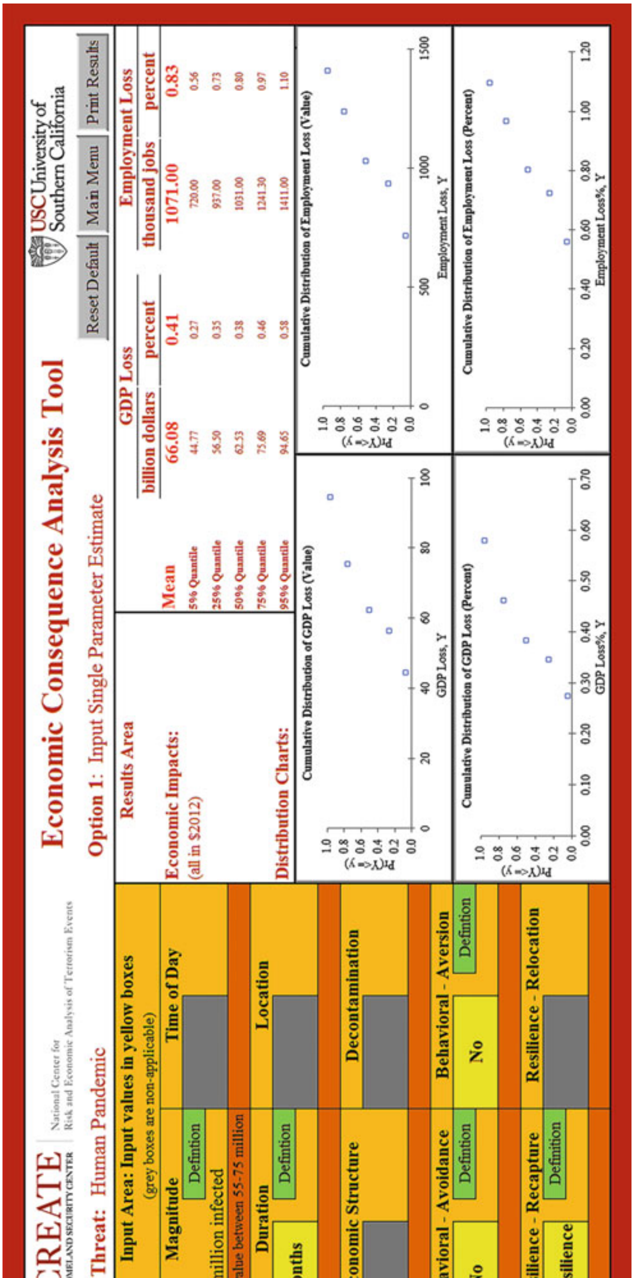


Fig. 9.3 E-CAT user interface option 1 (Human pandemic)

categorical selection from a drop-down list. For instance, the "time of day" variable allows the user to choose either a daytime or a nighttime option. The "duration" variable allows the user to choose either a 6-month period or a 9-month period. The "resilience" variable provides the user with three options: no resilience, lower-bound resilience and upper-bound resilience, whereas the two variables denoting behavioral effects only provide a "Yes or No" option for the user. Any change of an input variable would lead to an immediate update of results presented in the white color area. Outputs are presented in both numerical terms and cumulative distribution graphs. The numerical outputs of the mean estimates and estimates at various quantile levels are presented in both level change and percent change, respectively.

As shown in Fig. 9.3, without considering behavioral effects and resilience, in a human pandemic scenario where 60 million people are infected during a 6-month period, the mean GDP loss is $66.08 billion dollars, which is around a 0.405 % decline in the U.S. national GDP, with a mean employment loss is 1071 thousand jobs, which is equivalent to a 0.834 % reduction in jobs nationally. Behavioral effects in terms of avoidance and aversion, and resilience in terms of production recapture could have substantially altered the bottom-line. For instance, the mean estimate of GDP loss is amplified significantly to $79.88 billions of dollars if the behavioral-avoidance option is switched on in this case. However, if lower-bound resilience-recapture is selected, the mean estimate of GDP loss then reduces to $55.33 billion dollars. If an upper-bound resilience-recapture is selected, the mean estimate of GDP loss then reduces to $35.76 billion dollars.

Option 2 of the E-CAT user interface provides interval estimates (Fig. 9.4), which allows the user to calculate economic consequences of a selected threat in terms of GDP and employment losses based on the given range of magnitude, together with other user input variables. The key difference between Option 1 and 2 is that the latter option allows the user to specify both lower- and an upper-bound values of magnitude, with the capability to interact with other user input variables. Economic consequences are updated automatically in the output area once an input specification is changed. The interface design of Option 2 is the same as Option 1. The user input area is highlighted in the yellow boxes, whereas grey boxes are not applicable for the specified threat type. In the case of Option 2 for the human pandemic scenario, the user is provided with input options in terms of magnitude, duration, behavioral-avoidance, behavioral-aversion and resilience-recapture. After all inputs are specified, the results are presented in the white color area, which includes both numerical values and cumulative distribution charts for both GDP loss and employment loss, by value and percent, respectively.

The uncertainty distribution estimate as illustrated in Fig. 9.5 provides the user with an option to calculate GDP and employment losses based on a triangular distribution of the magnitude inputs, with interactions from other user input variables. In this option, the user is able to specify the magnitude values in terms of lower, middle and upper bounds. In addition, the user could also specify attributes, such as duration, behavioral-avoidance, behavioral-aversion and resilience-recapture. Numerical estimates of GDP and employment losses are displayed automatically in the output area. In addition, the cumulative frequency distribution charts and the relative frequency distribution charts of the mean estimates of GDP and employment losses are updated automatically.

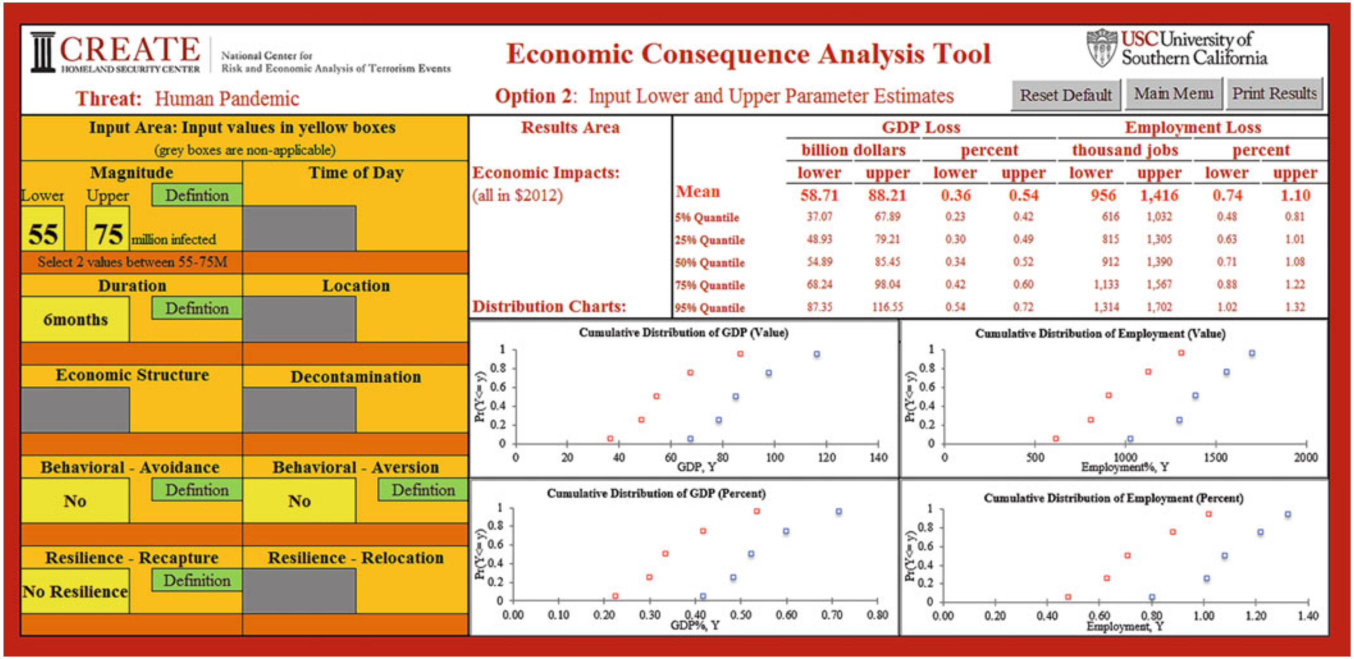


Fig. 9.4 E-CAT user interface option 2 (Human pandemic)

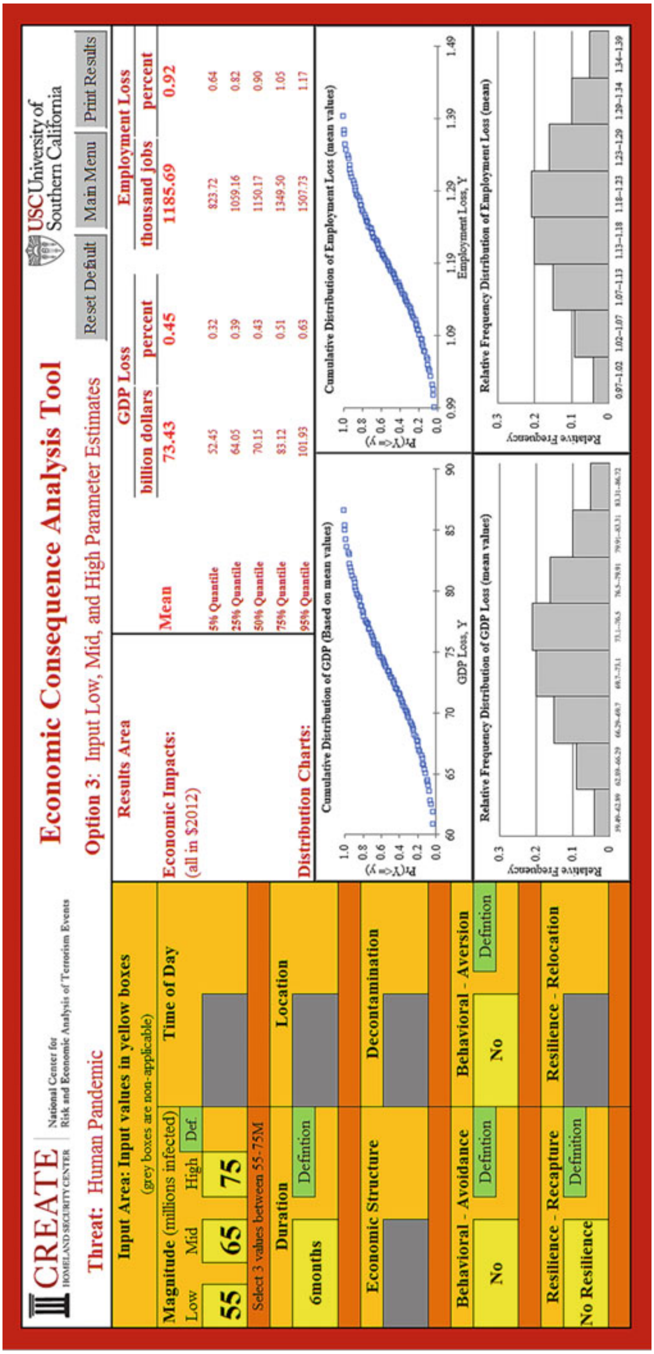


Fig. 9.5 E-CAT user interface option 3 (Human pandemic)

Appendix A: USCGE Model Description

A.1 Overview

The United States Computable General Equilibrium (USCGE Model was originally developed by Adam Rose and Gbadebo Oladosu in the late 1990s, based primarily on the CGE modeling structure developed by Sherman Robinson (see, e.g., Robinson et al. 1990). It was first applied in an analysis of the aggregate and distributional impacts of a cap and trade system for greenhouse gases in the US (Rose and Oladosu 2002). The model structure was also used to generate regional models to perform analyses of the economic impacts of climate policy in the Susquehanna River Basin area of the Mid-Atlantic States of the US (see, e.g., Oladosu 2000; Oladosu and Rose 2007) and economic consequences of various types of disasters in areas such as Memphis, Portland, Los Angeles, and New York City (Rose and Guha 2004; Rose and Liao 2005; Rose et al. 2007, 2009, 2011, 2014). The USCGE Model has been updated over the years. More recently, it has been significantly refined and updated by the co-authors Fynnwin Prager and Zhenhua Chen in conjunction with the lead author to perform both national and regional analyses (see, e.g., Prager 2013; Chen et al. 2017; Prager et al. 2015; Rose et al. 2015; Prager et al. 2016), including refinements used in this volume.

The USCGE Model consists of 57 producing sectors, along with multiple institutions: households (split into nine household income groups), government (split into two groups of state and local, and federal), and external agents (i.e. foreign producers). The model represents production activities as a series of nested constant elasticity of substitution (CES) functions. For international trade, the model employs Armington functions for imports and the constant elasticity of transformation function for exports. These functions separate out imported and domestically produced goods, ideally to reflect differential quality and consumer preferences. After governments collect taxes from labor and capital income, the

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9

remaining income goes to households and foreign entities according to fixed shares. Transfers also occur between institutions in the form of subsidies, social security payments, and income taxes.

A Linear Expenditure System of aggregate commodities (such as Food, Housing, and Gasoline) represents household consumption behavior, while a Leontief expenditure function characterizes government consumption. Household and government borrowing and saving functions are specified, and the consequent investments are allocated to finance capital goods. Equilibrium conditions include the balancing of supply and demand across sectoral product markets, while the labor market follows Keynesian assumptions to allow for underemployment equilibrium. Data from government and the academic literature is used to formulate key aspects of this model: Social Accounting Matrices for national and selected states, as well as wage and employment data.[1]

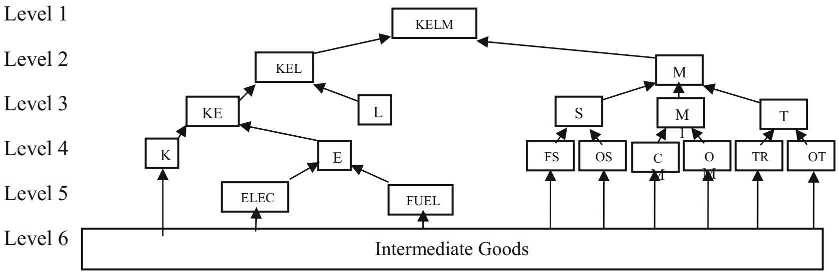
Elasticity of substitution values plays an important role in CGE models. As with each stage of the USCGE model development, a literature review has been performed to ensure that elasticity of substitution values are consistent with other studies (Rose et al. 2009). One complication here is that nesting structures can also vary across CGE models. For example, the Phoenix model developed by Fisher-Vanden et al. (2012) focuses electricity sector nesting on the substitutions between Base Load, Intermediate Load, and Peak Load periods of electricity demand. Nonetheless, where nesting structures are comparable, the elasticity of substitution values used in this analysis are consistent with those used by Fisher-Vanden and colleagues.

A.2 Producers

In line with CGE theory, producers are treated as profit maximizers. To implement this mathematically, the duality principle is applied, which states that “any concept defined in terms of the properties of the production function has a ‘dual’ definition in terms of the properties of the cost function and vice versa” (Varian 1992). As such, a cost function is minimized in the profit equation. This allows for theoretical properties such as Shepard’s Lemma to allow input demand function derivation from cost functions. More practically, cost and price data required for the cost function are readily available, while profit functions data requirements are difficult to obtain. The use of cost data also allows for different physical measurements to be combined into a single dollar value.

Each sector is assumed to be model by a representative producer. “The aggregate profit obtained by each production unit maximizing profit separately taking prices as given is the same as that which would be obtained if they were to coordinate their

[1]These data are acquired from IMPLAN, a national and regional economic accounts data provider (IMPLAN 2015), and government sources.



L = Labor	T = Transport	FS = Finance
K = Capital	S = Services	CM = Chemicals
E = Energy	M = Materials Aggregate	OM = Other Materials
FUEL= Fossil Fuels	MS = Materials Substitution	TR = Transport (Truck, Rail, Water and Air)
ELEC = Electricity Generation	OT = Other Transport Services	

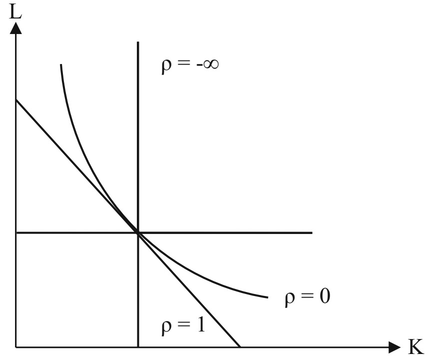
Fig. A.1 USCGE production function nesting structure

decision” (Mas-Collel et al. 1995). Aggregation issues for input combinations are also relevant when considering substitution functions. “Separability” is a fundamental assumption of many CGE model formulations. A group of goods or services is defined as separable when the marginal rate of substitution between any two factors (see Fig. A.1 for the nesting structure) in the group is independent from the level of factors elsewhere in the nesting structure. Strong separability requires that all factors in the separable group have the same elasticity of substitution with respect to any factor outside the group. Instead, weak separability is assumed here because it allows for within-group factors to have equal elasticity of substitution among input pairs with respect to a factor, yet these need not be equal with respect to all factors outside of the separable group. Weak separability therefore allows for substitutions of different values to be applied to multiple stages of nested production functions.

Producer behavior in CGE models is usually represented by the constant elasticity of substitution (CES) functional form. Examples of CES and CET (constant elasticity of transformation, the corollary function using a negative elasticity of substitution, in this case to represent shifts between domestic and foreign sales) functions are presented in Eqs. (A.1) and (A.8) below. A more general form of Eq. (A.1) is: $Q = \gamma\{\alpha K^{\rho} + (1-\alpha)L^{\rho}\}^{1/\rho}$, where K is capital, L is labor, Q is output, γ is a productivity factor, α is a share parameter, ρ is the parameter of substitution, whereby σ, the elasticity of substitution is $1/(1\text{-}\rho)$.

CES functions have elasticities that range from perfect to no substitution between factors. Perfect substitution means that two factors, for example Labor and Capital, can be substituted without a change in the level of output. This implies that an increase in the price of one good or factor would increase demand for the other good or factor. Perfect substitution is represented in Fig. A.2 by the straight line isoquant with an elasticity of substitution value of 0 ($\rho = 1$). At the other extreme, no substitution, also known as the Leontief or fixed input coefficient function, is represented by the right-angled isoquant ($\rho = -\infty$). In between is unit

Fig. A.2 CES production function isoquants



elasticity of substitution, which corresponds to the Cobb-Douglass function, and is represented in Fig. A.2 by a curved isoquant with an elasticity of substitution of 1 ($\rho = 0$).

The cost functions used in the USCGE model are constant returns to scale form, non-separable, nested constant elasticity of substitution (NNCES), which is shown in Eqs. (A.11) and (A.12) below. As shown in Fig. A.1, the nesting structure is divided into 9 levels. The top level ("KELM") represents substitution possibilities between aggregates of Capital (K), Labor (L), Energy (E) and Materials inputs (M). Level 2 separates substitution possibilities into two groups – an aggregation of Capital, Energy, and Labor inputs (KEL), and a material input aggregate (M). Level 3 further separates the KEL nest into an aggregate of Capital and Energy inputs (KE) on one side, and Labor inputs on the other (L). In addition, the materials nest is separated into three further sub-aggregates: 1) Services (S), which further disaggregates in Level 4 to Financial Services (FS)[2] and Other Services (OS)[3]; 2) Manufactured Goods (M1), which disaggregates to Chemical Materials (CM)[4] and Other Materials (OM)[5]; and 3) Transport, which disaggregates to Transport

[2]The Financial Services nest is an aggregate of the intermediate good inputs of Finance Banking and Credit (BANK), Security Brokers (SECB), and Insurance (INSR).

[3]The Other Services nest is an aggregate of the intermediate good inputs of Sanitary Services (SANT), Wholesale Trade (WTRD), Retail Trade (RTRD), Real Estate (REST), Owner-Occupied Dwellings (OODW), Hotel and Restaurants (HOTR), Personal Services (PSRV), Veterinary Services (VSRV), Waste Management and Remediation (WAST), Other Business Services (OBSV), Entertainment (ENTR), Education (EDUC), Medical Services (MEDC), Other Health and Social Services (OSOC), Federal Military (FGML), Other Government (OGOV), and State and Local Government (SGGV).

[4]The Chemical Materials nest is an aggregate of the intermediate good inputs from Chemicals Manufacturing (MCHM), Private Water Utilities (PWAT), and Government Utilities (GVUT).

[5]The Other Materials nest is an aggregate of the intermediate good inputs from Agriculture (ABEEF, ADARY, AOLVS, APOUL, AFISH, AOTH), Mining (CRUD, OMIN), Construction (CNSR), Food Manufacturing (MFML, MOML, MANM, MPTY, MFSH, MOFD), other Durable and Non-Durable Manufacturing (MOND, MPRM, MORD, MSEM, MODR), Communications (COMC, INFO) and Non-comparable Imports (NCMP).

Services (TR)[6] and Other Transport (OT).[7] Also in Level 4, Capital (K) and Energy (E) are separated. Level 5 separates the Energy nest (E) into Electricity Generation (ELEC) and Fuel (FUEL).

A.3 International Trade

International trade is represented by the Armington relationship for imports (Eq. A.8) and the constant elasticity of transformation for exports (Eq. A.1) below. An Armington elasticity represents the elasticity of substitution between products made in different countries, or in this case, the degree of substitution between imported and domestic goods. One might expect it to be the case of perfect substitution (sigma = infinity), because the same goods are competing; however, this is likely to lead to corner solutions and dramatic "switching" when prices change. Armington elasticities have values less than infinity, and are justified by quality differences between domestic and imported goods. As shown in Eq. (A.8), a CES function allows for demand substitution between domestic goods and competitive imports. Eq. (A.1) represents the corollary for substitutions between exports and domestic markets to characterize the revenue-maximizing behavior of domestic firms. In line with the small country assumption, import and export prices are fixed as equivalent to world prices. Constant elasticity of transformation is the corollary of the CES, and represents the extent to which industries can alter their output mix in response to changes in relative commodity prices.

A.4 Households

Labor and capital income payments from producing sectors are allocated to the nine household income brackets (HH1-9). Labor income is subject to social security government taxes (Eq. A.17), while capital income is subject to profit taxes by government and depreciation charges and retained earnings functions by industries (Eqs. A.19, A.20 and A.21). Labor and capital income are distributed to households according to the Multi-Sector Income Distribution Matrix (MSIDM), which uses exogenously sourced data to relate sectors of the economy to income brackets in terms of both labor and capital income payments (Eqs. A.17 and A.20). The MSIDM data are explicitly incorporated into the USCGE model labor and capital income equations, ensuring that the sector-household income relationships are

[6]The Transport Services nest consists of Air Transport (TAIR), Truck Transport (TRUK), Water Transport (TWAT), and Rail Transport (TRAL).

[7]The Other Transport nest consists of Other Transport (TOTH), Private Transit (TLTP), and Local Public Transportation (TLTG).

incorporated into the production calculations (Rose et al. 1988, 2012). Transfers between institutions are also represented – please refer to Eq. A.26.

Household consumption is divided across numerous aggregate commodities via a Linear Expenditure System. The linear expenditure system is a system of demand functions that assumes that household spending on each group of commodities varies with respect to income level above a subsistence level (reflected in a constant term). The cost of goods and services consumed by households (Eqs. A.31 and A.32) incorporates household demands along with the changes to prices of composite goods adjusted for household substitution elasticity values. These factors, along with the household consumption data, inform expenditure shares on household services (Eqs. A.33 and A.34) and household disposable income (SY_{hh}, which is household labor and capital income less taxes and transfers), which combine to determine household demand and total purchases across these aggregate commodity groups (Eqs. A.35, A.36 and A.38). Finally, the household utility function (Eq. A.37) accounts for impacts on utility of changes to household disposable income, commodity price changes, and household substitution effects. The household utility function is also summed across households to represent total societal utility.

A.5 Government

Government consumption is represented by a Leontief expenditure function. Household and government savings are determined as fixed proportions of disposable income (i.e. income following adjustments for taxes and transfers), and are balanced in their respective equations by savings by foreign sources (see Eq. A.25 for Government savings). Each of these institutions also undertakes capital borrowing. Investments are financed by net institutional savings plus depreciation charges and retained earnings.

A.6 USCGE Model Equations

Key

- Variables – capitalized elements;
- Parameters from pre-policy base data – capitalized elements with “0” at the end;
- Other parameters (shares, factors, etc.) – lower case elements;
- Arrays/Matrices – lower case subscript;
- Specific cell/row or column within arrays/matrices – capital subscript.

For example, in the equation following this paragraph, representing Capital Income Formation, the variable $INC_{K,s}$ refers to *capital* income (the subscript K) across all relevant institutions (s), which in this case are the nine household income brackets (HH1-9). The parameters $msidm_{K,I,s}$ and re_K both refer to the capital, the former being a matrix of sectors (i) and relevant institutions (s). Both *INC* and *FCPS* are (post-policy) variables with corollary parameters *INC0* and *FCPS0* that represent pre-policy base data values.

$$INC_{K,s} = \sum_i (msidm_{K,i,s} \cdot (FCPS_{K,i} \cdot (1 - re_K)))$$

CET between Exports (*EXPS*) and Domestic sales (*DSL*) for exporting sectors. Determines PRD_i.

$$PRD_i = PRD0_i \left(sh_{EP,i} \left(\frac{EXPS_i}{EXPS0_i} \right)^{\rho_{i,EOW}} + \quad sh_{EP,i} \left(\frac{DSL_i}{DSL0_i} \right)^{\rho_{i,EOW}} \right)^{1/\rho_{i,EOW}} \tag{A.1}$$

$$sh_{EP,i} = PE0_i \cdot EXPS0_i \cdot \left(\frac{PRD0_i}{PX0_i} \right) \tag{A.2}$$

$$sh_{DS,i} = 1 - sh_{EP,i} \tag{A.3}$$

where:

PRD_i and $PRD0_i$ are output variables and pre-policy value respectively[8] across i sectors; *EXP* is exports and *DSL* is domestic sales; *sh* are cost share parameters for exports *EP* and domestic sales *DS* respectively; ρ are exogenously derived cost function exponents for exports to the rest of the world (*EOW*).

Determines $\mathrm{DSL_i}$

$$DSL_i = \left(\frac{PRD_i}{PRD0_i} \right) \cdot \left(\left(\frac{PD_i}{PD0_i} \right) \cdot \quad \left(\frac{PX0_i}{PX_i} \right) \right)^{\sigma_{i,EOW}} \tag{A.4}$$

where:

PD and *PX* are domestic and output price respectively; σ are exogenously derived cost function exponents for exports to the rest of the world (*EOW*).

Determines $\mathrm{EXPS_i}$

$$PX_i \cdot PRD_i = PE_i \cdot EXPS_i + PD_i \cdot DSL_i \tag{A.5}$$

where:

PE and *PM* are export and import prices respectively.

Determines PC_j and PD_i

[8]Henceforth, the variable/pre-policy value distinction will be implied; variable, parameter, and sub- and superscript definitions will be defined only once and implied thereon. A list of variable and parameter definitions is provided in Table A1 below.

$$PC_j = \sum_i PD_i \cdot mpr_{i,j} \tag{A.6}$$

$$PD_i = \sum_j DCQ_j \cdot mpr_{i,j} \tag{A.7}$$

where:

PC the price of domestic goods; *mpr* are make coefficients derived from the make matrix (the supply matrix representing commodities produced by each industry).

CES between Imports (*IMPS*) and Domestic sales (*DCQ*) for importing sectors. Determines SUP_i[9]

$$SUP_i = SUP0_i \left(sh_{MP,i} \left(\frac{IMPS_i}{IMPS0_i}\right)^{-\rho_{i,MOW}} + \quad sh_{DD,i} \left(\frac{DCQ_i}{DCQ0_i}\right)^{-\rho_{i,MOW}} \right)^{-1/\rho_{i,MOW}} \tag{A.8}$$

where:

SUP is the composite goods supply; *sh* are cost share parameters for imports *MP* and domestic demand *DD* respectively, and follow the same calculation process as *sh* for *EP* and *DS above*; ρ are exogenously derived cost function exponents for imports from the rest of the world (*MOW*). *SUP*, *DCQ*, and *DSL* are all fixed at zero if and only if the corresponding values in the base data for *SUP0, DCQ0* and *DSL0* for any given sectors are zero. In other words, no transactions can emerge between any given sectors/institutions pairings where they did not exist in the base data.

Determines DCQ_{gi}

$$DCQ_{gi} = DCQ0_{gi} \cdot \left(\frac{SUP_{gi}}{SUP0_{gi}}\right) \cdot \left(\left(\frac{PC0_{gi}}{PC_{gi}}\right) \cdot \left(\frac{PQ_{gi}}{PQ0_{gi}}\right) \right)^{\sigma_{gi,MOW}} \tag{A.9}$$

where:

gi represents goods produced by sectors across the economy; *PQ* equals the composite goods supply price; σ are exogenously derived cost function exponents for imports from the rest of the world (*MOW*).

Determines $IMPS_{gi}$

$$PQ_{gi} \cdot SUP_{gi} = PM_{gi} \cdot IMPS_{gi} + PC_{gi} \cdot DCQ_{gi} \tag{A.10}$$

Import and Export taxes are set to zero. Elasticity values are multiplied by 0.5 and plus 0.001. Efffac (Factor of Productivity for these purposes) are set to 1 for all sectors at the KELM level of the nesting structure.

[9]Non-comparable imports are an exception, as imports equal supply.

Determine $PDMD_{fi,i}$ and $DMD_{inpt,i}$ respectively.

$$PDMD_{fi,i} = \delta_{fi,i} \cdot PDMD0_{fi,i} \cdot \sum_{inpt} \left(sh_{i,inpt} \left(\frac{PDMD_{inpt,i}}{PDMD0_{inpt,i}} \right)^{1-\sigma_{i,fi}} \right)^{1/1-\sigma_{i,fi}} \tag{A.11}$$

$$PDMD_{inpt,i} \cdot DMD_{inpt,i} = \sum_{fi} \left(DMD_{fi,i} \cdot PDMD_{fi,i} \cdot sh_{i,inpt} \left(\frac{PDMD_{fi,i}}{PDMD0_{fi,i}} \right)^{\sigma_{i,fi}-1} \cdot \left(\frac{PDMD_{inpt,i}}{PDMD0_{inpt,i}} \right)^{1-\sigma_{i,fi}} \right) \tag{A.12}$$

where:

PDMD is the demand price; *fi* and *inpt* are composite factor inputs,[10] with *fi* representing the upper level in a nest and *inpt* representing the lower level in a nest (e.g. KELM is *fi* to the *inpt*s of KEL and MAT); δ is the factor of productivity, set to 1 across all nests and with respect to all sectors, except where changed at the KELM level of the nesting structure for the purposes of modeling technology change. Demand and demand price are fixed at zero where base data entry was zero (i.e. no new transactions between given sectors can appear).

Determines $DMD_{KELM,i}$

$$PRD_i \cdot DMD0_{KELM,i} = PRD0_i \cdot DMD_{KELM,i} \tag{A.13}$$

where:

DMD is determined for the top-level nest (KELM) only.

Determines $PX(i)$

$$PX_i \cdot PRD_i = PDMD_{KELM,i} \cdot DMD_{KELM,i} \cdot (1 + tr) \tag{A.14}$$

where:

tr is the sum of tax rates across government institutions.

PDMD for labor, capital, and goods equal *PL*, *PK*, and *PQ* respectively. *PK* equals the capital return rate. Factor use of labor and capital,[11] $FCU_{f,i}$, equal demand for labor and capital, $DMD_{f,i}$, and sales across goods and sectors, $SAL_{gi,i}$, equals demand, $DMD_{gi,i}$.

Determines net price PV_i

[10]Composite factor inputs are provided in Table X; the nesting structure in Fig. A.1 for provides detailed relationships between composite factor inputs across nest levels.

[11]Labor and capital factors are represented as *f* in sub-scripts when combined.

$$PV_i \cdot PRD_i = PX_i \cdot PRD_i - TAX - \sum_{gj} \left(PQ_{gj} \cdot SAL_{gj,i} \right) \tag{A.15}$$

where:

TAX is the sum of taxes collected by all government institutions.

Import and export prices are set as equal to world prices (except when small country assumption is relaxed). Indirect taxes equal DMD(kelm,i) times PDMD (kelm,i) times the tax rate.

Emissions constraint function

$$TOTEMS = \sum_i \left((PRD_i \cdot emsfac_i) + \left(DMD_{fuel,i} \cdot fuelfac_{fuel,i} \right) \right) \tag{A.16}$$

where:

TOTEMS is the emissions cap; *emsfac* and *fuelfac* are, respectively, industrial process and fuel combustion emissions factors across all regulated industries (i.e. unregulated industries are set to zero); *fuel* refers to commodities demanded from the Coal Mining (COAL), Crude Oil and Natural Gas (CRUD), Petroleum Refining (MPET), and Gas Utilities (GASU) sectors.

Income allocation

Distributed Labor Income

$$FCPS_{L,i} = PL_i \cdot FCU_{L,i} \cdot (1 - tr_L) \tag{A.17}$$

where:

FCPS are factor income distribution coefficients across sectors, in this case for labor income, which are equal to *PL* the price of labor less the labor tax rate times the factor use of labor across sectors.

Labor income allocation

$$INC_{L,s} = \sum_i msidm_{L,i,s} \cdot FCPS_{L,i} \tag{A.18}$$

where:

$INC_{L,s}$ is labor income across *s* household income brackets; $msidm_{L,i,s}$ is the multi-sector income distribution matrix for *L* labor income, representing shares of labor income by sector paid to household income brackets.

Distributed Profit Income

$$FCPS_{K,i} = PK_i \cdot FCU_{K,i} \cdot (1 - tr_K) - DEPR_i + \left(\frac{FCU_{K,i}}{FCS_K}\right) \cdot INC_{L,ENT}$$
$$+ \sum_{za} TRNRC_{za,ENT} + PQ_i \cdot ssup_{i,ENT} \quad \text{(A.19)}$$

$$DEPR_i = PK_i \cdot FCU_{K,i} \cdot dpr_i \quad \text{(A.20)}$$

where:

K refers to capital income; *ENT* refers to incomes paid to enterprises; $TRNRC_{ENT,za}$ are transfers from government institutions (Federal Government Defense and Non-Defense, and State Government) to *ENT* enterprises; $ssup_{i,ENT}$ refers to transactions between *i* sectors and *ENT* enterprises from the institutional supply section of the social accounting matrix; *DEPR* is capital depreciation and *dpr* is the depreciation rate parameter, calculated by dividing capital payments from investments less indirect capital taxes by the factor use of capital, all for pre-policy data.

Retained earnings, *REAN*

$$REAN = re_K \cdot \sum_i FCPS_{K,i} \quad \text{(A.21)}$$

where:

re is the retained earnings rate, calculated by dividing pre-policy retained capital earnings (*REAN*) by capital factor use.

Profit income allocation

$$INC_{K,s} = \sum_i (msidm_{K,i,s} \cdot (FCPS_{K,i} \cdot (1 - re_K))) \quad \text{(A.22)}$$

where:

$msidm_{K,i,s}$ is the multi-sector income distribution matrix for *K* capital income, representing shares of capital income by sector paid to household income brackets.

Federal and State government taxes on Labor income (social security) and Capital profits, $TAX_{f,gv}$

$$TAX_{f,gv} = \sum_i PL_i \cdot FCU_{f,i} \cdot tr_{f,gv} \quad \text{(A.23)}$$

Government income

$$INC_{gv} = TAX_{f,gv} + \sum_{hh} TAX_{HH,hh,gv} + \sum_{i} TAX_{t,i,gv} + \sum_{gi} ssup_{gi,gv} \cdot PQ_{gi} + \sum_{za} TRNRC_{gv,za} \tag{A.24}$$

where:

t refers to the tax types indirect tax (tx), export tax (te) and import tax (tm); f refers to factor inputs (labor and capital).

Government expenditure balance

$$INC_{gv} = GVSAV_{gv} + \sum_{gi} PQ_{gi} \cdot SAL_{gi,gv} + \sum_{za} TRNRC_{za,gv} \tag{A.25}$$

where:

INC_{gv} is income across government institutions; $GVSAV$ is government savings; and $TRNRC_{za,gv}$ is transfers received by government institutions from government institutions and foreign sources.

Government purchases are fixed as equal to pre-policy levels.
Transfers calculations

$$TRNRC_{z,za} = trcof_{z,za} + INC_{za} \tag{A.26}$$

where:

z and za are institutions engaging in transfer activity, including households (*HH1-9*), government (Federal Government Defense and Non-Defense, and State Government), enterprises (*ENT*). Additional detail for international transfers is provided via Rest of World (*ROW*) and Stock Change (*STK*) functions.

Balance of payments of foreign countries

$$INC_{ROW} = \sum_{gi} PM_{gi} \cdot IMPS_{gi} + \sum_{za} TRNRC_{za,ROW} + \sum_{fi} INC_{f,ROW} \tag{A.27}$$

$$BOP_{ROW} = INC_{ROW} + \sum_{i} PE_{i} \cdot EXPS_{i} + \sum_{za} TRNRC_{za,ROW} \tag{A.28}$$

where:

$TRNRC_{za,ROW}$ are transfers to foreign sources from US households and federal government institutions.

Household income, INC_{hh}

$$INC_{hh} = \sum_{fi} INC_{f,hh} + \sum_{gi} \left(ssup_{gi,hh} \cdot PQ_{gi} \right) + HHBW_{hh} + \sum_{za} TRNRC_{za,hh} \tag{A.29}$$

$$INC_{hh} = HHSV_{hh} + SY_{hh} + \sum_{za} TRNRC_{za,hh} + \sum_{gv} TAX_{HH,hh,gv} \tag{A.30}$$

where:

$HHBW_{hh}$ and $HHSV_{hh}$ are household borrowings and savings across income brackets respectively. *HHBW* and *HHSV* equal household income multiplied by the marginal propensity to borrow and save (respectively) for each income bracket, which are derived from pre-policy borrowing and saving as a ratio of total income. $TRNRC_{za,hh}$ are transfers to households from households, government institutions, and foreign sources; $TAX_{HH,hh,gv}$ are household taxes across *hh* income brackets to *gv* government institutions. Household tax equals household income multiplied by the tax rate for each government institution.

Household expenditure balance

Household savings or borrowings equal income multiplied by a marginal propensity to save and borrow parameters across household brackets, which are derived from pre-policy saving and borrowing as a ratio of total income.

Household Production Function

Unit cost of Household Services, *PSRV*

$$PSRV_{hsrv,hh} = PSRV0_{hsrv,hh} \cdot \sum_{gi} \left(hgishr_{gi,hsrv,hh} \cdot \left(\frac{PQ_{gi}}{PQ0_{gi}} \right)^{\sigma_{hsrv,hh}} \right)^{1/\left(1-\sigma_{hsrv,hh}\right)} \tag{A.31}$$

$$hgishr_{gi,hsrv,hh} = \left(HDMD0_{gi,hsrv,hh} \cdot PQ0_{gi} \right) / \left(PSRV0_{hsrv,hh} \cdot HDSRV_{hsrv,hh} \right) \tag{A.32}$$

where:

hsrv are services purchased by households,[12] the parameter *higshr* are the shares of household spending (for each income bracket) for each *hsrv* group that are spent on each commodity (e.g. the share of the lowest income bracket's food spending that is spent on fish); $\sigma_{hsrv,hh}$ are household substitution elasticity values; *HDMD* is household demand for commodities; *HDSRV* is the total household expenditure on *hsrv* household service groups across *hh* household income brackets.

[12]Services are grouped into Food, Housing, Gasoline, Public Transport, Other Transport, Medical, Household Goods, Other Goods, Other Services, Water, Electricity, and Other Fuels.

Share of inputs into services, $HIDEM_{gi,hsrv,hh}$ (31 is intermediate variable used to calculate 32)

$$HIDEM_{gi,hsrv,hh} = higshr_{gi,hsrv,hh} \cdot \left(\frac{PQ_{gi}}{PQ0_{gi}}\right)^{\sigma_{hsrv,hh}} \tag{A.33}$$

$$HIDEM_{gi,hsrv,hh} = HGISH_{gi,hsrv,hh} \cdot \sum_{gj} HIDEM_{gj,hsrv,hh} \tag{A.34}$$

where:

The variable $HGISH_{gi,hsrv,hh}$ are shares of household spending (for each income bracket) for each *hsrv* group that are spent on each commodity.

Demand for inputs into services

$$PQ_{gi} \cdot HDMD_{gi,hsrv,hh} = HGISH_{gi,hsrv,hh} \cdot PSRV_{hsrv,hh} \cdot HDSRV_{hsrv,hh} \tag{A.35}$$

Total input purchases

$$SAL_{gi,hh} = \sum_{hsrv} HDMD_{gi,hsrv,hh} \tag{A.36}$$

Parameter HHCAL calculated from various sources including SAL0, mpet spend hh table, disposable income.

Utility function

$$UTILI_{hh} = \left(SY_{hh} - \sum_{hsrv} PSRV_{hsrv,hh} \cdot hhcal_{SPEXPD,hsrv,hh}\right) \cdot \prod_{hsrv1} 1/\left(PSRV_{hsrv1,hh}{}^{hhcal_{MSHARE,hsrv,hh}}\right) \tag{A.37}$$

$$\begin{aligned} PSRV_{hsrv,hh} \cdot HDSRV_{hsrv,hh} = {} & PSR \cdot V_{hsrv,hh} \cdot hhcal_{SPEXPD,hsrv,hh} \\ & + \; hhcal_{MSHARE,hsrv,hhmslPD,ands} \end{aligned} \tag{A.38}$$

where:

$UTILI_{hh}$ is utility per household income bracket; *SY* is disposable income; *PSRV* is the unit cost of household services; $hhcal_{SPEXPD,hsrv,hh}$ are *HDSRV* (total household expenditure on *hsrv* household service groups across *hh* household income brackets) adjusted for income substitution elasticity values; $hhcal_{MSHARE,hsrv1,hh}$ are the shares of household disposable income (by income bracket) spent on each hsrv commodity group, adjusted for income substitution elasticity values.

Objective function

$$\max PRODU = \sum_i PRD_i \cdot PX_i \tag{A.39}$$

where:

PRODU is gross domestic product; PRD_i is gross sectoral product; and PX_i is the output price for each sector.

Total savings

$$\begin{aligned} TSAV = & \sum_{hh} HHSV_{hh} - \sum_{hh} HHBW_{hh} + \sum_i DEPR_i + REAN \\ & + BOP_{ROW} + \sum_{gv} GVSAV_{gv} + \sum_{gi} \left(PQ_{gi} \cdot ssup_{gi,IV} \right) + \sum_{gi} \left(PQ_{gi} \cdot ssup_{gi,STK} \right) \\ & + TRNRC_{ROW,\ STK} + \sum_{gi} \left(PQ_{gi} \cdot SKT_{gi} \right) \end{aligned} \tag{A.40}$$

where:

SKT represents stock change.

Investment demand equals investment (*INVEST*) times pre-policy investment parameter. Investment demand equals investment demand times Capital consumption matrix (*cac*) parameters (and summed across industries). Investment price equals quantity price times Capital consumption matrix (*cac*) parameters (and summed across goods). Stock change (*SKT*) equals pre-policy stock change parameters times supply (*SUP*).

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Appendix B: E-CAT User Guide

The Economic Consequence Analysis Tool (E-CAT) generates ball-park estimates of the economic consequences of numerous threats in a matter of minutes.

E-CAT accounts for the cumulative direct and indirect impacts (including resilience and behavioral factors that significantly affect base estimates) on the national economy for numerous threats within the general categories of including terrorism, natural disasters, and technological accidents.

E-CAT is implemented in Excel using Visual Basic for Applications (VBA) programming language, and is based on a careful assessment of direct impact drivers, computable general equilibrium (CGE) analysis to estimate indirect impacts, and reduced-form regression analysis to translate the complex analysis into a compact form that can yield quick-turn results under various assumptions relating to background conditions and the direct drivers, under various representations of uncertainty. Uncertain threat inputs are quantified and propagated through the analysis process resulting in appropriate representations of economic consequence uncertainties as output.

B.1 Step 1: User Interface

Select a Threat and an Uncertainty Display Option The main menu of the user interface is shown in Fig. B.1. Descriptions of the threats included are given in Table B.1, and descriptions of the Uncertainty Display Options are given in Table B.2. Then press the Go! button.

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9

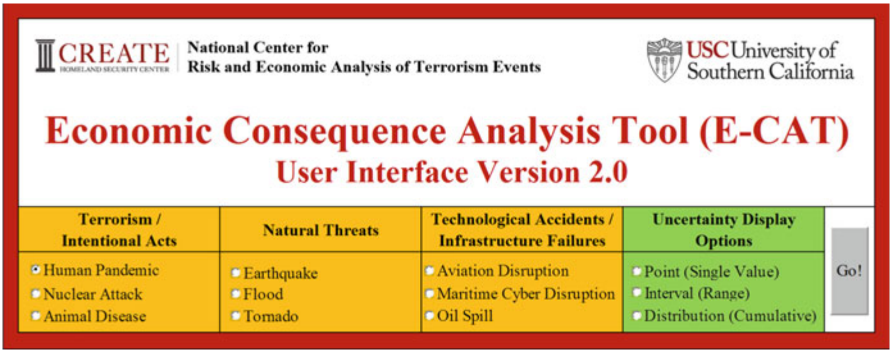

Fig. B.1 E-CAT user interface main menu (threat and uncertainty display options selection)

Table B.1 Threat descriptions

Threat	Description
Human pandemic	Influenza outbreak ranging from mild (10 % of national population infected) to severe (25 % of national population infected).
Nuclear attack	Improvised nuclear device attack with weapon yields ranging from 0.01 to 10 kilotons.
Animal disease	Foot-and-mouth disease outbreak, ranging from 5000 to 13,750 animals infected, which relates to 10.8 and 30 % of animals (cattle, sheep, and pigs) slaughtered.
Earthquake	Earthquake event, ranging on the Richter Scale between magnitudes of 5.1 and 7.8.
Flood	A major flood event, ranging from a 20-year flood to a 100-year flood.
Tornado	A tornado event, ranging from F3 to F5.

The current version of the E-CAT software only includes Human Pandemic, Nuclear Attack, Animal Disease, Flood, Earthquake, and Aviation Disruption. Analysis and Software Development are underway for the Tornado, Maritime Cyber Disruption and Oil Spill threats, in addition to numerous other threats

B.2 Step 2: User Inputs

Select Values for Each User Input Variable The user input variables are place into generic categories, yet are specific to each case, as shown in Table B.3. For example, for Human Pandemic:

- The Magnitude variable is the infection rate within the US population.
- The Duration variable is the length in months of the outbreak (6 months or 9 months).
- The Resilience recapture refers to the production recapture associated with labor.

Table B.2 Uncertainty display option descriptions

Uncertainty display option	Description
Option 1. Point estimate	User selects a single value for the "magnitude variable" (see description below). Crisp estimates of GDP and employment impacts at the mean and quantile levels are presented in the Economic Impacts area, while Distribution charts represent the GDP and employment distributions across various quantiles (5 %, 25 %, 50 %, 75 %, 95 %). The quantile results represent the likelihood of not exceeding a particular level of consequence.
Option 2. Interval estimate	User selects lower and upper bound values for the "magnitude variable" (see description below). Crisp estimates of GDP and employment impacts at the mean and quantile levels are presented for the lower and upper bounds in the Economic Impacts area, while distribution charts represent the GDP and employment distributions across various quantiles (5 %, 25 %, 50 %, 75 %, 95 %) at both the lower and upper bound levels. The quantile results with bounds represent the likelihood of not exceeding particular consequence bounds.
Option 3. Distribution	Triangular Distribution: Low, Most Likely and High estimates. Empirical cumulative distribution functions of GDP and employment impacts at the mean and quantile levels are generated within this option. Please note that, for the distribution charts presented in this option, the mean and quantile economic impacts are expected values estimated by calculating the area above the empirical cumulative distribution functions. The charts below display the probability distributions only for the mean impacts.

- The Behavioral Avoidance variable refers to whether or not foreign tourists would avoid travelling to the US or whether people would avoid public areas (train stations, sports events, etc.).
- The Behavioral Aversion variable refers to whether or not workers would be offered wage incentives to return to work.

Functional user input variables are highlighted in yellow, whereas unavailable variables are colored in grey. The green box provides specific explanation of the corresponding variable (Fig. B.2).

Please see descriptions of results options above.

B.3 Step 3: Completion/Continuation

The grey buttons on the upper-right hand corner of each page allow the user to:

1. Reset to the default settings
2. Return to the main menu
3. Preview and print results

Table B.3 Examples of user input variables for four threats

Threat	Magnitude	Location	Time of day	Economic structure	Duration	Decon-tamination and clean up	Resilience recapture	Resilience relocation	Behavioral avoidance	Behavioral aversion
Human pandemic	Infection rate	n.a.	n.a.	n.a.	Duration of outbreak	n.a.	Business recapture	n.a.	Tourism/ Public areas	Aversion
Nuclear attack	Bomb size	Point of attack	Night /Day	Attacked region structure	Radiation is in excess of 1 year	Yes	n.a.	Business relocation	Tourism	Aversion
Animal dis-ease outbreak	Animal infection rate	n.a.	n.a.	n.a.	Duration of outbreak	Yes	Business recapture	n.a.	n.a.	Aversion
Tornado	F category	Counties/ States	n.a.	Affected region structure	n.a.	Yes	Business recapture	Business relocation	n.a.	n.a.

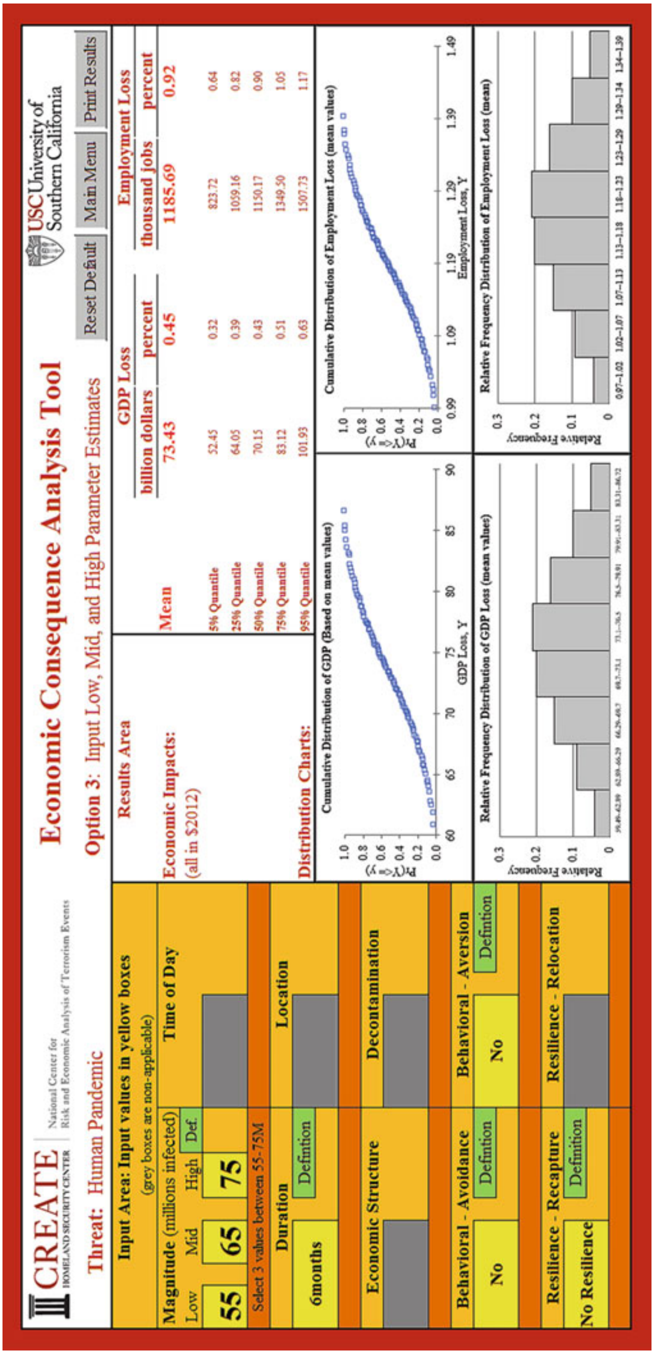

Fig. B.2 E-CAT user inputs and results

Appendix C: The E-CAT Tool Software

E-CAT can be downloaded from the USC Center for Risk and Economic Analysis of Terrorism Events (CREATE) website at: create.usc.edu

A. Rose et al., *Economic Consequence Analysis of Disasters*, Integrated Disaster Risk Management, DOI 10.1007/978-981-10-2567-9