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DISASTER IMPACT AND INPUT–OUTPUT ANALYSIS

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Macroeconomics models, such as the input–output model, the social accounting matrix, and the computable general equilibrium model, have been used for impact analysis of catastrophic disasters for some time. While the use of such models to disaster situation, which may quite differ from the ordinary economic setting, has been critiqued (for recent example, see Albala-Bertrand, 2013), there are still valuable reasons for the use of such models. In particular, such models can be used in order to quickly provide a ballpark estimate of the system-wide impact for recovery plan and finance and/or to evaluate disaster countermeasures in the pre-event period. This paper presents how these methodologies have evolved to incorporate with disaster-specific feature and discusses how far they still need to go from the current stage. This paper also serves as a preface to this special issue, which encompasses several papers devoted to the use of macroeconomic data and models to assess economic losses from disasters.

Keywords: Disaster impacts; Input–output analysis

1. INTRODUCTION

The urgent need for disaster impact analysis has steadily grown and has gained worldwide recognition in recent years. In 2007, a special issue of *Economic Systems Research* (Volume 19, Number 2) was published on the economic modeling for disaster impact analysis, having five research papers and one introduction paper. This issue tackled and introduced new and innovative ways to deal with the modeling issues for disaster impact analysis, such as speed of event, geographic scale, and in-built countermeasures of an economy. These papers have contributed to the advancement of modeling framework and the better understanding of disaster situations. Since then, new issues and challenges have confronted the disaster modeling community, thus the need for further progress of modeling strategy for disaster impact analysis has been revitalized. Recent catastrophic events, such as 2008 Cyclone Nargis in Myanmar, the 2008 Sichuan Earthquake in China, the 2011 East Japan Earthquake and Tsunami, the 2011 Thailand Floods, and 2013 Typhoon Haiyan in Philippines, among others, brought a new spectrum of issues that have to be addressed in the impact analysis, for example, the impact propagation of stretched supply chains over the globe. Moreover, because the behavioral nature of economic activities is well influenced by the dire and severe

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situations not only in the damaged areas but also in the non-damaged regions, changes in labor productivity and/or consumption pattern in a disaster situation may lead to sizable economic impact via asymmetry of information and/or self-restraint.

Disaster impact analysis using quantitative models has been challenged also within the disaster research community. Many quantitative analyses of disasters, including some of the papers in the aforementioned 2007 special issue, were recently critiqued in a detailed manner, based on the following three 'interactive insufficiencies': (1) the quality of basic data; (2) inherent limitations of any quantitative technique; and (3) the paramount issue of the interpretation of results (Albala-Bertrand, 2013, chapter 1 "The Problem with Quantitative Studies": pp. 5–29).[1] Nevertheless, an alternative but still quantitative analytical framework is proposed with some examples (Albala-Bertrand, 2013).[2] It has been well known that quantitative macroeconomic models, such as the models in this and 2007 special issues, are the representation of one or more particular aspects of the reality, and that the results of simulations employing such models have to be treated only to highlight the influence from such aspects, not to show how the economy behaves in a disaster situation. Nevertheless, the quality of input data has been a critical issue for disaster impact analysis (West and Lenz, 1994), as well as the analytical frameworks (or even the definitions of the parameters being estimated). Thus, the extent of results has differed from one study to another, leading to conflicting conclusions even with the same event (Hallegatte and Przyluski, 2010). Whereas disaster impact analysis is an 'inexact science' (Hewings and Mahidhara, 1996), these shortcomings have to be overcome in quantitative analysis of disasters to make the analysis credible and accountable. Furthermore, the uniqueness of each hazard and region-specific behaviors present enormous challenges in economic modeling for disaster impact analysis.

In this paper, the studies of disaster impact analysis with quantitative models are reviewed. The above issues and challenges are further analyzed, and some directions of further modeling efforts are discussed. In the following section, economic modeling practice for disaster impact analysis to this date is summarized and reviewed. Section 3 presents the long-run analysis of disaster impact and discusses its necessity. Section 4 discusses how the disaster impact analysis, with input–output analysis, can provide better information to research and practice communities. The final section concludes with some future directions for promoting and improving the methodologies.

2. MODELS FOR DISASTER IMPACT ANALYSIS

As in the previous special issue in 2007, we first define the terminologies related to disaster impact analysis. *Disaster* is the consequences of a *natural or man-made hazard*, such as earthquakes, flooding, severe storms, droughts, terrorist attacks, industrial accidents, and

[1] The methodologies for impact estimation are categorized into two groups in Albala-Bertrand (2013): (a) black-box methods (notably econometrics) for long-run analysis and (b) simulation methods for short-run analysis. It is claimed that "(b)oth types of methods are somehow valuable, if only to call attention about certain aspects of the disaster phenomenon" (p. 10).

[2] The alternative analytical framework is proposed from the perspective of "a political economy argumentation. . . , as disaster responses represent discontinuities and ensuing societal network shifts" (Albala-Bertrand, 2013, p. 2).

so forth, and what disaster impact analysis investigates is the extent and intensity of a disaster. And, these natural and man-made hazards cause destructions to built-environment and also cause loss and injuries to human lives. These destructions are defined as *damages* on stocks, including both physical and human capitals. Meanwhile, damages can lead to business interruptions, causing the *loss* of productions and/or consumptions. The losses of production in the damaged firms can potentially spread to other firms via backward and/or forward linkages, proceeding to become the ripple effect of the original loss. This type of system-wide effect from loss can be defined as the *higher order effect* (Rose, 2004). Loss and higher order effect are flow measures, thus cannot be added to damages, which is again a stock measure. Loss and higher order effect can be added to form the total (flow) impact of a particular disaster.

The *raison d'être* of disaster impact analysis, particularly the estimation of damages and total impact, can be roughly twofold: (1) the post-hazard estimation of disaster impact for recovery and reconstruction plans and finance and (2) the pre-hazard estimation of a hypothetical natural hazard in order to evaluate the preparedness and mitigation strategies. The post-hazard estimation has been done to grasp the intensity and extent of the disasters and to appraise the cost for recovery and reconstruction of damages. This post-hazard estimation can be done relatively quickly, if some macroeconomic models are readily available for the damaged region or nation. For example, after the 2011 East Japan Earthquake and Tsunami that occurred on 11 March, the Cabinet Office of Japan released the first estimate of damage on 23 March (Cabinet Office of Japan, 2011a), followed by a bit more detailed damage estimate on 24 June in the same year (Cabinet Office of Japan, 2011b). While these are the so-called 'ballpark estimate' of the damages and total impact, the estimated values were used for the budget appraisal of the Japanese Government's reconstruction plan. On the other hand, the pre-hazard estimate, often with more sophisticated models, can be utilized to evaluate the preparedness and mitigation policies, or even to show how the pre-hazard countermeasures are more cost effective when compared with the post-hazard recovery and reconstruction. As an informative example about how pre-hazard mitigation is cost saving, Healy and Malhotra (2009) illustrated based on the empirical data that in the USA \$1 spend on preparedness is worth \$15 in terms of the future damage it mitigates. This is crucial information for the public decision-making regarding how policy against natural hazards and disasters ought to be allotted. In order to provide this type of information for the future disasters, the estimation methodologies should be rather accurate and comprehensive rather than being quick.

Various economic modeling frameworks have been employed to estimate the higher order effects of a disaster. In the previous special issue, Okuyama (2007) reviewed and summarized the models used in the past; hence in this paper the recent efforts of disaster modeling are reviewed. The input–output (IO) model has been most widely used for disaster impact analysis (for examples, Van der Veen and Logtmeijer, 2005; Hallegatte, 2008; Okuyama, 2010; Rose and Wei, 2013). The advantages of the IO model for disaster impact analysis is based mainly on the ability to reflect the economic interdependencies within a regional (or national) economy in detail for deriving higher order effects, and partly on its simplicity. On the other hand, this simplicity of the IO model creates a set of weaknesses, including its linearity, its rigid structure with respect to input and import substitutions, a lack of explicit resource constraints, and a lack of responses to price changes (Rose, 2004). These weaknesses have been tackled and somewhat overcome through refinement and extension of the IO framework, including the recent examples of Hallegatte (2008) and Uda (2011) among others.[3] As a notable alternative approach to accommodate disaster features within the IO framework, the inoperability input–output model (IIM) has been proposed and applied. Traditional IO analysis estimates higher order effects in terms of monetary or physical units; nevertheless recent disaster impact analysis has incorporated the use of the *inoperability* index – a dimensionless number ranging between 0 (ideal system state) and 1 (total failure state), as one of the extensions of the IO framework for disaster situation. Haimes and Jiang (2001) laid the conceptual and theoretical foundations for the IIM, while Santos and Haimes (2004) developed a process in which IO data can be utilized to study the higher order effects of inoperability across interdependent economic systems. Since then, several scholars from USA, Italy, China, and the Philippines have published dozens of journal articles on various methodological extensions and practical applications of the IIM.

The computable general equilibrium (CGE) model has also been employed for disaster impact analysis and has been gaining its popularity (Tsuchiya et al., 2007; Rose et al., 2011). Unlike IO models, CGE models are non-linear in common practice, can respond to price changes, can accommodate input and import substitutions, and can explicitly handle supply constraints. As a simulation model, the CGE model can integrate disaster-specific features as an endogenous function, such as resilience (Rose and Liao, 2005). However, the CGE model potentially provides lower impact estimates than IO models, partly because "not all causations in CGE models are unidirectional, i.e., functional relationships often offset each other" (Rose, 2004, p. 27).

The SAM has also been utilized to examine the higher order effects across different networks of socio-economic agents, activities, and factors. Notable disaster impact analysis studies using a SAM or one of its variants include, for example, Okuyama and Sahin (2009) among others. Like IO models, the SAM approach has similar advantages and weaknesses to the IO model. Another advantage of SAM for disaster impact analysis is that its framework is used to form the damage and loss assessment in the Economic Commission for Latin American and the Caribbean (ECLAC, 2003) methodology. Therefore, if the damages and losses are surveyed based on the ECLAC methodology, the corrected data can be directly plugged into a SAM for the estimation of the higher order effect.

Most of the above methodologies reviewed are considered as flow impact models estimating the higher order effects of a disaster, which are the effects on flows, for a short run. The reason for the popularity of flow impact models in estimating disaster impacts, according to Rose (2004), is that "flow measures are superior to stock measures in many ways" (Rose, 2004, p. 14). The strengths of flow measures can be summarized as follows: (1) it can measure the impacts (business interruptions) without stock damages; (2) it is a performance measure whereas stock measure involves the life-cycle assessment of capital with depreciation; (3) it is more consistent with other conventional macroeconomic indices, such as gross domestic (regional) product (GDP or GRP); and (4) it shows the

[3] Hallegatte (2008) extended the IO framework, the *adaptive input–output model*, to incorporate production bottlenecks, changes in production capacity, and changes in prices, profits, and labor demand in somewhat ad hoc ways. However, these can be easily dealt with by the CGE model, which may be based on either IO or the social accounting matrix (SAM), and in a more theoretical way rather than an ad hoc way. In order to deal with demand–supply mismatch in the equilibrium-oriented IO framework, Uda (2011) proposed an iterative procedure to adjust input and interregional multipliers.

short-run impact of a disaster, which is oftentimes convenient for policy discussions against disasters.

3. DISASTER IMPACT IN THE LONG RUN

The methodologies reviewed above, mainly flow impact models, can cover only the short-run economic consequences and can hardly cover the full scale of impacts, including the long-run effect on economic growth, psychological impacts, deterioration of public health, personal losses, and livelihood disruptions (Pelling et al., 2002). In addition, those empirical studies often found that the estimated total impact of a disaster in a short-run horizon, i.e. the sum of negative impacts originating from the destructions that the event brought and the positive impacts from recovery and reconstruction activities in the years following the event may become negligible or even positive (Albala-Bertrand, 1993a; 1993b; Tol and Leek, 1999; Okuyama et al., 1999, among others). The question of whether or not a catastrophic disaster generates any fundamental deviations in an economy and the thirst to reveal the comprehensive figure of disaster impact necessitate the investigation of the long-run effect of such events.

However, only a limited number of empirical studies, compared to the number of studies on estimation of short-run impacts, have been carried out for investigating the effects of disasters in long-run economic growth caused by stock damages.[4] For example, based on cross-country data, Skidmore and Toya (2002) found that while climatic disasters are positively correlated with long-run economic growth, investment on human capital, and total factor productivity growth, geological disasters are negatively correlated (or sometimes statistically insignificant) with economic growth. Their results indicate that climatic disasters are associated with the growth of total factor productivity, implying that climatic disasters may provide an opportunity to update capital stock and to adapt new technologies. This point is the motivation for Cuaresma et al. (2008), in which the relationship between technological transfer and disaster impact in developing countries in the long run was examined. Their results contradict with Skidmore and Toya's (2002) findings and instead found that disaster risk is negatively correlated with technological transfer, while only countries with a higher level of development can benefit from technological transfer after a disaster. Similar results to Cuaresma et al. are found in Rasmussen (2004) with the data of countries in the Eastern Caribbean Currency Union, indicating that the long-run effects of disasters on growth are inconclusive. This disagreement of the results among the above studies may be due to the fact that "disaster variables are somewhat crude measures" (Skidmore and Toya, 2002, p. 682), and especially for the intensity of disaster variable (physical or economic losses), there is no standard definition or method devised and applied across the cases, as Albala-Bertrand's (2013) first point indicates.

Lack of research in this area may have resulted from several other reasons as well: the (un)availability of reliable data on capital damages, particularly on human capital; the complexity of assessing the value of capital over time; the intricacy of investment decisions on damaged capital under and after a disaster (Okuyama, 2003); policy-maker's priority to

[4] The recovery from war destructions has been studied but not included in this paper (interested readers can refer to, for example, Davis and Weinstein, 2002; 2004; Miguel and Roland, 2005). Cavallo and Noy (2010) have an excellent summary of other studies on long-run impact of disasters.

the problems at hand rather than the ones in the distant future; and the difficulty of separating the long-run disaster-induced effects from usual macroeconomic indicators, especially for developing countries where the influences to their macroeconomic conditions from other factors, such as political instability, and debt burden, among other things, appear much greater than in developed countries.[5]

In contrast to the short-run impact estimation of an event or to the long-run trend analysis with cross-country data, Coffman and Noy (2011) measured the long-run economic impact of a hurricane based on the empirical data with econometric models. Using the synthetic control method, they found that the damaged region has yet to recover in 18 years after the hurricane hit, in terms of the regional population, aggregate personal income, and the number of private sector jobs. As far as the disaster-related literature we covered, this is the only study to empirically measure the long-run effect of a particular disaster, except a few studies including Okuyama for the 1995 Kobe earthquake in this issue. This line of study is particularly important not only to disclose the actual impact of a disaster but also to fine-tune those short-run impact estimations for more accurate estimates. As the data availability of damages and losses improves, measurement and analysis of the actual impact of disasters is an urgent task.

In the context of long-run growth and disasters, the studies on the impact of human capital damage have been also very limited. While the publicity of human toll, such as deaths, injuries, and missing, is usually very high in disasters, these human capital damages are usually counted as the decrease of labor and/or consumers in flow impact models (see, for example, Okuyama et al., 1999) or are left out (Albala-Bertrand, 1993b), because the effect of human capital damages has the long-run implications and cannot be fully incorporated in the short-run analysis. In general, human capital is much more difficult to 'recover' or 'reconstruct' than physical capital per se, because its formation requires education and/or training, health investments, and so on; and the accumulation takes some time. This reasoning is, to some extent, supported by Noy and Nualsri (2007) that loss of human capital resulted in a decreased growth rate, while loss of physical capital has little impact on long-run growth.

4. CURRENT STATE OF DISASTER IMPACT ANALYSIS

In this special issue, a range of disaster impact analyses, from the method for the input data and new ways for modeling strategy to the analysis of long-run effects of a disaster, is presented in the following three categories.

4.1. Input Data for Impact Analysis

As discussed in Section 2, the data often collected for a disaster are stock damages, i.e. the number of physical structure damaged or collapsed, the number of damaged or interrupted lifeline networks, and so on, which cannot be directly plugged into the models. These

[5] Chambers (1989) stated that the demands of poverty usually out-compete the demands of vulnerability in developing countries. Kahn (2005), Anbarci et al. (2005), Rashcky (2008), and Noy (2009) investigated the influence of institutional settings in their analysis of disaster impacts over cross-country data.

physical damage data need to be converted to the economic data with a monetary value. This conversion is rather difficult and problematic, since not all the physical structures are brand new and assessing the value of used structure or equipment requires the inventory of asset evaluation (Rose, 2004). In order to make this process manageable, Heatwole and Rose (2013) devised a reduced-form regression model to estimate the property damages for the future US earthquakes, based on empirical data. While this model can only derive rough estimates of damages, the estimated values are quite an improvement over the prorated damage estimation typically used in the ballpark estimate of short-run impact. In its nature, this type of damage estimation models needs to be tailored to a particular country or region and to a specific type of natural hazard; however, once they are developed, it will become a powerful tool for the quick evaluation of economic impact of disasters, at least for damage estimation.

Kajitani and Tatano's (2014) 'Estimation of Production Capacity Loss Rate after the Great East Japan Earthquake and Tsunami in 2011' in this special issue proposes a new methodology to estimate the changes in the production capacity rate based on the projected ground motion of an earthquake, through functional fragility curves and lifeline resilience factors estimated from the empirical case of the 2011 East Japan Earthquake and Tsunami. While their methodology is tailored to earthquake and Japanese case, the framework can be applied to other types of natural hazards and to other countries where similar data are available. One of the advantages in this methodology is that once ground motions of a particular earthquake are given, the estimated changes in the production capacity rate can be derived in the damaged area. In this way, there is no need to convert available physical damage data to monetary values, then to further transform these estimated monetary values to loss data, in which unavoidable noises and errors can be potentially included. Moreover, they claim that in addition to estimate damages and losses as in Heatwole and Rose (2013) the change in the production capacity rate is also a crucial index to be estimated for disaster impact analysis, because this may bridge the conversion between damage and loss estimates utilizing engineering information and resilience.

Nevertheless, West and Lenze's (1994) caution – the more sophisticated impact models become, the more precise numerical data are required, while imperfect measurements of the damages and losses of a disaster are often the case – is still persuasive. In this context, this line of research can improve the availability and reliability of input data for the impact estimation, and consequently improve the estimation results of higher order effects.

4.2. Modeling for Decision-Making

Any quantitative model is the representation of some particular aspects in the real world, not the comprehensive replication of the reality. As such, the derived results are "(D)epending on the purpose and of the decision-making spatial scale, the perimeter of the cost analysis will be different" (Hallegatte and Przyluski, 2010, p. 16). In particular, the pre-hazard analysis often investigates the impact (benefit) of specific countermeasure or mitigation policy, and the modeling strategy tends to focus on where such policies aim, such as infrastructure and lifelines. In 'Modeling Critical Infrastructure Failure with a Resilience Inoperability Input–Output Model', Jonkeren and Giannopoulos (2014) extended the IIM framework for the impact analysis of critical infrastructure failure. Their extension starts from the Dynamic Inoperability Input–Output Modeling, proposed by Haimes et al. (2005), and proposes alternative resilience formulations to create more flexible disaster recovery paths. The reformulated dynamic model generates other convex and concave variants of the exponentially decreasing recovery formulation. With a numerical example of a severe winter storm in Europe, their Resilience IIM is able to present several optimal resilience strategies for critical infrastructure analysis.

The process of recovery and reconstruction in the aftermath of a disaster requires the timely and effective decision-making. At the same time, due to the interindustry linkages, the decision-making process associated with a projected recovery path needs to be considered as sequential rather than simultaneous across sectors. A paper by Santos et al. (2014), 'Time-Varying Disaster Recovery Model for Interdependent Economic Systems using Hybrid Input–Output and Event Tree Analysis', develops a hybrid model between IIM and event tree analysis that can adjust the inoperability parameters to reflect successive events that can either degrade or enhance the predicted paths of sector recovery. This type of modeling strategy can become appealing to the decision-makers at the recovery and reconstruction stage, since this hybrid model can demonstrate an extended capability to utilize new information to update recovery projections for interdependent sectors.

Policy-making and decision-making for both post-hazard recovery and reconstruction and for pre-hazard mitigation policies are usually a multi-objective problem. In particular, the evaluation of vulnerability of an economy to natural hazards is a multi-dimensional assessment of risks. Also in this special issue, a paper by Yu et al. (2014), 'A Vulnerability Index for Post-Disaster Key Sector Prioritization', proposes a multi-attribute disaster vulnerability index comprising three components (economic impact, propagation length, and sector size). Whereas the economic impact component is based on IO multipliers and the propagation length component utilizes the average propagation length method, the proposed index can capture the distribution of welfare improvements among sectors in the aftermath of disasters. They argue that different weight assignments for such components will result in different key sector prioritization strategies for post-disaster resource allocation as well as for pre-hazard policy evaluation.

These three papers employ new variants of the IIM, indicating the increasing popularity of the IIM framework in the disaster-related research and its use for empirical cases. As discussed in the previous section, IIM is an extension of the IO model; thus IIM can be constructed relatively quickly where the IO table exists. The use of IIM is not only limited to disaster impact analysis but also includes critical infrastructure risk management, development planning, energy policy, and key sector analysis.

4.3. Impact on Economic Structure

As discussed in the previous section, a catastrophic natural hazard will bring considerable short-run impact as well as substantial long-run effect. The investigation of the long-run effect is quite delicate, since the effect is the combination of the changes caused by the disaster and the alterations resulting from the recovery and reconstruction activities. It is also extremely complicated to extract only the disaster effects from the macroeconomic indicators, such as GDP or GRP, due to the other macroeconomic disturbances (e.g. the changes in the currency exchange rate, in the interest rate, and the regional and/or national development policies may severely influence such macroeconomic indicators).

However, it is crucial to investigate the long-run effects of disasters, because disaster may cause significant structural changes in economies, potentially leading toward a shift in the long-run growth trend. In fact, aforementioned Coffman and Noy's (2011) study revealed that some macroeconomic indicators of the damaged region, such as population, aggregate personal income, and the number of private sector jobs, were still proportionally lower comparing to the control group. Okuyama's (2014) 'Disaster and Economic Structural Change: Case Study on the 1995 Kobe Earthquake' in this special issue goes one step further to investigate the structural change caused by a disaster. Employing the 1995 Kobe Earthquake as the case study, he analyzed how the economic structure of Kobe has changed based on a time series of IO tables through structural decomposition analysis. The results unfold the considerable structural changes during 1990 and 2000, but these changes vary across sectors. In order to extract the region-specific changes, potentially resulting from the Kobe earthquake, shift-share analysis is integrated with structural decomposition analysis. This leads to the results that the changes in regional final demand are found to be most influential to the changes in output for many sectors, while the changes in regional input coefficients and in regional purchase coefficients also have some tractable effects to the region-specific changes.

This line of research is particularly critical not only to understand the long-run effects of disasters but also to fine-tune the models for short-run impact analysis, because the estimated short-run impacts have been rarely tested and verified with the actual impact measured through the empirical data. Increasing availability of IO data in many developing countries as well as increasing interests in disaster impact on economy, the opportunities to examine the long-run effects of disasters on structural change are in our hands.

5. CONCLUSIONS

Quantitative models have proven useful in a broad array of economic analysis and risk management problems. In a report published by The World Bank and United Nations (2010), the theme of disaster impact analysis is discussed as well as issues associated with quantifying the multifaceted consequences from disasters. The report recognizes that the type of 'economic lens' used in the analysis may distort the results; nevertheless, when used and interpreted correctly, the consequence estimates and forecasts can help create effective policies for disaster prevention and mitigation.

We acknowledge the importance of the issues raised by Albala-Bertrand (2013) pertaining to data quality, model limitations, and interpretation of results. We argue, however, that these issues are not only endemic to macroeconomic models such as IO, SAM, and CGE. At the same time, addressing the difficulties associated with harmonizing scenario definitions (i.e. assumptions pertaining to disaster magnitude, geographic scope, and recovery horizon) along with available data resolutions and model requirements can be extremely challenging. We recognize the complexity and the foregoing issues associated with the estimation of impacts associated with disasters; nevertheless, these issues should not unnecessarily impede the development and extension of quantitative models for disaster impact analysis, while we bring our best efforts to improve the delivery of data quality, model representation, and policy implications.

At least two more issues need to be addressed as the further improvements of disaster impact analysis: uncertainty, and globalization and localization. The world is fraught with uncertainties and there is no such thing as a 'crystal ball' that model developers, analysts, and policy-makers could use to predict what exactly would occur in the future. In order to enhance the robustness of results from quantitative models, it is important to recognize and distinguish different types and categories of uncertainty. For example, O'Hagan and Oakley (2004) related the two main categories of uncertainty (i.e. aleatory and epistemic) with various sources of uncertainty (i.e. parameter, model, variability, and code). Several methods are available to better understand how uncertainties could affect model outputs, such as sensitivity analysis, simulations, confidence intervals, 'what-if' analysis, and brainstorming, among others. Gerking (1976) asserted that a deterministic model forecast needs to be supplemented with uncertainty analysis because 'to contend that this forecast will come true with certainty is optimism to a fault', and this could not be more true to disaster impact analysis.

As Albala-Bertrand's (2007) 'Globalization and Localization: An Economic Approach' suggested, while the regional impact of a disaster will be economically localized and will be insignificant to the macro economy even in the long run, it provides a context into how other indirectly affected regions could prepare to mute the supply chain disruptions and other spillover effects that may be spawned by a disaster. For example, MacKenzie et al. (2012) used a multi-regional IO analysis to decompose the short-term supply chain disruption rendered by the 2011 East Japan Earthquake to the automobile sector of selected countries and the rest of the world. On the other hand, it is vital in focusing on regionally specific elements of quantitative models to more accurately forecast the magnitude of higher order effects and ultimately provide insights into prioritization of constrained resources, reconstruction and recovery efforts, and addressing other important public policy concerns in the aftermath of disasters.

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