Markhvida, M., and Baker, J. W. (2023). "Modeling future economic costs and interdependent industry recovery after earthquakes." *Earthquake Spectra*, 39(2), 914–937. https://doi.org/10.1177/87552930231162385

Modeling future economic costs and interdependent industry recovery after earthquakes

Maryia Markhvida,[a] and Jack W. Baker[a]

Large earthquakes cause widespread damage and can result in substantial direct and indirect economic losses. Previous researchers have proposed separate models for predicting region-wide direct and indirect losses due to future earthquakes; however, comprehensive simulation approaches that include both remain underdeveloped. In particular, the propagation of uncertainty along the various modeling steps has not been previously considered. This paper addresses that gap by proposing a three-stage model to assess economic impacts of possible future earthquakes, consisting of regional ground motion simulation, damage and direct loss modeling, and macroeconomic recovery modeling. In this model, economic indicators such as direct asset losses and changes in economic sectors' value added and employment are quantified. The model also captures uncertainty in the spatial distribution of earthquake shaking and damage patterns, which in turn is reflected in post-disaster economic indicators. The results show that considering uncertainty leads to a wide range of possible economic outcomes and high variance in direct and indirect losses. A cross-model sensitivity analysis is performed to evaluate the effect of different model parameters on the quantification of economic consequences.

INTRODUCTION

Disasters affect societies in many ways; they cause injuries and fatalities, displacement of the population, societal disruptions, damages to man-made and natural capital, and economic losses. Economic impacts are commonly classified into direct and indirect losses (Rose and Lim, 2002; Brookshire et al., 1997; Hallegatte and Przyluski, 2010). One definition of direct economic losses is that they stem from damages to productive capital (i.e. physical capital used in the production process) and are measured in terms of the value of destroyed assets or the cost of repairing damaged assets (Hallegatte, 2008; Howe and Cochrane, 1993). Some authors also include business interruption losses that result from direct damage (e.g. loss to a business that cannot operate due

[a]Department of Civil and Environmental Engineering, Stanford University, Stanford, CA 94305, USA

to damage to its facilities) as direct losses (Brookshire et al., 1997; Rose et al., 1997), while others consider such losses as indirect (Federal Emergency Management Agency, 2012; Grossi and Kunreuther, 2005). Indirect economic losses are associated with the disruption of services and reduction in output, and can be measured in terms of losses to value added (Hallegatte and Przyluski, 2010; Howe and Cochrane, 1993). Value added can be approximated by compensation to employees and profits before taxes. Indirect losses include "higher-order effects" such as output changes resulting from supply and demand changes, also known as forward and backward linkages (Rose, 2004). Such losses can result even when no direct damage to an entity is observed.

Indirect losses can make up a significant portion of the overall economic impact of a disaster, and sometimes exceed direct losses (Daniell et al., 2011). Direct and indirect losses during five large earthquakes are provided in Table 1. The loss amplification factor, or total economic loss (direct plus indirect) divided by direct loss, ranges from 1.08 to 1.37, signifying the wide range of indirect impacts that can occur. Previous research suggests that in addition to the magnitude of damage, indirect losses are influenced by the state of the economy at the time of disaster, where during the economy's expansion stage losses can be amplified and during recession dampened by the utilization of unused resources (Hallegatte and Ghil, 2007). Indirect losses also vary depending on the sector, where some sectors such as construction often experience gains due to reconstruction stimulus (Parker et al., 2012).

Table 1. Direct and indirect losses from five large earthquakes.

Earthquake name and year	M_w*	Direct loss (billion USD)	Indirect loss (billion USD)	Loss amplification factor**	Reference
1989 Loma Prieta	6.9	5.9	0.2-0.7	1.08	Brady and Perkins (1991)
1994 Northridge	6.7	42	7.3	1.17	Petak and Elahi (2000)
1999 Marmara	7.6	3.0-6.5	1.2-2.0	1.34	World Bank (2003)
2008 Wenchuan	7.9	124	44	1.35	Wu et al. (2012)
2011 Tohoku ***	9.0	211	78	1.37	MacKenzie et al. (2012) Kajitani et al. (2013)

*M_w = moment magnitude
** Loss amplification factor is calculated using the midpoint for direct and indirect loss ranges
*** Earthquake and tsunami damages are considered

Direct and indirect economic losses are typically quantified following a disaster or predicted before a disaster even occurs. Government entities and insurers routinely estimate economic losses following an earthquake for loss accounting, forensic loss analysis, claim settlement, budgeting, and future planning. Prediction of economic losses due to potential future earthquakes (i.e., seismic risk assessment) is also a common practice in the insurance industry and is starting to be used by government entities in planning and mitigation efforts (Brechwald, 2018b,a; Detweiler and Wein, 2018; Rose et al., 2011b; Jones et al., 2008). Historically, regional seismic risk assessments have focused on predicting direct losses (e.g. Silva et al., 2015; Grossi and Kunreuther, 2005); more recently, potential indirect losses stemming from disruption of lifelines and utility services have been increasingly investigated (e.g. Chang et al., 2015; Martinelli et al., 2014; Rose and Liao, 2005). However, unlike direct losses associated with damaged buildings and infrastructure, quantification of indirect losses is not yet a standard practice in regional seismic risk assessments, leading to a systematic underestimation of overall economic losses. In addition, predictions of indirect losses have not previously considered the large uncertainties stemming from ground shaking and damage patterns, which can lead to misrepresentation of disaster impacts. Inclusion of uncertainty has been highlighted as one of the needed areas of improvement in post-disaster economic impact assessment (Okuyama and Santos, 2014). Engineering estimations of the physical recovery of productive capital are not commonly considered in economic recovery models, where previous implementations either make assumptions about the recovery rate (Hallegatte, 2014) or do not explicitly take the rate into account (Cutler et al., 2016; Sue Wing et al., 2021).

The research presented in this paper integrates regional earthquake risk analysis with an input-output (I-O) economic recovery model (Adaptive Regional Input-Output model, Hallegatte, 2014, 2008). The integrated end-to-end approach creates a pipeline for quantifying total economic losses, considering how uncertainty in the ground shaking and damage propogate to post-disaster economic recovery indicators, such as value added, employment, and regional capital reconstruction time. This approach also allows one to constrain the economic capital recovery model using physical asset repair times, and on the other hand, constrain the physical reconstruction with macro-economic conditions – a two-way relationship not previously considered in regional seismic risk analysis. The methodology is applied to a hypothetical $M_w 7.2$ earthquake scenario on the Hayward fault to model the impact on the San Francisco Bay Area's economy. Physical damages, direct losses, and changes in value added and employment in 15 interdependent economic sectors are modeled as a function of time. The results bring insight into how uncertainty from the seismic risk analysis affects economic recovery predictions. In addition, a cross-model sensitivity analysis of parameters from different stages of modeling is performed, evaluating their effect on the prediction of economic consequences.

OVERVIEW OF PREVIOUS ECONOMIC LOSS MODELING APPROACHES

DIRECT ECONOMIC LOSSES DUE TO EARTHQUAKE DAMAGE

Several engineering frameworks and computational tools exist for predicting regional direct asset losses and business interruption losses that result from an earthquake (Elhaddad et al., 2019;

FEMA, 2015; Pagani et al., 2014; Rojahn and Sharpe, 1985). These frameworks require categorization of the building stock in the region of interest into a set of representative structural and occupancy typologies. Different frameworks employ either analytical or simulation approaches, but in general the analysis is performed in several computational stages. First, regional ground motion maps that represent ground shaking caused by an earthquake scenario are produced. Then, discrete damage states or damage ratios that depend on the ground shaking are predicted for each building in the building stock. This is typically done using building-level fragility or vulnerability functions. Finally, the damage states or damage ratios are translated into monetary losses, using a replacement cost corresponding to the building's occupancy type.

Business interruption losses require an additional computational step that estimates the repair and re-occupancy time of a building given a damage state. The time is then used to calculate income losses. While several methodologies exist to quantify this time (Burton et al., 2015; FEMA, 2015; Almufti and Willford, 2013), these times do not explicitly incorporate regional factors such as the capacity of the construction sector, post-earthquake cordons, or real estate market conditions.

There are also several rapid, empirically-based direct economic loss models such as the Prompt Assessment of Global Earthquakes for Response (PAGER) (Jaiswal and Wald, 2013) and the reduced-form rapid economic consequence model (Heatwole et al., 2013). While these models are simple, transparent, and provide rapidity, they do not quantify loss metrics (e.g. sector-specific direct losses) that can be linked to indirect economic loss modeling.

INDIRECT ECONOMIC LOSSES

The two most common approaches to computing indirect economic losses are input-output (I-O) (Giannopoulos, 2018; Okuyama and Santos, 2014; Rose and Wei, 2013; Haimes et al., 2005) and computable general equilibrium (CGE) (Prager et al., 2018; Pauw et al., 2011; Rose and Liao, 2005) economic models. The I-O framework is widely used in disaster economics, typically with linear models that use an I-O matrix to represent all the purchases and sales between different industry sectors in a bounded economy (Okuyama, 2007). I-O models allow one to see the effects of changes in demand and supply due to disaster damage on the output of businesses along the supply chain (i.e. higher-order effects). These models are popular due to their ability to reflect industry inter-dependencies, their relative simplicity, and the easy link that can be made between direct damages and losses originating from engineering risk models and higher-order impacts. Some shortcomings of traditional I-O models are their linearity, lack of behavioral content (e.g. consumer behavior change based on commodity prices), lack of input and import substitutions, lack of explicit resource constraints, and lack of interdependence between price and output (Rose, 2004).

Several extensions of the I-O model have been proposed to overcome some of the shortcomings, including the Adaptive Regional Input-Output (ARIO) model (Hallegatte, 2014, 2008). The ARIO model captures demand-driven changes in output caused by changes in inter-industry and household consumption, reduction in productive capacity of industries due to earthquake damage, and supply constraints. In addition, it considers the role of input inventories and adaptive behavior of industries and households following a disaster. This model has been validated against Hurricane Katrina economic losses (Hallegatte, 2008), and used to assess economic losses after the 2008 Wenchuan earthquake (Wu et al., 2012).

CGE analyses model the entire regional economy based on a behavioral model of individual producers and consumers in response to multi-market price signals (Rose and Liao, 2005). A CGE model retains multi-sector characteristics and interdependence of the I-O model, but also explicitly considers supply constraints, input and import substitutions, and behavioral response to price changes (Rose, 2004). However, a CGE model without extensions assumes generous input and import substitution elasticities and optimizes behavior based on non-disaster assumptions, which can lead to over-estimates of resilience and business adaptation, and thus under-estimate economic impacts (Rose and Liao, 2005). In addition, a CGE model requires many more parameters and has larger data requirements than an I-O model.

The above models have largely been used to analyze previous disasters (e.g., Oosterhaven and Többen, 2017; Okuyama, 2014; Wu et al., 2012; Guimaraes et al., 1993). Several authors have used them to model future indirect economic impacts of earthquakes, in particular the influence of lifeline disruptions on business activities (e.g., Chang et al., 2015; Martinelli et al., 2014; Rose et al., 2011a; Rose and Liao, 2005). However, these studies do not consider uncertainty in the ground shaking or building damage distribution, nor do they include hazard-dependent recovery times of the overall capital stock in economic recovery modeling. Such assumptions can lead to misrepresentation of disaster impacts, where consideration of uncertainty has been highlighted as one of the needed areas of improvement in post-disaster economic modeling (Okuyama and Santos, 2014).

METHODOLOGY

In order to model regional direct and indirect economic losses during an earthquake considering uncertainty, three separate models are integrated: a regional ground motion simulation, a physical damage and direct loss model, and an ARIO economic recovery model. In this integrated model we define direct and indirect loss as in Hallegatte (2014), where direct loss is the aggregate value of asset damages and indirect loss results from reduced economic value added.

First, for a given earthquake scenario, multiple regional ground motion maps are simulated to represent the possible ground shaking that can occur across the region. Then, physical damage to the built environment and losses associated with the cost of damage repair are predicted for each of the simulations. The time required to repair the damage is also quantified. Once the asset losses and repair times are calculated, they become an input into the ARIO economic model, which evaluates the effect of the damages on the production of economic sectors. Unlike previous implementations of the ARIO model that do not explicitly quantify damage repair time, this study considers both the damage repair time and the ability of economic sectors to satisfy reconstruction demand. The three-stage model is used to assess the economic impact of a possible earthquake scenario on the San Francisco Bay Area (herein referred to as the Bay Area) – a region in Northern California comprised of nine counties.

REGIONAL GROUND MOTION SIMULATION

In order to simulate damage due to an earthquake, ground motion maps that represent ground shaking across the region must be generated for a particular scenario. To generate the ground motion maps, Ground Motion Prediction Equations (GMPEs) are used (Abrahamson et al., 2014; Boore et al., 2014; Campbell and Bozorgnia, 2014; Chiou and Youngs, 2014). GMPEs predict the median and standard deviation of ground shaking intensity, for a particular magnitude, distance to rupture, and faulting type. Ground shaking intensity can be expressed as, for example, peak ground acceleration (PGA) or spectral acceleration at a period of vibration and it is characterized by between- and within-even uncertainty. Between-event uncertainty captures the variability between different earthquakes events, and within-event uncertainty represents ground motion variability between different locations for the same event. Within-event uncertainty exhibits spatial correlation and cross-correlation between different ground motion intensity measures.

In order to capture the large variability in ground motion considering multiple locations, Monte Carlo simulation can be used to generate numerous ground motions maps using a spatial correlation model (Goda and Hong, 2008; Loth and Baker, 2013; Markhvida et al., 2018).

This study considers a moment-magnitude (M_w) 7.2 scenario on the Hayward fault from the U.S. Geological Survey (USGS) UCERF2 Earthquake Rupture Forecast (Field et al., 2003). In order to capture uncertainty in the ground motion, 1000 peak ground acceleration (PGA) ground motion maps were generated using (Abrahamson et al., 2014) GMPE and (Markhvida et al., 2018) cross-correlation model. Three sample simulations are shown in Figure 1. For each of the ground motion maps, PGAs are simulated at the census tract centroids, which is where building stock information is aggregated.

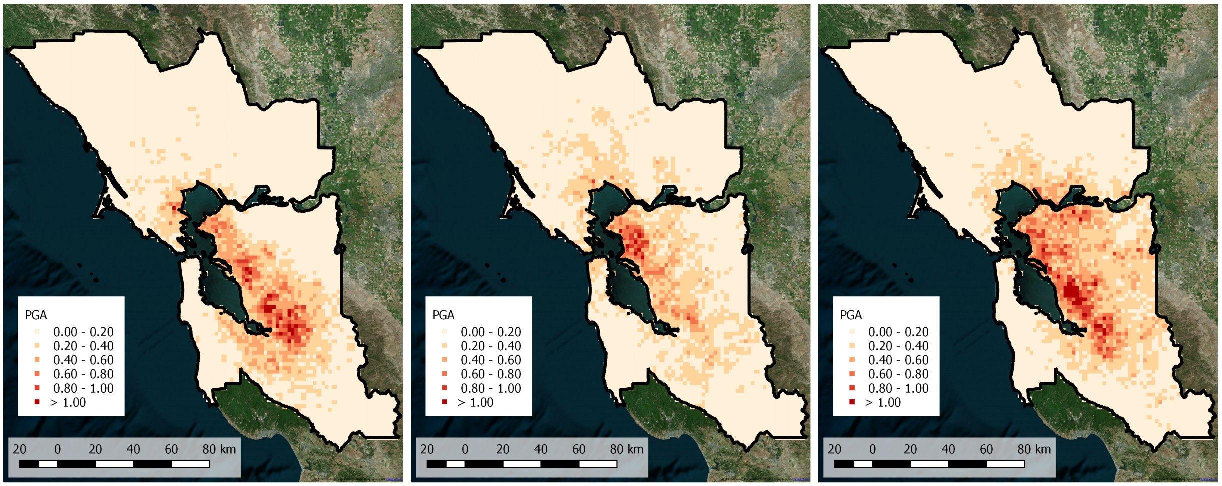


Figure 1. Example simulations of ground motion maps for the San Francisco Bay Area, using peak ground acceleration (PGA) as the ground shaking intensity.

PHYSICAL DAMAGE AND DIRECT LOSS MODELING

This study uses FEMA's regional loss estimation framework – HAZUS earthquake model – which is intended to be used by the government at different administrative levels for emergency preparedness, response, recovery, risk mitigation and planning (FEMA, 2015). In addition to being a computational engine, the publicly available software contains a large amount of data on building stock and lifelines in the United States. The HAZUS model is primarily aimed at estimating economic losses and casualties associated with physical damage to building infrastructure. Direct loss estimation includes buildings' structural and non-structural repair costs and the value of lost contents. In this study, we only consider structural and non-structural repair costs as direct losses, as data on contents is not readily available.

The exposure dataset in this study is built using building stock data from the HAZUS database. This database contains information on the number of buildings and their replacement costs subdivided into 33 occupancy categories. In addition, a region-dependent mapping scheme is provided to further subdivide occupancy categories into structural types considering different heights and design levels. The resulting dataset contains the building count for each census tract in the Bay Area (aggregated at the centroid of the tract), subdivided into 698 building categories varying by occupancy, structural type, height, and design level. For example, single-family residential/light-frame wood/low-rise/high-code is one of the building categories in the final dataset. The building replacement costs are also adjusted to 2016 dollars (i.e. the study base rate).

HAZUS provides a methodology for calculating the mean building loss for a specified level of ground shaking intensity. We extend this formulation to arrive at a probabilistic distribution of loss considering uncertainty in the ground motion and building damage. For each of the 1000 ground motion maps, damage for each building in the exposure dataset is simulated given a PGA at a centroid of the census tract to which that building belongs. For simulation i, a damage state (DS) is drawn from a categorical distribution for each building j in the Bay Area (Equation 1). Damage states, ds_1-ds_5, correspond to none, slight, moderate, extensive, and complete.

$$DS_{i,j} \sim \text{Categorical}\Big(P(ds_1), P(ds_2), P(ds_3), P(ds_4), P(ds_5)\Big) \tag{1}$$

The probability of building j being in a particular damage state (Equation 2) is calculated using probability of damage state exceedance (Equation 3), which is conditioned on the structural typology (s_j) and peak ground acceleration at the building location ($pga_{i,j}$).

$$P(DS_{i,j} = ds_k) = \begin{cases} 1 - P(DS_{i,j} \geq ds_k | s_j, pga_{i,j}) & \text{for } k = 1 \\ P(DS_{i,j} \geq ds_k | s_j, pga_{i,j}) - P(DS_{i,j} \geq ds_{k+1} | s_j, pga_{i,j}) & \text{for } 1 < k < 5 \\ P(DS_{i,j} \geq ds_k | s_j, pga_{i,j}) & \text{for } k = 5 \end{cases} \tag{2}$$

The probability of being in or exceeding a particular damage state is expressed through a fragility function as:

$$P(DS_{i,j} \geq ds_k | s_j, pga_{i,j}) = \Phi\left(\frac{ln(pga_{i,j}/\theta_{s_j})}{\beta_{s_j}}\right) \tag{3}$$

where $P(DS_{i,j} \geq ds_k | b_j, pga_{i,j})$ is the probability of building type j being in or exceeding damage state ds_k when $PGA = pga_{i,j}$, $\Phi(.)$ is the standard normal cumulative distribution function, and θ_{s_j} and β_{s_j} are median and logarithmic stanrdard deviation for building type j. This study uses simplified HAZUS fragility functions that use peak ground acceleration as the input ground motion.

Once the damage state for building j is simulated, the loss is determined by multiplying the building replacement cost and a loss ratio that corresponds to the simulated damage state. Loss ratio is the repair cost associated with structural and non-structural damage expressed as a fraction of the building replacement cost, and it is a function of the building occupancy category (e.g. single-family house, multi-family apartment, commercial) and the damage state. In order to obtain the probability distribution of the aggregate direct loss, for each of the 1000 ground motion simulations, individual building losses are summed up across the region. The probability distribution is then constructed considering multiple simulations.

The building repair time at an economic sector level is also of interest, as it constrains the rate of reconstruction of productive capital (i.e. physical capital used in the production process) across different sectors – an input requirement for the economic recovery modeling. This study considers only buildings as productive capital, due to limited data on machinery and equipment values. The HAZUS methodology provides repair times for buildings in different occupancy categories and damage states. For each of the 1000 simulations, a repair time is assigned to each damaged building in accordance with its simulated damage state. Then, for each simulation, i, we construct an aggregate reconstruction trajectory for productive capital within each occupancy category as per Equation 4:

$$PC_{i,occ}(t) = \sum_{j \in Occ} \big(1 - \mathbb{1}(t < RT_{i,j}) \times LR_{i,j}\big) \times RC_j \tag{4}$$

where $PC_{i,occ}(t)$ is the aggregate productive capital of occupancy category occ for simulation i at time t after the earthquake; $RT_{i,j}$ and $LR_{i,j}$ are building j's repair time and loss ratio, respectively, corresponding to its damage state in simulation i; RC_j is the replacement cost of building j; and $\mathbb{1}(t < RT_{i,j})$ is an indicator function that evaluates to 1 when $t < RT_{i,j}$ or is otherwise 0. Once productive capital's recovery trajectory is calculated, the time required to repair 95% of damaged capital in each of the occupancy categories, τ_r^{occ}, not considering factors such as availability of construction workers, is determined and used in the following model stage.

ARIO ECONOMIC RECOVERY MODELING

The macroeconomic recovery model described herein is based on the ARIO model and other methods described in (Hallegatte, 2014). This model was chosen due to its relative simplicity of implementation and a smaller number of modeling parameters requiring calibration. Details related to its implementation in this research are provided in this section.

Input data pre-processing

In order to apply the ARIO model, data on different economic sectors must be gathered and pre-processed. Required data include the regional input-output matrix as well as data on sectors' productive capital, employment, and annual value added. In our analysis, we describe the Bay Area economy using 15 aggregate economic sectors, or industries, (see Table 2) as defined by the U.S. Bureau of Economic Analysis (BEA). BEA data from 2016 is used as the base for modeling pre-earthquake conditions (U.S. Bureau of Economic Analysis, 2016a,c,b).

The pre-disaster productive capital in the Bay Area is imputed using the region's value added and a ratio of productive capital (or fixed assets) to value added, which is calculated using national statistics. This data along with the number of employees in each sector is summarized in Table 2.

Table 2. San Francisco Bay Area pre-earthquake industry data summary.

Industry	Productive capital stock, billion USD	Value added, billion USD	Ratio of capital stock to value	Employed
Agriculture, forestry, fishing, & hunting	25.98	6.89	3.8	27,800
Mining	6.34	0.82	7.8	2,400
Utilities	115.29	14.02	8.2	24,700
Construction	10.30	29.25	0.4	189,600
Manufacturing	225.84	124.56	1.8	386,200
Wholesale trade	30.04	50.51	0.6	88,500
Retail trade	45.90	35.37	1.3	371,800
Transportation & warehousing	26.41	10.67	2.5	120,300
Information	146.12	61.28	2.4	118,500
Finance, insurance, real estate, rental, & leasing (including housing)	897.19	148.24	6.1	239,300
Professional & business services	77.09	143.40	0.5	620,400
Educational services, health care, & social assistance	72.07	51.76	1.4	773,400
Arts, entertainment, recreation, accommodation, & food services	35.05	27.79	1.3	336,800
Other services, except government	24.38	13.96	1.7	185,400
Government	379.22	62.65	6.1	132,100

Data is taken from U.S. Bureau of Economic Analysis, considering 2016 as the base year (U.S. Bureau of Economic Analysis, 2016a,c).

To calculate the sector's loss of productive capital, direct losses calculated for different HAZUS occupancy categories are converted to losses in 15 BEA economic sectors, using a mapping scheme similar to the one in the HayWired study (Wein, 2018). This mapping scheme is also used to calculate τ_r^{ind} – the time required to repair 95% of the regional damage in each of the 15 economic sectors, or industries.

The final data pre-processing step is the derivation of a local input-output matrix that reflects interdependencies of local economic sectors. The appendix provided in the electronic supplement provides a summary of the method used to derive the input-output matrix suitable for this analysis. Following the pre-processing, the economic recovery and indirect loss modeling is performed on the aggregate sector level, where final indirect losses are reported at the regional (Bay Area) level.

ARIO formulation

A summary of the ARIO model and its extension are provided below; for a complete model formulation, the reader should refer to Hallegatte (2008) and Hallegatte (2014). The model is applied to each of the ground motion simulations and direct loss results in order to quantify uncertainty on the economic recovery.

In this model, at each time step t, N_{ind} sectors produce commodities to satisfy demand from final consumption, intermediate consumption (i.e. inter-industry), export, and post-earthquake reconstruction. During the production process, industries use stocked inventories of input commodities in accordance with I-O matrix coefficients. It is assumed that input commodities and services from sectors such as utilities and transportation cannot be stocked. At each time step the used inventories are then replenished by placing orders to other sectors.

The process and equations described below are repeated for each time step throughout a 10 year recovery period, considering a time increment, Δt, of one week. First, demand to sector j, $D_j(t)$, is calculated as per Equation 5, without considering supply bottlenecks. In this equation, $O_{i,j}(t)$ is order from sector i to sector j to restore inventories, $C_j(t)$ is local final demand to sector j, $R_j(t)$ is the reconstruction demand to sector j, and $E_j(t)$ is demand to sector j related to export.

$$D_j(t) = \sum_{i=1}^{N_{ind}} O_{i,j}(t) + C_j(t) + R_j(t) + E_j(t) \tag{5}$$

Reconstruction demand to a sector is calculated using a reconstruction demand matrix (RDM) as follows,

$$R_j(t) = \sum_{i=1}^{N_{ind}} \frac{RDM_{i,j}(t)}{\tau_r^i} \tag{6}$$

where $RDM_{i,j}$ is the reconstruction demand from sector i to sector j and τ_r^i is the recovery time calculated using HAZUS. The use of τ_r based on asset repair time has not been considered in previous ARIO models.

Several indirect loss frameworks suggest that reconstruction expenditures should be primarily assigned to the construction and manufacturing sectors (FEMA, 2015; Hallegatte, 2008). To populate the reconstruction matrix, we use the previous assumption in Hallegatte (2008) which is based on insurance data that 75% of direct losses incurred by sector i translate into a demand to the construction sector and 25% to the manufacturing sector. This assumption requires further investigation, in particular the contribution of reconstruction expenditures to the 'margin' sectors such as wholesale, retail, and transportation, which do not include the cost of items sold or shipped but rather the cost of doing business.

Each sector, j, tries to satisfy the initial demand, $D_j(t)$, through production of commodities and services, $P_j(t)$. However, the sector's ability to satisfy the initial demand and its actual production, $P_j^a(t)$, are subject to several constraints. We assume that the production capacity is reduced as a results of damage to the productive capital. In this model, reduction of production capacity is proportional to the reduction in productive capital. In addition, the production capacity can be limited by insufficient inventories of production inputs. Production can also increase due to overproduction capacity stemming from utilization of unused resources. Further details on each of these constraints can be found in Hallegatte (2014).

If supply constraints exist, i.e. $D_j(t) > P_j^a(t)$, a proportional rationing scheme is applied across inter-industry demand, local final demand, reconstruction demand, and exports such that:

$$O_{i,j}^*(t) = O_{i,j}(t) \cdot \frac{P_j^a(t)}{D_j(t)} \tag{7}$$

$$C_j^*(t) = C_j(t) \cdot \frac{P_j^a(t)}{D_j(t)} \tag{8}$$

$$R_j^*(t) = R_j(t) \cdot \frac{P_j^a(t)}{D_j(t)} \tag{9}$$

$$E_j^*(t) = E_j(t) \cdot \frac{P_j^a(t)}{D_j(t)} \tag{10}$$

The resultant demand, $D_j^*(t)$, to sector j at time t is equal to the sector's actual production $P_j^a(t)$, as in Equation 11.

$$D_j^*(t) = \sum_{i=1}^{Nind} O_{i,j}^*(t) + C_j^*(t) + R_j^*(t) + E_j^*(t) = P_j^a(t) \tag{11}$$

At the end of each time step, the inventory orders are updated as per Equation 12, to account for intermediate input inventory used up in the production process ($A(j,i)P_i^a(t)$) and any further depletion of the stock, i.e. the difference between target stock levels ($S_{i,j}^t(t)$) and current stock levels ($S_{i,j}(t)$).

$$O_{i,j}(t + \Delta t) = A(j,i)P_i^a(t) + \frac{1}{\tau_s^j}(S_{i,j}^t(t) - S_{i,j}(t)) \tag{12}$$

In the above equation $A(j,i)$ is a coefficient from the local input-output matrix, representing the input from industry j required to produce \$1 of industry i output. $S_{i,j}(t)$ is the inventory level of commodity from industry j available as input for industry i at time t and $S_{i,j}^t(t)$ is the target level of inventory.

Reconstruction needs are also updated based on the ability of industries to satisfy reconstruction demand:

$$RDM_{i,j}(t + \Delta t) = RDM_{i,j}(t) - \frac{RDM_{i,j}(t)}{\tau_r^i \cdot R_j(t)} R_j^*(t)\Delta t \tag{13}$$

The value added for each sector j, $VA_j(t)$, is calculated at the end of each time step by rebalancing the economy as per Equation 14.

$$VA_j(t) = P_j^a(t) - \sum_{i=1}^{N_{ind}} A(i,j)P_j^a(t) - I_j(t) \tag{14}$$

In this equation, $I_j(t)$ is the import of commodity j from outside of the region, which helps satisfy demand to sector j (for details see Hallegatte (2014)). The change in employment is assumed to be proportional to the change in the value added.

Due to the lack of necessary data, the current implementation of the model does not consider indirect losses stemming from the disruption of lifelines. Transportation network disruptions caused by damages to roads, bridges, railways, ports, etc., increase travel time and travel distance and can result in passengers and freight flow perturbations. Previous research has translated these disruptions into indirect economic impacts by introducing changes in household consumption, reducing labor efficiency, and increasing labor and transportation margin costs (Wei et al., 2022). Damages to utility networks, such as electricity, gas, data and voice, potable water and wastewater can lead to service interruption and reduced operational and productive capacities. For example, disruptions in electricity, water supply, and data and voice networks in the HayWired scenario (i.e., M_w 7.0 earthquake scenario on the Hayward Fault) are estimated to result in a 0.1% reduction in California's gross regional product (Sue Wing et al., 2021).

SAN FRANCISCO BAY AREA ECONOMIC RECOVERY AND RECONSTRUCTION

REGIONAL DIRECT AND INDIRECT ECONOMIC LOSSES

There is a large variability in potential economic consequences from a M_w7.2 earthquake event on the Hayward fault. The aggregate direct losses are shown in Figure 2, left, where the mean direct loss is \$116 billion, and \$45 to \$201 billion is the 80% confidence interval. Direct losses have high variance and a heavy right tail, meaning that very large, rare losses are possible. Therefore it is important to consider the full distribution of direct losses in economic recovery modeling, and not just the mean direct losses as commonly done in risk assessment methodologies such as HAZUS.

Running the modified ARIO model on the 1000 direct loss simulations yields 1000 economic recovery paths. Figure 2, right, shows how the value added changes throughout the recovery for different simulations. On average, value added initially reduces by 6.1% and recovers in approximately 2.6 years, after which the economy experiences a period of production that is slightly higher than the pre-disaster one. In several cases, where direct losses are large, supply bottlenecks cause exhaustion of sector inventory, leading to a rapid decrease in production and value added, which can be seen in Figure 2, right. The recovery of large fluctuations can take several years. The possible exhaustion of inventories and large output losses point to the need for post-disaster economic resilience tactics, such as scarce input conservation and substitution (Rose, 2007).

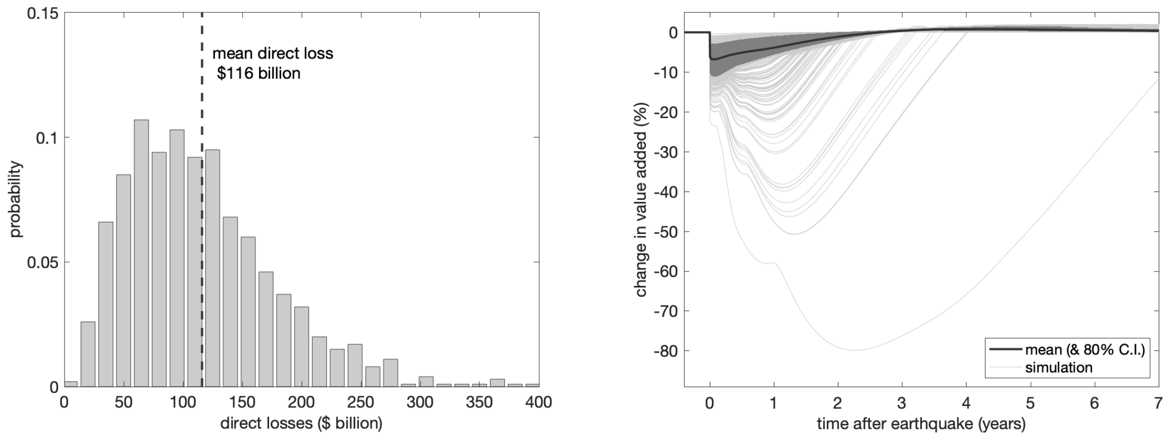
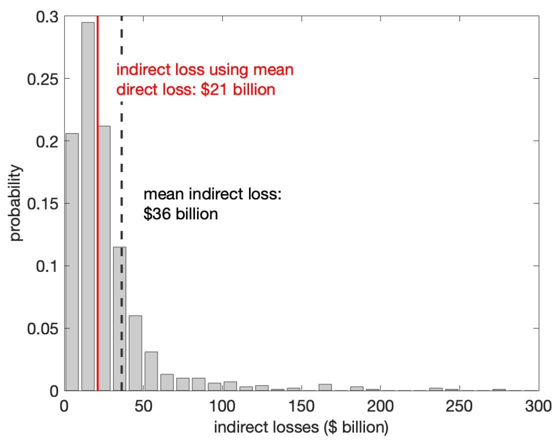


Figure 2. Left: probability distribution of aggregate Bay Area direct economic losses; Right: results from 1000 simulations of post-earthquake changes in value added over the recovery period.

Integrating the area under value added curves in Figure 2, right, will result in a net indirect economic loss metric, which represents lost profits, wages, and taxes over the recovery period. Figure 3, left, shows the distribution of the indirect losses, which is more positively skewed than the distribution of the direct loss. The mean indirect loss is \$36 billion and the 80% confidence interval is \$6.7 billion to \$52 billion. If we only use the mean direct loss as an input into ARIO model, the indirect loss is \$21 billion, which is only 58% of the mean indirect loss. This points to the non-linearity of the economic recovery model and the resulting skewness of the indirect loss distribution, showing the importance of considering the full distribution of results and not just the mean values.The mean loss in value added is comparable to the results obtained in the HayWired scenario that considered a smaller M_w 7.0 earthquake on the Hayward Fault, where the loss in Bay Area gross regional product was estimated to be \$37.9 billion 2012 dollars (Sue Wing et al., 2021). It should be noted that the HayWired study also included losses due to fire following earthquake, aftershocks and utility-service disruption.

The variation in loss amplification factor, or total economic loss divided by direct loss, is shown in Figure 3, right, where 80% of the simulations lie in the range of 1.15 to 1.37. For direct losses below \$200 billion, the amplification factor tends to increase linearly with greater losses. Once direct losses exceed \$210 billion, the sectors in the model start experiencing large production constraints and inability to satisfy reconstruction demand, causing larger indirect losses. This result is in line with previous observations where indirect loss can be small for one threshold of direct losses and large for another threshold. For example, in the 1989 Loma Prieta earthquake, while direct losses were $5.9 billion, the amplification factor was estimated to be 1.03-1.12 (Brady and Perkins, 1991). On the other hand, a larger 1994 Northridge earthquake caused $41.8 billion in direct and $7.3 billion in indirect losses, resulting in an amplification factor of 1.17 (Petak and Elahi, 2000).



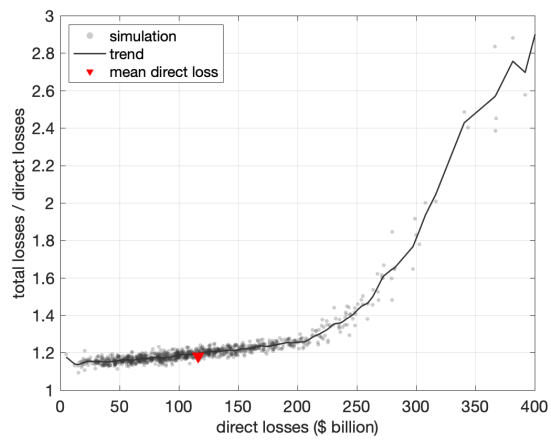


Figure 3. Left: probability distribution of Bay Area indirect economic losses for all sectors. Right: loss amplification factor, defined as total loss divided by direct loss. Total loss is the sum of direct and indirect economic losses.

Reconstruction time

We examine the regional capital reconstruction time with and without considering productive constraints of the construction sector. The regional reconstruction trajectory without production constraints is obtained by aggregating individual building repair times from HAZUS, as described in the Physical damage and direct loss modeling section. To consider economic sectors' productive constraints, we derive a reconstruction trajectory from the ARIO model, which encompasses both building repair times and the construction and manufacturing sectors' ability to satisfy reconstruction demand. Lastly, we also compare a reconstruction trajectory from ARIO that uses assumed repair times as in Hallegatte (2014), i.e. repair times that are not based on the level of physical damage.

The capital reconstruction trajectories and distribution of reconstruction time are shown in Figure 4. The region is assumed to be reconstructed when 99% of the capital is repaired. The average reconstruction time considering HAZUS repair times is 2.1 years. Like other engineering risk assessment methodologies (e.g. Almufti and Willford, 2013), this repair time does not take into consideration supply constraints and the ability of the construction sector to satisfy reconstruction demand.

Previous implementations of the ARIO model assume a 0.5 year repair time for all buildings and infrastructure, since there is no explicit repair time quantification. Under this assumption, the average reconstruction time of Bay Area capital is 2.0 years. This result assumes a uniform reconstruction rate for all economic sector, which does not depend on the level of asset damage.

Combining both building repair time and construction and manufacturing sectors' constraints more than doubles the average reconstruction to 5.6 years. This result takes into account the variability in the repair time across different sectors as a result of the variable level of damage.

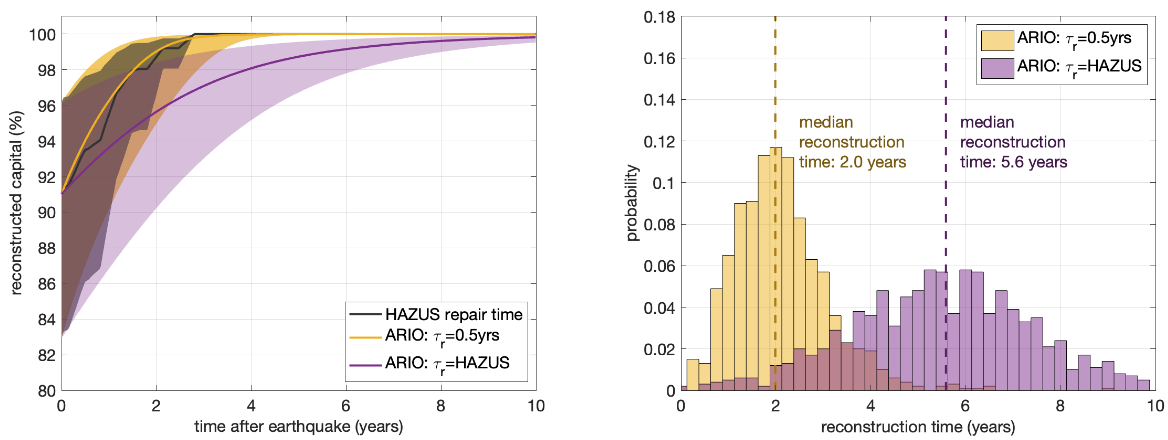


Figure 4. Left: capital reconstruction path for three models: HAZUS repair time, ARIO with assumed 0.5 year repair time for all sectors, and current ARIO model with HAZUS repair time for each sector. The shaded region represents 80% confidence interval. Right: distribution of time to full reconstruction (99% capital reconstructed) for ARIO model with assumed 0.5 years repair time across all sectors, and current ARIO model with HAZUS repair time for each sector.

INDIVIDUAL SECTOR RESULTS

Insight into each sector's physical and productive vulnerability can be gained by looking at individual sectors' economic losses. Direct losses (Figure 5, right) are the largest in the finance and real estate sector (58% of the direct losses), which includes residential housing. This is consistent with observations in previous disasters. The next three sectors with the largest direct economic losses are educational services, health care, and social assistance (7% of the all direct losses); manufacturing (6%); professional and business services (5%).

The industries suffering the largest indirect losses are professional and business services (22% of all indirect losses); finance, insurance, and real estate (21%); and education services, health care, and social assistance (15%). Industries involved in reconstruction, such as construction and manufacturing, on average experience a net gain in value added, where the construction value added gain over the recovery period is on average $14.5 billion.

When we consider the most affected sectors in relative terms (i.e. total economic losses as a percentage of the annual value added), the most vulnerable sector is other services (see Figure 5, right), which includes services such as equipment and machinery repairing, promoting or administering religious activities, grant-making, advocacy, dry-cleaning and laundry, personal care, death care, pet care, photofinishing, temporary parking, and dating services. The mean total loss amounts to 82% of value added.

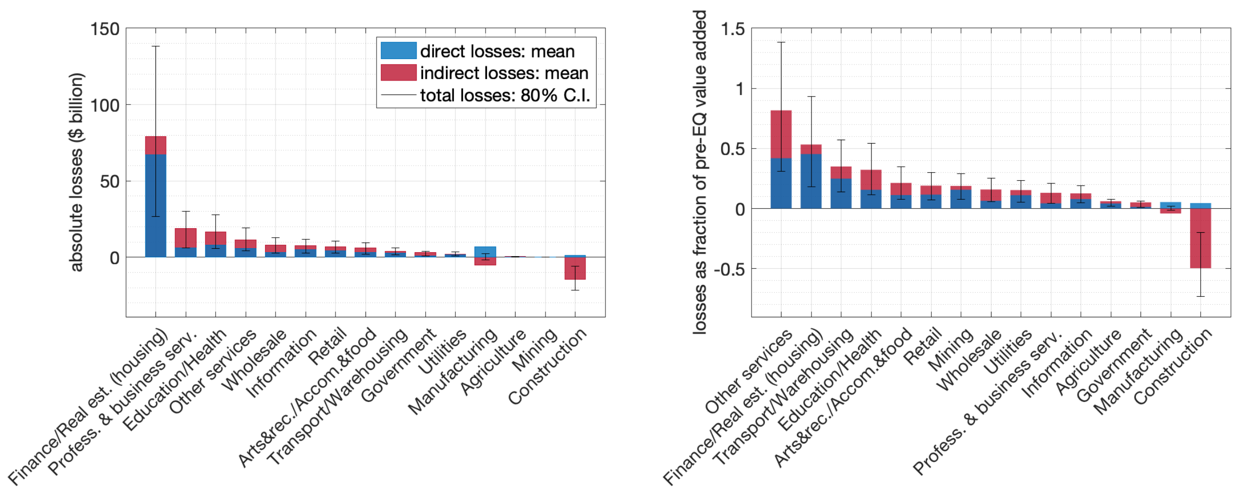


Figure 5. Direct, indirect and total economic losses for the 15 sectors in terms of absolute monetary value (left) and as fraction of pre-earthquake annual value added, sorted by total economic losses (right). An 80% confidence interval is indicated by vertical error bars.

Reconstruction of different sectors occurs at different rates. These rates depend on the level of damage within a particular sector and the construction sector's ability to supply services. For example, as shown in Figure 6, left, while the mining sector has the largest percentage of initially destructed capital, the residential (finance and real estate) and other services sectors take longer to recover. When considering sectors' value added (Figure 6, right) the recovery occurs at a faster rate than capital reconstruction due to the sector's post-disaster increase in production capacity (overproduction). For example, the manufacturing sector takes on average 5.7 years to reconstruct 99% of pre-earthquake productive capital, but the value added recovers in 1.6 years. The eventual increase in value added of several sectors is consistent with previous research, which partially attributes such increases to reconstruction-boom and accelerated replacement of capital (Hallegatte and Dumas, 2009).

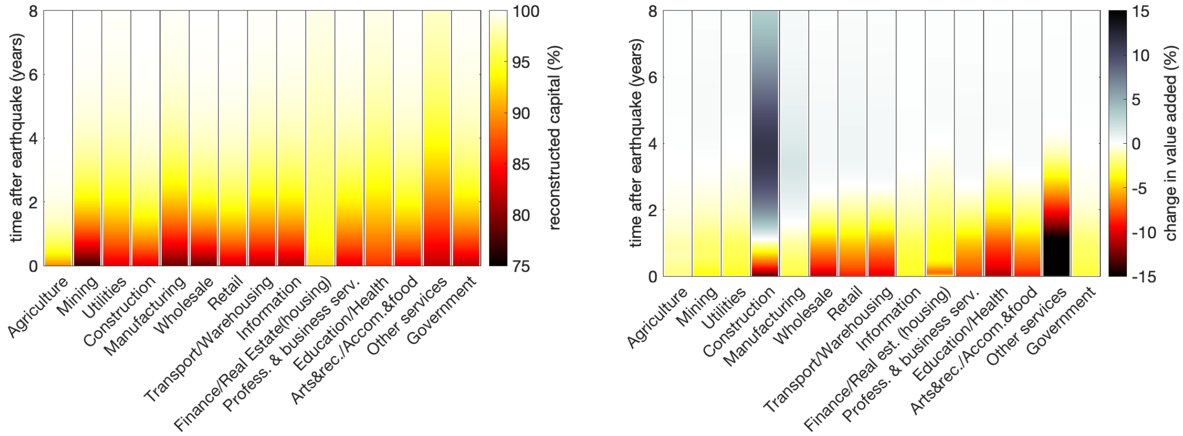


Figure 6. Left: mean productive capital reconstruction path for the 15 economic sectors, expressed a percentage of the pre-earthquake productive capital value. Right: mean value added recovery for the 15 economic sectors, expressed as percent change from the pre-earthquake value added.

Lastly, changes in industries' human capital related to employment are determined based on the changes in value added. Figure 7, shows that educational services, health care, and social assistance will be heavily impacted, along with other services, and professional and business services.

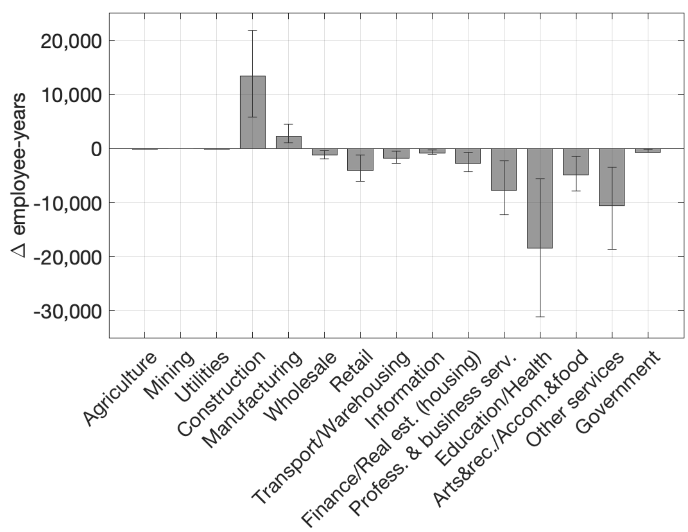


Figure 7. Mean changes in sector employment over the recovery period, and 80% confidence interval (indicated by error bars), expressed as employee-years.

SENSITIVITY ANALYSIS

The proposed methodology is comprised of multiple stages, and it is of interest to investigate how model parameters from different stages influence the aggregate direct and indirect losses. We perform a sensitivity analysis using the regression tree ensemble method, which is described in Grujic (2017) and applied in the context of seismic risk assessment in Markhvida et al. (2020). In this analysis, 5000 samples of model parameters that are characterized by epistemic uncertainty are randomly drawn and the three-stage indirect loss calculation is performed. Then, a sensitivity index is calculated by fitting regression trees and using bagging, where the model parameters are predictor variables and indirect loss is the output variable. The model parameters considered in this sensitivity analysis are described below and the associated probability distributions are summarized in Table 3.

Ground motion simulation parameters: for regional hazard modeling, variation in ground motion prediction equation (GMPE), and median ground motion predictions are considered. The choice of GMPEs can affect the spatial distribution and scale of the ground shaking. In this case, a GMPE model is sampled from four models (Abrahamson et al., 2014; Boore et al., 2014; Campbell and Bozorgnia, 2014; Chiou and Youngs, 2014) using a discrete uniform distribution. Lastly, the epistemic uncertainty in the median ground motion intensity is considered using a three-point discrete approximation of a normal distribution (Atik and Youngs, 2014).

Direct loss modeling parameters: for damage and loss predictions, epistemic uncertainty in HAZUS fragility functions, loss ratios, and repair times is considered, following the approach in Markhvida et al. (2020). For building fragility functions (as in equation 3), large variations can occur as a result of using different methodologies to derive fragility functions (Silva et al., 2014). To account for this influence, we introduce uncertainty in the median of the HAZUS fragility functions, θ, considering θ to have a lognormal distribution with $\sigma_{\ln\theta} = 0.1$.

There is a large amount of uncertainty around the cost of repair given a particular damage state of a building. To test its influence on the final loss metrics, we introduce uncertainty in the HAZUS loss ratios for the four damage states by assuming normal distributions with coefficients of variation $CV = [0.430, 0.308, 0.201, 0.134]$, as reported in Table VI of Martins et al. (2016). Any sampled loss ratios that are below 0 or above 1 are assumed to be 0 or 1, respectively. A similar approach is applied to the HAZUS repair times given a particular damage state. Given the lack of studies on the uncertainty of repair times for different damage states, we assume that the coefficients of variation are the same as the loss ratio coefficients.

Economic recovery modeling parameters: for the ARIO model, we consider the influence of all model parameters specified in Hallegatte (2014). Considered parameters are the capacity of sectors to overproduce in a post-disaster setting (α^{max}), the time it takes to ramp up overproduction (τ_α), pre-disaster commodity inventory expressed in days of consumption (n_j), the time is takes to restock commodity's inventory (τ_s), and heterogeneity of economic sectors (ψ). The last parameter describes the extent to which businesses in a particular sector produce non-substitutable goods and services. If ψ is low, the sector is assumed to be homogeneous, where other sectors can keep consuming the commodity until the entire sector inventory is empty. Conversely, if $\psi = 1$ it is assumed that the sector is fully heterogeneous, where x% decrease in inventory means that x% of businesses who consume the commodity are unable to produce. The range for the five parameters is summarized in Table 3, where for each sample, parameters were drawn from a uniform distribution.

Table 3. Input model parameters considered in the sensitivity analysis

Param.	**Description**	**Baseline**	**Probability distribution**
	Ground motion parameters		
M_w	moment-magnitude	7.2	uniform(6.2,7.2)
GMPE	ground motion prediction equation	Abrahamson et al. (2014)	discrete uniform((Abrahamson et al., 2014; Boore et al., 2014; Campbell and Bozorgnia, 2014; Chiou and Youngs, 2014))
$\overline{\mathrm{IM}}$	median ground motion modification	0	as per Atik and Youngs (2014)
	Direct loss modeling parameters		
θ	median of fragility function	${y_\theta}^*$	lognormal$\big(ln(y_\theta), 0.1\big)$
LR	loss ratios for four damage states	${\mu_{LR}}^*$	$\mathcal{N}(\mu_{LR}, CV_{LR} \times \mu_{LR})^{**}$
RT	repair time for four damage states	${\mu_{RT}}^*$	$\mathcal{N}(\mu_{RT}, CV_{RT} \times \mu_{RT})^{**}$
	Economic recovery modeling parameters		
α^{max}	overproduction capacity	125%	uniform(100,150)
τ_α	characteristic time of overproduction capacity	12 months	uniform(6,18)
n_j	pre-disaster days of stocked commodity j^{***}	90 days	uniform(60,120)
τ_s	characteristic time of stock restoration	30 days	uniform(15,45)
ψ	sector heterogeneity	0.8	uniform(0.7,0.9)

* the baseline values for these variables are defined as in HAZUS (FEMA, 2015).
** $CV_{LR} = CV_{RT} = [0.430, 0.308, 0.201, 0.134]$ for damage states slight, moderate, extensive and complete, respectively.
*** it is assumed that utility and transportation sectors provide nonstockable goods, where the inventory cannot be larger than 3 days.

As shown in Figure 8, considering epistemic uncertainty in the modeling parameters results in longer value added recovery times and higher variation in indirect loss and loss amplification factor. The longer economic recovery times associated with variable model parameters can be partly explained by the instances where the modeled economy fully collapses and the production reduces to zero without being able to recover. As suggested in Hallegatte (2014), this collapse can happen when sectors cease production because they run out of input inventories, in turn making it impossible for their client sectors to produce without external support. This is particularly the case with lower pre-disaster days of stocked commodity and longer times required for inventory restocking.

Figure 8 highlights the effect of using only one model without any epistemic uncertainty in contrast with a model that considers uncertainty in the modeling parameters. While there is a larger variability in the results with epistemic uncertainty, the general trend of economic recovery and non-linearly in amplification factor is preserved.

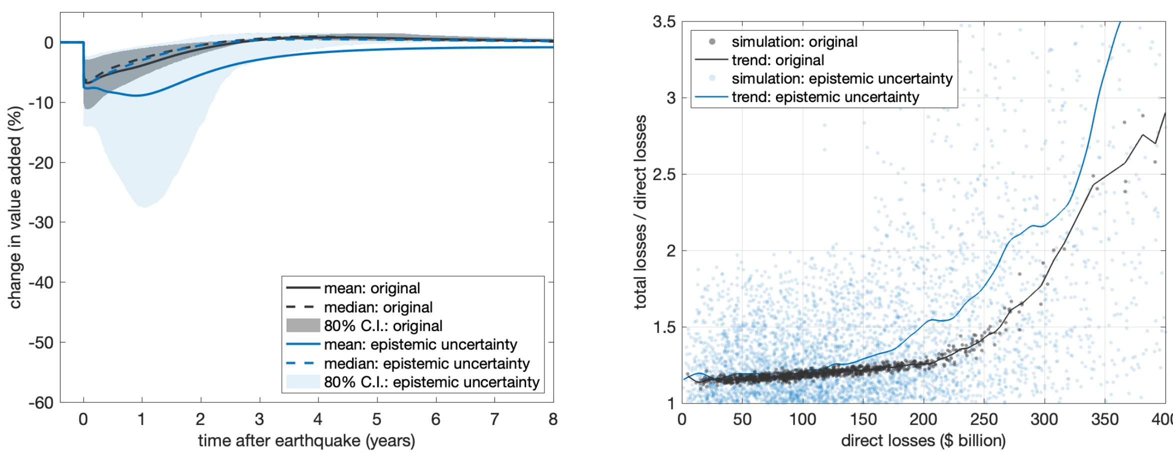


Figure 8. Left: the change in value added over the recovery period (i.e. indirect loss) with and without (original) considering epistemic uncertainty in the modeling parameters. Right: loss amplification factor trends as a function of direct economic losses with and without (original) considering epistemic uncertainty in the modeling parameters.

Figure 9 shows the results of the sensitivity analysis for regional direct and indirect losses. Any parameter whose sensitivity index is similar to or less than that of a randomly sampled integer used as an additional input variable can be considered of negligible importance. Direct losses are sensitive to ground motion parameters and most of the direct loss modeling parameters with the exception of repair time, which does not factor into direct loss calculation. In particular, loss ratio, fragility function, and GMPE are of importance.

Indirect loss, which is dependent on inputs from all of the three modeling stages, is the most sensitive to inventory parameters such as stock days, time to restock, overproduction capacity, and fragility functions. Indirect loss is also moderately sensitive to loss ratios, the choice of GMPE, and less so to sector heterogeneity. Indirect loss is not sensitive to uncertainty in parameters such as characteristic time of overproduction capacity, median ground motion, and repair time. Indirect loss seems to be more sensitive to uncertainty in the economic parameters than seismic risk modeling parameters, and is in general less sensitive to input model parameters than direct loss.

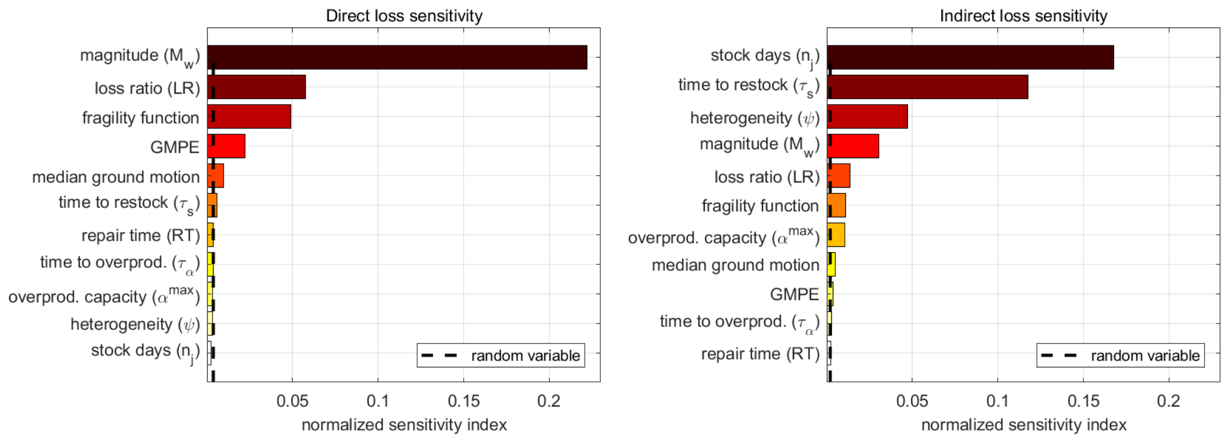


Figure 9. Sensitivity of regional direct loss (left) and regional indirect loss to model parameters (right). The sensitivity index is normalized by the sensitivity index of using the loss itself as an input, i.e. the perfect predictor. A variable can be considered unimportant if its sensitivity index is comparable to or less than the index of a randomly drawn variable (dashed line).

SUMMARY AND CONCLUSIONS

This research proposes a framework that synthesizes regional direct loss modeling with the ARIO economic recovery model to predict direct and indirect economic losses, and employment changes following a large earthquake. This is done through a series of simulations of regional ground motion maps, physical damage, direct losses, capital repair times, and finally, changes in industries' value added and their recovery. As a result, indirect losses in sectors that might not have experienced earthquake damage are captured. The proposed approach creates a pipeline for performing end-to-end simulations to quantify total economic losses and incorporate variations and uncertainty arising along different stages of the simulation. The proposed model is applied to estimate the total economic impact of a Hayward fault earthquake on the San Francisco Bay Area.

Important limitations of the proposed model include the tendency of the economy to return to pre-disaster condition and the lack of lifeline disruption modeling. Since the changes in value added are estimated assuming equilibrium in the pre-disaster economy, the ARIO model tends to return to this equilibrium and does not reflect any long-term post-disaster changes. In addition, lifeline disruptions such as damages to the transportation network and interruption of the electricity, gas, data and voice, potable water, and wastewater services are not explicitly modeled due to data limitations. Such disruptions, however, can be significant contributors to indirect losses: transportation disruption can impede the movement of people and goods causing travel time increase and supply chain issues, and utility outages can cause production and service interruptions.

Despite the limitations, the model achieves several outcomes. First, it captures the uncertainty in the predictions of earthquake shaking and damage, which is then reflected in the post-disaster economic indicators such as value added and employment. For a single event scenario, propagating the uncertainty in the ground motion and building damage results in high variance and long right tail distribution of indirect losses. Indirect losses scale non-linearly with direct losses leading to a wide range of possible loss amplification factors. The cases with high loss amplification factors capture instances where sectors run out of inventory and the economy becomes constrained, leading to long output recovery times. These cases are not captured if only mean direct losses are considered in economic recovery modeling, thereby underestimating potential economic consequences. In the case of the Bay Area, the mean regional direct economic loss is $116 billion, the mean indirect loss is $36 billion (total economic loss of $152 billion), and the mean loss amplification factor is 1.23. There is also a significant variation in the amplification factor for this scenario, which ranges from 1.15 to 1.37 (80% confidence interval) – a range consistent with the scale of indirect losses in previous large earthquakes.

Second, the proposed model quantifies indirect losses across all sectors, whether or not they experienced direct damage during the earthquake. For the Bay Area scenario, while the largest direct loss is in the housing sector, the professional and business services sector is the most impacted in terms of indirect loss. In addition, four out of 15 sectors experience a larger indirect loss than direct loss (professional and business services; education and health; wholesale; and government). Some sectors that benefit from the reconstruction demand, such as the construction sector, experience a net gain in value added. The model also reveals that a large earthquake in the Bay Area can cause significant changes in labour income and unemployment. The results of this model suggest that 8,800 to 59,900 employee-years (80% confidence interval) would be lost as a result of a M_w7.2 earthquake on the Hayward fault.

Third, the synthesis of direct loss estimation and economic recovery modeling enables one to consider variable repair times that depend on the level of damage when predicting sectors' productive capital recovery. This means that the recovery is constrained by both the time needed to repair damaged infrastructure and the construction and manufacturing sectors' ability to satisfy reconstruction demand. These constraints lead to a substantial increase in the overall reconstruction time, as compared to an analysis considering only physical repair time or an assumed fixed recovery rate in the economic model. In the case of the Bay Area, the median time to 99% capital recovery increases from 2.0 years (for both HAZUS and fixed ARIO recovery rates) to 5.6 years (when using variable recovery rates plus HAZUS repair times).

Lastly, the proposed approach allows one to perform cross-model sensitivity analysis that evaluates the effect of different model components – ground motion simulation, physical damage and direct loss, and the ARIO model – on the prediction of economic consequences. A sensitivity analysis of indirect losses to uncertain modeling parameters from the three modeling stages reveals that indirect losses are more influenced by economic parameters (within the chosen parameter ranges), namely the number of days of stocked inventory, the time it takes to restock the inventory, and overproduction capacity. In addition, indirect losses are comparably sensitive to fragility functions, which predict the level of damage in a building. Loss ratios, ground motion prediction equations, and sector heterogeneity also have an influence, but to a lesser degree. When it comes to direct economic losses, all parameters pertaining to regional ground motion simulation, and physical damage and loss modeling are significant (except repair time), with the highest sensitivity to loss ratios, fragility functions, and ground motion prediction equations.

The work presented in this paper aims to help stakeholders, such as municipalities and regional authorities, to have a more complete understanding of potential earthquake consequences in their region. Explicit incorporation of uncertainty provides more transparency in terms of the range of possible economic outcomes and allows stakeholders to use different metric thresholds that are in line with their risk tolerance (e.g., 50th, 75th or 90th percentile). The proposed approach can be used to evaluate various risk management strategies, ranging from pre-disaster risk reduction investments into infrastructure to post-disaster economic stimuli and adaptive resilience measures. Furthermore, the modular nature of the end-to-end simulation framework enables researchers and modelers to incorporate future advancements in the fields of seismology, earthquake engineering, and disaster economics.

APPENDIX - CONSTRUCTION OF THE LOCAL INPUT-OUTPUT MATRIX

An appendix that summarizes the data and methods used to derive the local input-output (I-O) matrix for the ARIO model is provided in an electronic supplement.

REFERENCES

Abrahamson, N. A., Silva, W. J., and Kamai, R. (2014). Summary of the ASK14 ground motion relation for active crustal regions. *Earthquake Spectra*, 30(3):1025–1055.

Almufti, I. and Willford, M. (2013). Resilience-based earthquake design (REDi) rating system, version 1.0. Arup.

Atik, L. A. and Youngs, R. R. (2014). Epistemic uncertainty for NGA-West2 models. *Earthquake Spectra*, 30(3):1301–1318.

Boore, D. M., Stewart, J. P., Seyhan, E., and Atkinson, G. M. (2014). NGA-West2 equations for predicting PGA, PGV, and 5% damped PSA for shallow crustal earthquakes. *Earthquake Spectra*, 30(3):1057–1085.

Brady, R. J. and Perkins, J. B. (1991). Macroeconomic Effects of the Loma Prieta Earthquake. Technical report, Association of Bay Area Governments.

Brechwald, D. (2018a). Bay Area Earthquake Residential Building Damage & Displacement White Paper. Technical report, Metropolitan Transportation Commission (MTC).

Brechwald, D. (2018b). Bay Area Earthquake Shelter Needs White Paper. Technical report, Metropolitan Transportation Commission (MTC).

Brookshire, D. S., Chang, S. E., Cochrane, H., Olson, R. A., Rose, A., and Steenson, J. (1997). Direct and indirect economic losses from earthquake damage. *Earthquake Spectra*, 13(4):683–701.

Burton, H. V., Deierlein, G., Lallemant, D., and Lin, T. (2015). Framework for incorporating probabilistic building performance in the assessment of community seismic resilience. *Journal of Structural Engineering*, 142(8):C4015007.

Campbell, K. W. and Bozorgnia, Y. (2014). NGA-West2 ground motion model for the average horizontal components of PGA, PGV, and 5% damped linear acceleration response spectra. *Earthquake Spectra*, 30(3):1087–1115.

Chang, S., Cho, S., Gordon, P., Moore, J. E., Richardson, H. W., and Shinozuka, M. (2015). Estimating the costs of a large urban earthquake. *Regional Economic Impacts of Terrorist Attacks, Natural Disasters and Metropolitan Policies*, pages 115–127.

Chiou, B. S.-J. and Youngs, R. R. (2014). Update of the Chiou and Youngs NGA model for the average horizontal component of peak ground motion and response spectra. *Earthquake Spectra*, 30(3):1117–1153.

Cutler, H., Shields, M., Tavani, D., and Zahran, S. (2016). Integrating engineering outputs from natural disaster models into a dynamic spatial computable general equilibrium model of centerville. *Sustainable and Resilient Infrastructure*, 1(3-4):169–187.

Daniell, J., Vervaeck, A., and Wenzel, F. (2011). A timeline of the socio-economic effects of the 2011 Tohoku earthquake with emphasis on the development of a new worldwide rapid earthquake loss estimation procedure. In *Australian Earthquake Engineering Society 2011 Conference, Nov*, pages 18–20.

Detweiler, S. T. and Wein, A. M. (2018). The HayWired earthquake scenario – Engineering implications. Technical report, Reston, VA. Report.

Elhaddad, W., McKenna, F., Rynge, M., Lowe, J. B., Wang, C., and Zsarnoczay, A. (2019). *NHERI-SimCenter/WorkflowRegionalEarthquake: rWHALE (Version v1.1.0)*. Zenodo.

Federal Emergency Management Agency (2012). FEMA P-58-1: Seismic Performance Assessment of Buildings. Volume 1–Methodology. *Federal Emergency Management Agency Washington, DC*.

FEMA (2015). *HAZUS MH-2.1 Earthquake Model Technical Manual*. Federal Emergency Management Agency Washington, DC.

Field, E. H., Jordan, T. H., and Cornell, C. A. (2003). OpenSHA: A developing community-modeling environment for seismic hazard analysis. *Seismological Research Letters*, 74(4):406–419.

Giannopoulos, G. (2018). On input-output economic models in disaster impact assessment. *International Journal of Disaster Risk Reduction*, 30:186–198.

Goda, K. and Hong, H. P. (2008). Spatial Correlation of Peak Ground Motions and Response Spectra. *Bulletin of the Seismological Society of America*, 98(1):354–365.

Grossi, P. and Kunreuther, H. (2005). *Catastrophe modeling: a new approach to managing risk*. Springer Science & Business Media.

Grujic, O. (2017). *Subsurface modeling with functional data*. PhD thesis, Stanford University.

Guimaraes, P., Hefner, F. L., and Woodward, D. P. (1993). Wealth And Income Effects Of Natural Disasters: An Econometric Analysis Of Hurricane Hugo. *The Review of Regional Studies*, 23(2).

Haimes, Y. Y., Horowitz, B. M., Lambert, J. H., Santos, J. R., Lian, C., and Crowther, K. G. (2005). Inoperability Input-Output Model for Interdependent Infrastructure Sectors. I: Theory and Methodology. *Journal of Infrastructure Systems*, 11(2):67–79.

Hallegatte, S. (2008). An adaptive regional input-output model and its application to the assessment of the economic cost of katrina. *Risk Analysis: An International Journal*, 28(3):779–799.

Hallegatte, S. (2014). Modeling the role of inventories and heterogeneity in the assessment of the economic costs of natural disasters. *Risk analysis*, 34(1):152–167.

Hallegatte, S. and Dumas, P. (2009). Can natural disasters have positive consequences? Investigating the role of embodied technical change. *Ecological Economics*, 68(3):777 – 786.

Hallegatte, S. and Ghil, M. (2007). Endogenous Business Cycles and the Economic Response to Exogenous Shocks. *SSRN Electronic Journal*.

Hallegatte, S. and Przyluski, V. (2010). *The economics of natural disasters: concepts and methods*. The World Bank.

Heatwole, N., Rose, A. Z., and Rose, A. (2013). A Reduced-Form Rapid Economic Consequence Estimating Model: Application to Property Damage from U.S. Earthquakes. *International Journal of Disaster Risk Science*, 4(1):20–32.

Howe, C. W. and Cochrane, H. C. (1993). Guidelines for the uniform definition, identification, and measurement of economic damages from natural hazard events: With comments on historical assets, human capital, and natural capital.

Jaiswal, K. and Wald, D. J. (2013). Estimating Economic Losses from Earthquakes Using an Empirical Approach. *Earthquake Spectra*, 29(1):309–324.

Jones, L. M., Bernknopf, R., Cox, D., Goltz, J., Hudnut, K., Mileti, D., Perry, S., Ponti, D., Porter, K., Reichle, M., et al. (2008). The ShakeOut scenario. *US Geological Survey Open-File Report*, 1150:308.

Kajitani, Y., Chang, S. E., and Tatano, H. (2013). Economic Impacts of the 2011 Tohoku-Oki Earthquake and Tsunami. *Earthquake Spectra*, 29(S1):S457–S478.

Loth, C. and Baker, J. W. (2013). A spatial cross-correlation model of spectral accelerations at multiple periods. *Earthquake Engineering & Structural Dynamics*, 42(3):397–417.

MacKenzie, C. A., Santos, J. R., and Barker, K. (2012). Measuring changes in international production from a disruption: Case study of the japanese earthquake and tsunami. *International Journal of Production Economics*, 138(2):293 – 302.

Markhvida, M., Ceferino, L., and Baker, J. W. (2018). Modeling spatially correlated spectral accelerations at multiple periods using principal component analysis and geostatistics. *Earthquake Engineering & Structural Dynamics*, 47(5):1107–1123.

Markhvida, M., Cremen, G., Grujic, O., Ceferino, L., and Baker, J. (2020). Methods for evaluation and treatment of epistemic uncertainty in portfolio losses due to earthquakes. *Proceedings of the 17th World Conference on Earthquake Engineering*.

Martinelli, D., Cimellaro, G. P., Terzic, V., and Mahin, S. (2014). Analysis of Economic Resiliency of Communities Affected by Natural Disasters: The Bay Area Case Study. *Procedia Economics and Finance*, 18:959–968.

Martins, L., Silva, V., Marques, M., Crowley, H., and Delgado, R. (2016). Development and assessment of damage-to-loss models for moment-frame reinforced concrete buildings. *Earthquake Engineering & Structural Dynamics*, 45(5):797–817.

Okuyama, Y. (2007). Economic modeling for disaster impact analysis: past, present, and future. *Economic Systems Research*, 19(2):115–124.

Okuyama, Y. (2014). Disaster and economic structural change: case study of the 1995 Kobe Earthquake. *Economic Systems Research*, 26(1):98–117.

Okuyama, Y. and Santos, J. R. (2014). Disaster impact and input-output analysis. *Economic Systems Research*, 26(1):1–12.

Oosterhaven, J. and Többen, J. (2017). Wider economic impacts of heavy flooding in Germany: a non-linear programming approach. *Spatial Economic Analysis*, 12(4):404–428.

Pagani, M., Monelli, D., Weatherill, G., Danciu, L., Crowley, H., Silva, V., Henshaw, P., Butler, L., Nastasi, M., Panzeri, L., et al. (2014). Openquake engine: An open hazard (and risk) software for the global earthquake model. *Seismological Research Letters*, 85(3):692–702.

Parker, M., Steenkamp, D., et al. (2012). The economic impact of the canterbury earthquakes. *Reserve Bank of New Zealand Bulletin*, 75(3):13–25.

Pauw, K., Thurlow, J., Bachu, M., and Van Seventer, D. E. (2011). The economic costs of extreme weather events: a hydrometeorological CGE analysis for Malawi. *Environment and Development Economics*, 16(2):177–198.

Petak, W. J. and Elahi, S. (2000). The Northridge earthquake, USA and its economic and social impacts.

Prager, F., Chen, Z., and Rose, A. (2018). Estimating and comparing economic consequences of multiple threats: A reduced-form computable general equilibrium approach . *International journal of disaster risk reduction*, 31:45–57.

Rojahn, C. and Sharpe, R. L. (1985). *Earthquake damage evaluation data for California*. Applied Technology Council.

Rose, A. (2004). Economic principles, issues, and research priorities in hazard loss estimation. In *Modeling spatial and economic impacts of disasters*, pages 13–36. Springer.

Rose, A. (2007). Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. *Environmental Hazards*, 7(4):383–398.

Rose, A., Benavides, J., Chang, S. E., Szczesniak, P., and Lim, D. (1997). The regional economic impact of an earthquake: Direct and indirect effects of electricity lifeline disruptions. *Journal of Regional Science*, 37(3):437–458.

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

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

Rose, A. and Lim, D. (2002). Business interruption losses from natural hazards: Conceptual and methodological issues in the case of the Northridge earthquake. *Global Environmental Change Part B: Environ-*

mental Hazards, 4:1–14.

Rose, A. and Wei, D. (2013). Estimating the economic consequences of a port shutdown: the special role of resilience. *Economic Systems Research*, 25(2):212–232.

Rose, A., Wei, D., and Wein, A. (2011b). Economic Impacts of the ShakeOut Scenario. *Earthquake Spectra*, 27(2):539–557.

Silva, V., Crowley, H., Varum, H., and Pinho, R. (2015). Seismic risk assessment for mainland Portugal. *Bulletin of Earthquake Engineering*, 13(2):429–457.

Silva, V., Crowley, H., Varum, H., Pinho, R., and Sousa, R. (2014). Evaluation of analytical methodologies used to derive vulnerability functions. *Earthquake Engineering & Structural Dynamics*, 43(2):181–204.

Sue Wing, I., Rose, A., Wei, D., and Wein, A. (2021). Economic consequences of the haywired scenario—digital and utility network linkages and resilience.

U.S. Bureau of Economic Analysis (2016a). Gross domestic product (GDP) by metropolitan area. https://apps.bea.gov/iTable/index$_regional.cfm$.

U.S. Bureau of Economic Analysis (2016b). Regional Input-Output Modeling System (RIMS II) Type I multipliers.

U.S. Bureau of Economic Analysis (2016c). Table 3.1ESI. Current-Cost Net Stock of Private Fixed Assets by Industry. https://apps.bea.gov/iTable/iTable.cfm?ReqID=10step=2.

Wei, F., Koc, E., Li, N., Soibelman, L., and Wei, D. (2022). A data-driven framework to evaluate the indirect economic impacts of transportation infrastructure disruptions. *International Journal of Disaster Risk Reduction*, 75:102946.

Wein, A. (November 6, 2018). Personal communication.

World Bank (2003). Turkey—Marmara earthquake assessment (English). http://documents.worldbank.org/curated/en/474251468781785112/Turkey-Marmara-earthquake-assessment.

Wu, J., Li, N., Hallegatte, S., Shi, P., Hu, A., and Liu, X. (2012). Regional indirect economic impact evaluation of the 2008 Wenchuan Earthquake. *Environmental Earth Sciences*, 65(1):161–172.