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A refined adaptive regional input-output model: Application to the 2016 Kumamoto Earthquake

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ABSTRACT

The Adaptive Regional Input-Output (ARIO) model is popular for quantifying indirect economic losses, which stem from business and supply chain interruption. However, refining this model to study new contexts is challenging in its basic form due to low-resolution modeling of behavioral parameters and temporally static reconstruction rates. This paper presents a refined ARIO, or R-ARIO model that incorporates dynamic reconstruction rates, sector-level modeling of behavioral parameters, and explicit modeling of housing losses separately from productive capital losses. We perform a global variance-based sensitivity analysis to identify the most influential parameters on predicted indirect loss from the R-ARIO model. A case study application to the 2016 Kumamoto Earthquake Sequence isolates trends in housing and economic recovery, capturing temporal differences in reconstruction demand and uncertainty across economic indicators.

INTRODUCTION

Indirect losses stemming from the disruptions in production and supply chains make up a substantial portion of post-disaster loss. The 1994 Northridge Earthquake, 2008 Wenchuan Earthquake, and 2011 Tohoku Earthquake generated 7.3, 124, and 211 billion U.S. dollars of indirect loss, respectively (Petak and Elahi 2000; Wu et al. 2012; MacKenzie et al. 2012). These losses, amounting to 17%, 35%, and 37% of the events' total post-disaster losses, illustrate that exclusive prediction of direct losses can significantly underestimate post-disaster impacts.

Several macroeconomic modeling tools, predominantly Computable general equilibrium (CGE) models, Input-output (I-O) models, and their extensions, have been developed to quantify post-disaster indirect loss across sectors in a regional economy (Botzen et al. 2019; Okuyama 2022). CGE models have been used to simulate post-disaster impacts by estimating how shocks to the supply and demand of goods and services affect interactions between different agents of an economy, including households, firms, and government (Rose and Liao 2005). They account for price adjustments, business adaptation behaviors, economies of scale, and nonlinear impact functions. Without refinement, CGE models tend to overestimate resilient response in the short run by assuming rational behavior of the market and allowing for substitution of commodities (Rose and Liao 2005; Okuyama 2007; Botzen et al. 2019). To address these limitations, recent developments in CGE modeling, such as time-varying CGE models (Rose and Guha 2004) and the dynamic equilibrium seeking (DES) model (McDonald and McDonald 2020), provide more accurate representations of short-term economic responses to disasters. Despite these improvements, CGE models often require extensive data and calibration, which can limit their practical application among emergency management practitioners (Okuyama 2022).

I-O models have been used for indirect loss prediction due to their simplicity, relatively low data requirements, and capacity to capture inter-sectoral dependencies (Botzen et al. 2019). These models leverage input-output tables that characterize production inputs and outputs of each sector. However, limitations of basic I-O models include fixed production coefficients, overlooked supply constraints, the absence of price adjustments, failure to account for business adaptation, and the assumption of constant linear relationships between inputs and outputs (Koks et al. 2016; Galbusera and Giannopoulos 2018). As a result, I-O models tend to overestimate disaster impacts (Galbusera and Giannopoulos 2018; Hallegatte 2014).

The Adaptive Regional Input-Output model (ARIO) extends the basic I-O model to address some of its limitations by incorporating changes in productive capacity due to productive capital losses and adaptive behaviors by individual sectors (Hallegatte 2008). Examples of adaptive behaviors include overproduction, which can be achieved through production recapture (e.g., overtime or extra shifts to compensate for lost production), or resource isolation (e.g., modifying operations to run without typical inputs). Both tactics have been highly effective in various post-disaster contexts (Wein and Rose 2011; Haywired 2019; Wei et al. 2020). The ARIO model has since been improved in Hallegatte (2014) to explicitly model inventories and production bottlenecking. Due to its ability to account for supply-side shocks and sectoral adaptations during recovery, the ARIO model has been widely applied in short-term disaster impact analyses, particularly in the period before the economy transitions to a new production pattern (Okuyama 2022; Guan et al. 2020). Initially used to assess economic recovery following Hurricane Katrina, the ARIO model has since been applied to analyze the impacts of many other hazards, including climate change, earthquake, wildfire, and flood impacts (Ranger et al. 2011; Zhang et al. 2017; Markhvida et al. 2020; Wang et al. 2021; Liu et al. 2023).

This paper refines the ARIO model to address several limitations in the ARIO model itself and other macroeconomic models for assessing indirect losses. First, few macroeconomic models account for the interactions between physical reconstruction (i.e., time it takes to repair a building or infrastructure considering its damage level) and economic activities and constraints during recovery, and those that do often simplify these dynamics. The ARIO model assumes a constant, temporally static reconstruction rate for each sector, leading to identical reconstruction demands across all time steps until all productive capital has been reconstructed. While this rate can be modified, it cannot capture differences across sectors or time. This limitation can misrepresent the evolving demands on the economy during different phases of recovery and lead to inaccurate estimates of sector-specific recovery trajectories.

Second, similar to other I-O models, the ARIO model does not have an explicit mechanism for handling housing losses, which often comprise a substantial portion of the total direct loss. Previous studies have assigned all housing reconstruction demand to the real estate sector (Hallegatte 2014; Markhvida and Baker 2023). This workaround captures housing-related reconstruction demands but distorts economic recovery for the real estate sector because it implies that housing is part of the productive capital of that sector. The extent of distortion will vary depending on the amount of damaged housing and productive capital in the real estate sector. Furthermore, this simplification limits the model's ability to evaluate the impact of housing recovery on economic resilience and vice versa, which is crucial for assessing the effectiveness of disaster risk reduction programs.

Finally, the ARIO model characterizes post-disaster inventory, overproduction, and heterogeneity through economy-wide behavioral parameters. These parameters capture the adaptability of the economy after a disaster and offer flexibility for modelers to tailor economic behavior to the specific characteristics of a study region. However, these parameters are modeled at an economy-level resolution. One consequence of low-resolution modeling is that a single change to one parameter must be applied to all sectors, regardless of inter-sector differences. Modelers wishing to select these parameters for new study regions must use a "one-size-fits-all" approach. As a result, several studies (e.g. Ranger et al. 2011; Zhang et al. 2017; Wang et al. 2018; Markhvida and Baker 2023) simply adopt the parameters used to model post-Katrina recovery introduced in Hallegatte (2008) or Hallegatte (2014), despite transferring them to a non-Katrina context. The effect of supplier disruption has been shown to vary by sector, where suppliers who produce differentiated goods, have a high level of research and development, or own patents cause greater disruption (Barrot and Sauvagnat 2016). Furthermore, low-resolution modeling makes it more difficult to refine specific parameters since empirical evidence often exists at the sector or sector-category level, and it is not clear from sensitivity analyses which sectors contribute the most to the variance in the predicted ARIO output. Due to these challenges, past studies have not been able to perform sector-level sensitivity analyses or uncertainty quantification.

To address the abovementioned issues, this paper proposes the R-ARIO model to simulate post-disaster economic recovery. The R-ARIO model improves on previous iterations of the ARIO model by introducing (i) dynamic reconstruction rates based on sector-specific reconstruction time curves, (ii) explicit modeling of housing losses separate from productive capital losses, and (iii) sector-level modeling and uncertainty quantification of behavioral parameters. In addition, we propose the use of global sensitivity analyses to identify the most important behavioral parameters for further refinement. The R-ARIO model and the accompanying sensitivity analysis approach are demonstrated in a case study that explores economic recovery following the 2016 Kumamoto Earthquake. As part of the case study, we explore the influence of each model enhancement on the predicted indirect loss and illustrate how global sensitivity analyses can be used to prioritize future refinement of behavioral parameters.

THE R-ARIO MODEL

This section provides an overview of the R-ARIO model and describes its inputs, outputs, and architecture. Subsections describe each model improvement in greater detail.

The R-ARIO model extends the work by Hallegatte (2014) in three ways:

1. Reconstruction demand is modeled dynamically throughout the recovery period using time-dependent, sector-specific reconstruction rates.
2. Housing losses are incorporated into the model explicitly and separately from productive capital losses.
3. Behavioral parameter modeling is performed at the individual sector level to enable parameter refinement that accounts for inter-sector differences and enables uncertainty quantification. We propose a set of updated parameters that reflect these differences based on documented cases of business adaptation.

Figure 1 illustrates the R-ARIO model workflow, which consists of three main steps.

First, a study region and disaster are defined for the analysis. Disasters are based on observed past events or hypothetical events (e.g., using simulation-based scenarios). The disaster is used to determine the spatial extent of the study and the amount of capital loss per sector resulting from the damage.

Next, input data specific to the regional economy (comprised of N_s sectors) is assembled. The required data falls into four categories: pre-disaster economic activity (e.g., value added, exports), monetary losses due to direct damage, reconstruction time curves, and behavioral parameters. These are detailed in Table 1.

Sector-level data encompasses a series of "baseline" inputs used to quantify steady-state economic activity. The first of these inputs is the local input-output (I-O) table, a matrix representing the flow of goods and services exchanged between sectors in the defined economy, indicating how the outputs of one sector become an input for others. This table is used to derive input-output ratios that control the amount of inputs necessary to fulfill productive tasks. Next, value added and fixed assets are provided for each sector. Value added represents each sector's net contribution to the defined economy's output. It is calculated as the difference between a given sector's total output and the value of intermediate inputs it consumes from supplying sectors. Fixed assets represent the value of productive capital leveraged by each sector to produce goods and services. Fixed assets are assumed to equal the total replacement value of buildings within a given sector. Finally, exports, imports, and local demand are provided. Exports represent the value of goods and services produced by each sector within the defined economy that are sold outside the study region. Imports represent the value of goods and services produced by each sector outside the study region that are brought into the defined economy. Local final demand refers to the total demand for goods and services by final consumers.

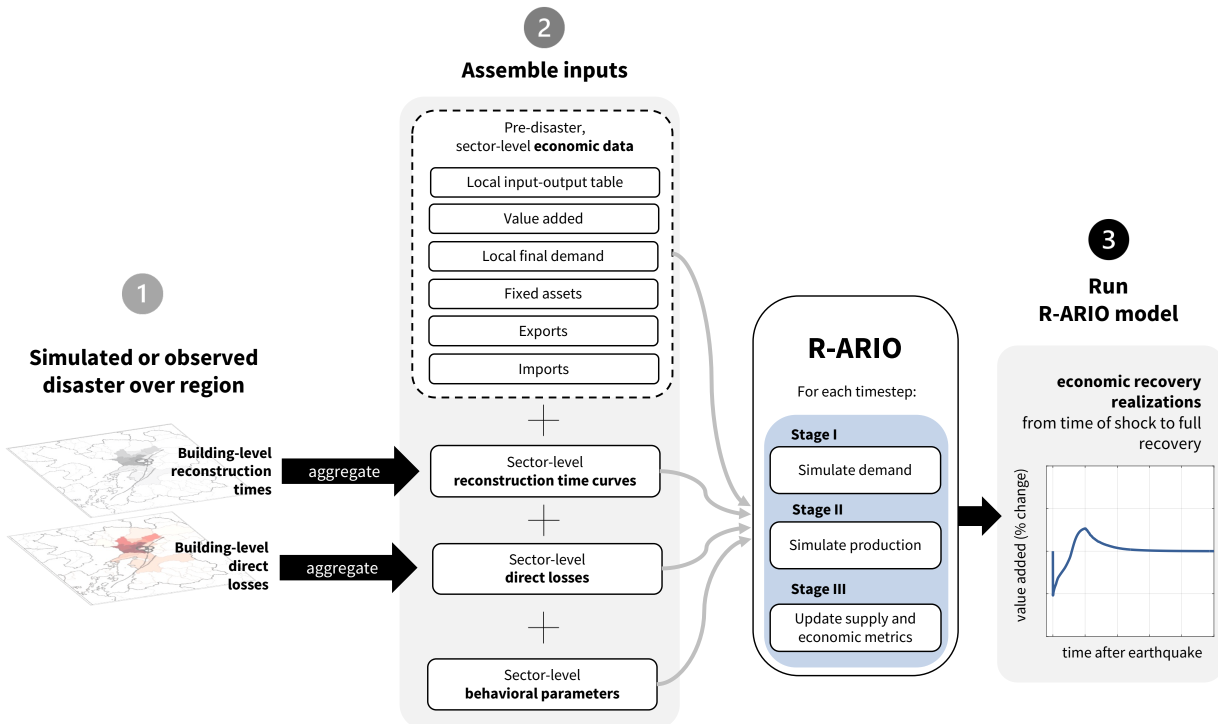

Fig. 1. General overview of the R-ARIO model workflow.

Sector-level reconstruction time curves are time-dependent functions representing the reconstruction trajectory of damaged buildings within a specific sector. These inputs are used to determine sector-specific reconstruction rates of productive capital as part of the first enhancement in this study. User-provided reconstruction time curves only account for the time it takes to reconstruct buildings and do not include indirect delays that impede the start of repairs or slow work due to a lack of needed inputs. We describe the dynamic reconstruction rates below.

Sector-level direct losses are monetary losses directly attributed to damage from the disaster. These inputs control the loss of productive capital and the approximate drop in productive capacity, at the onset of the disaster for each sector.

Finally, sector-level behavioral parameters characterize adaptation and inventory mechanics of each sector following the disaster. Like the ARIO model, the R-ARIO model considers five behavioral parameters selected by the user to characterize the regional economy. These are discussed in greater detail later.

Running the R-ARIO model

At the beginning of each simulation, behavioral parameters are sampled from user-defined distributions for uncertainty quantification purposes. Each simulation tracks economic recovery at discrete time steps over a user-defined period. At each time step, a three-stage calculation (as shown in Figure 1) is performed to estimate key economic metrics at the sector level.

Stage I: Simulate demand

Demand $D_i(t)$ for each sector i is computed at each time step (t) as the sum of inventory orders, local final demand, reconstruction demand due to damaged productive capital, and exports:

$$D_i(t) = \sum_{\text{all}\, j} O_{j,i}(t) + C_i(t) + R_i(t) + E_i(t) \tag{1}$$

TABLE 1. Inputs to the R-ARIO model. Here, N_s represents the number of sectors in the defined economy, and $(N_s + 1)$ represents the number of sectors, plus housing. N_{step} refers to the length of the time domain used as the x-axis of each recovery curve.

Input	**Category**	**Size**	**Units**	**Differences in treatment** (R-ARIO versus ARIO)
Local input-output table	Sector-level economic data	$N_s \times N_s$	Monetary value	None
Value added	Sector-level economic data	$N_s \times 1$	Monetary value	None
Exports	Sector-level economic data	$N_s \times 1$	Monetary value	None
Imports	Sector-level economic data	$N_s \times 1$	Monetary value	None
Local final demand	Sector-level economic data	$N_s \times 1$	Monetary value	None
Direct losses	Sector-level direct losses	$(N_s + 1) \times 1$	Monetary value	None
Reconstruction time curves	Sector-level reconstruction time curves	$(N_s + 1) \times N_{\text{step}}$	Unitless (Fraction of damaged capital reconstructed)	Used to determine time-dependant reconstruction time rates in R-ARIO. Not used in the ARIO model.
Behavioral parameters	Sector-level behavioral parameters	$N_s \times 5$	Varies by parameter	Modeled at the sector-level resolution in R-ARIO. Modeled at the economy-level in ARIO.

where:

$O_{j,i}(t)$ = Orders (intermediate consumption) from sector j to sector i at time t
$C_i(t)$ = Local final demand to sector i at time t
$R_i(t)$ = Reconstruction demand for sector i at time t
$E_i(t)$ = Exports of sector i at time t

At each time step, demand $D_i(t)$ is satisfied by two sources: production and imports. If these two sources cannot fulfill demand, sectors begin proportionally rationing (using the ratio between production and demand at the current time step) across $O_{j,i}(t)$, $C_i(t)$, $R_i(t)$, and $E_i(t)$.

A key component in the calculation of demand $D_i(t)$ is reconstruction demand $R_i(t)$. Fulfillment of reconstruction demand drives the restoration of productive capital over time. $R_i(t)$ is estimated using Equation 2:

$$R_i(t) = \sum_{\text{all} j} (RDM_{j,i}(t) \times \text{rate}_j(t)) \tag{2}$$

where:

$RDM_{i,j}(t)$ = Reconstruction demand from sector j to sector i at time t;
$\text{rate}_j(t)$ = Rate of reconstruction of sector j's productive assets at time t

To take into account the time-dependent nature of reconstruction, the R-ARIO model introduces the term $\text{rate}_j(t)$, which represents the rate of reconstruction at the current time step, described further below.

Stage II: Simulate production

In the absence of supply-side constraints, the production of sector i would equal the demand for sector i at each time step. However, the R-ARIO model constrains the estimated production in two ways. It is first constrained by production capacity, $P_i^{cap}(t)$, when productive capital is insufficient to meet demand (e.g., in cases with significant direct damage to a sector). Production is also constrained by inventories. It is assumed that if inventories are lower than their required levels, then production is reduced.

The final value of production, $P_i^a(t)$, accounts for both the production capacity and inventory constraints. Computing the value of $P_i^a(t)$ follows three principal calculations. First, each sector's required inventory levels $S_{j,i}^r(t)$ are computed. $S_{j,i}^r(t)$ represents the amount of input j necessary to meet the local production level of sector i over the duration of inventory j, calculated as:

$$S_{j,i}^r(t) = \begin{cases} n_j \times \left(P_i^{cap}(t) - I_i(t)\right) \times A_{j,i}(t) & \text{if } D_i(t) > P_i^{cap}(t) \\ \\ n_j \times D_i(t) \times \dfrac{P_i^{cap}(t) - I_i(t)}{P_i^{cap}(t)} \times A_{j,i}(t) & \text{if } D_i(t) \leq P_i^{cap}(t) \end{cases} \tag{3}$$

where:

n_j = Target inventory level of supplying sector j in days of demand
$P_i^{cap}(t)$ = Production capacity of sector i at time t
$I_i(t)$ = Imports of sector i at time t
$A_{j,i}$ = I-O table coefficients (required units of input from sector j to produce unit of sector i)

Next, the maximum possible production of sector i, $P_{j,i}^{max}(t)$, depends upon the actual inventory level of input j. If required inventory $S_{j,i}^r(t)$ is not met, then the maximum possible production $P_{j,i}^{max}(t)$ is reduced proportionally, taking into consideration inventory substitution effects (heterogeneity):

$$P_{j,i}^{max}(t) = \begin{cases} \left(P_i^{cap}(t) - I_i(t)\right) \times \min\left(1, \dfrac{S_{j,i}(t)}{\psi_j \times S_{j,i}(t)}\right) + I_i(t) & \text{if } D_i(t) > P_i^{cap}(t) \\ \\ \min\left(D_i(t), D_i(t) \times \dfrac{P_i^{cap}(t) - I_i(t)}{P_i^{cap}(t)} \times \min\left(1, \dfrac{S_{j,i}(t)}{\psi_j \times S_{j,i}(t)}\right) + I_i(t)\right) & \text{if } D_i(t) \leq P_i^{cap}(t) \end{cases} \tag{4}$$

where:

$P_{j,i}^{max}(t)$ = Maximum production of sector j to sector i
$S_{j,i}(t)$ = Actual inventory of input j for sector i at time t
$S^r(j,i)(t)$ = Required inventory of sector j to sector i at time t
ψ_j = Production reduction parameter (heterogeneity) of sector j

For each input sector j, if the current inventory is greater than or equal to $S^r_{j,i}(t)$, no sectoral constraints are applied. On the other hand, if a given sector cannot meet the required inventory, then its production is reduced using a ratio that considers heterogeneity in disaster losses and impacts. The top and bottom terms in Equation 4 account for the case in which the production capacity of sector i is insufficient and sufficient to fulfill demand, respectively.

Finally, the actual production $P^a_i(t)$ is taken as the minimum of all sectoral constraints:

$$P^a_i(t) = \min\left(P^{max}_{j,i}(t), \text{for all} j\right) \tag{5}$$

Stage III: Update supply and key economic metrics

Demand and production are then used to update supply and calculate key economic metrics such as value added, which is calculated as production minus intermediate production and imports:

$$VA_i(t) = P^a_i(t) - I_i(t) - \sum_{\text{all} j} A_{j,i} \times P^a_i(t) \tag{6}$$

where:

$VA_i(t)$	=	Value added of sector i at time t
$I_i(t)$	=	Imports to sector i at time t
$A_{j,i}$	=	Coefficients of the I-O table

By repeating the calculations in Stages I through III across all sectors, value added, production, and unsatisfied demand can be tracked over time to produce economic recovery curves. Uncertainty across different economic metrics can be captured by rerunning the R-ARIO model using different behavioral parameter samplings. The resulting recovery curve ensembles for each sector, which consider uncertainty in the assumed behavioral parameters, are the final output of the R-ARIO model.

The following three sections cover the implementation of three R-ARIO enhancements in greater detail.

Dynamic reconstruction rate

Reconstruction demand plays a significant role in the economic recovery process, since it is a critical component of sector-specific demand $D_i(t)$, and drives the restoration of productive capital (and hence, production capacity) over time. Equation 2 indicates that the reconstruction demand is driven by the assumed rate of reconstruction, $\text{rate}_j(t)$.

Past iterations of the ARIO model (Hallegatte 2008; Hallegatte 2014) assume a constant value of $\text{rate}_j(t)$ for all timesteps. The original ARIO model assumed a constant half-year reconstruction time for all sectors, and hence, a rate of $\frac{1}{0.5}$ throughout the recovery process. Markhvida and Baker (2023) extended this assumption to account for differences in reconstruction speed across sectors by using the time to 95% reconstruction for sector j (i.e., $\tau_{j,95}$), based on sector-specific reconstruction times. While this allows for differing reconstruction processes for each sector, it still employs a constant reconstruction rate equivalent to $\frac{1}{\tau_{j,95}}$ across the recovery period for each sector.

To account for temporal variations in this rate, the R-ARIO model leverages a "dynamic" reconstruction rate for each sector j that is updated throughout a simulation based on reconstruction progress (Figure 2b).

For a given sector, the mapping between $\text{rate}j(t)$ and the fraction of damaged productive capital reconstructed (Figure 2b) is derived using user-provided reconstruction time curves (Figure 2a). This is done by taking the derivative of the reconstruction time curve with respect to time and then mapping it directly to the fraction of damaged productive capital reconstructed.

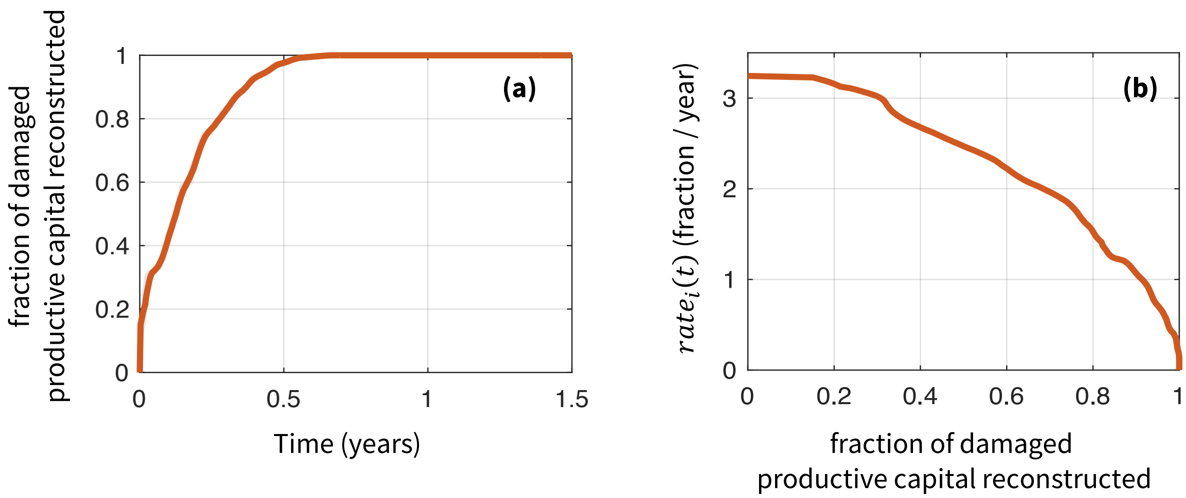

Fig. 2. In the R-ARIO model, the mapping between $\text{rate}_j(t)$ and reconstruction progress (right) is developed using the user-provided reconstruction time curve for sector j (left).

Explicit consideration of housing losses

Housing damage can produce a significant portion of post-disaster loss and reconstruction demand in an impacted region. Previous applications of the ARIO model typically assigned this reconstruction demand to the real estate sector (Hallegatte 2014; Markhvida and Baker 2023). While this approach accounts for housing loss in the analysis, it treats their replacement costs as productive capital. Since the ARIO model uses the ratio of loss to productive capital to estimate the initial drop in production, this approach can distort economic recovery for the real estate sector and cause unintended upstream and downstream ripple effects.

Rather than assigning housing losses and productive capital to an individual sector, the improved R-ARIO approach assigns housing losses to a distinct housing "sector." This sector only generates reconstruction demands, and is assumed to hold no productive capital. The housing sector does not contribute to any macroeconomic calculations of inputs, outputs, or production. As a result, these losses are accounted for in the analysis without influencing the initial drop in production for non-housing sectors.

Sector-level behavioral parameter modeling

Finally, the R-ARIO model utilitzes sector-level behavioral parameter modeling to enable more granular refinement, uncertainty quantification, and global sensitivity analysis. Behavioral parameters, which characterize sector-level adaptation and inventory mechanics, significantly influence the predicted economic recovery and indirect loss. For example, past sensitivity analyses have shown that the choice of inventory parameters n_s and τ_s can move predicted changes in value added shortly after the disaster from moderate ($<$ 20%) to economic collapse (100%) (Hallegatte 2014).

The R-ARIO model considers the same five ARIO behavioral parameters that control economic recovery dynamics. Time to maximum overproduction (τ_α) introduces a temporal dimension, defining the duration needed for the production system to adjust and reach peak overproduction capacity. Time of inventory restoration (τ_s) quantifies the duration required to restore inventory levels to the predefined target after a disruption. The maximum overproduction parameter (α_{max}) defines the upper limit of overproduction capacity in response to increased demand. Target inventory level (n_j) represents the temporal dimension of inventory management, specifying the duration for which available inventory can support production. Finally, the production reduction (or heterogeneity) parameter (ψ) captures the response of businesses to disaster impacts, influencing the extent to which production is reduced when inventories are insufficient.

Past studies (e.g. Ranger et al. 2011; Zhang et al. 2017; Wang et al. 2018; Liu et al. 2023; Markhvida and Baker 2023) assign identical parameter values for each sector in the economy, typically using the values proposed by Hallegatte (2014) and indicated in Figure 3. An exception to this is for sectors with non-stockable goods — in those cases, the target inventory level n_j is set to 3 days to account for the fact that many sectors cannot store long-lasting inventories (e.g., utilities).

The R-ARIO model includes updated behavioral parameters split across seven major sector categories (Figure 3). This proposed set retains some prior values and makes amendments where evidence is available. Furthermore, we maintain treatment for "non-stockable" goods for utilities sectors (Hallegatte 2014), as described earlier in this section. We use these parameters later as part of the case study.

For each category-parameter pair, we also define lower and upper bounds (denoted by the blue bars in Figure 3) for use in uncertainty quantification and sensitivity studies. Hence, the parameter values selected serve as the central values of their corresponding sampling distribution.

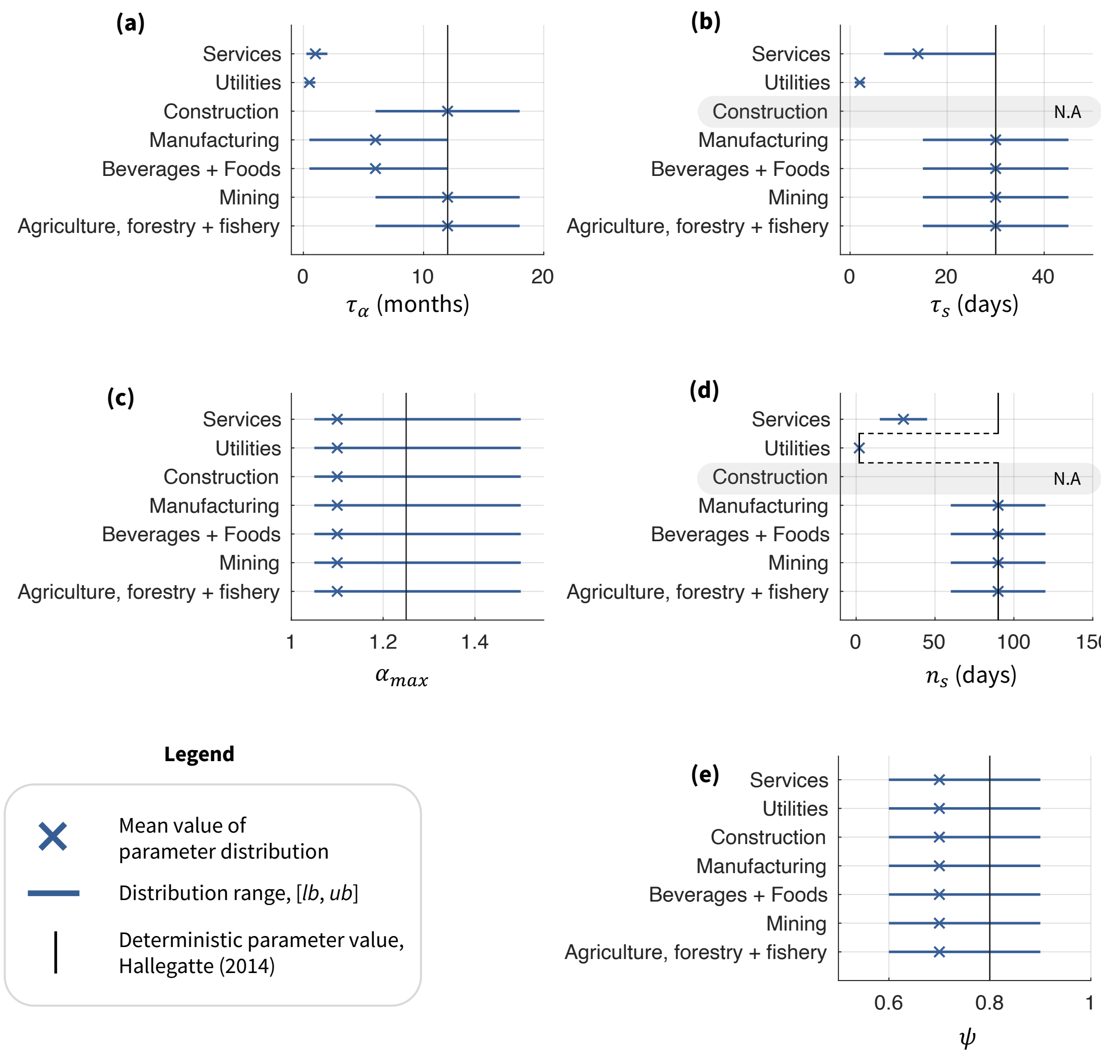

Fig. 3. Proposed distributions of behavioral parameters for each of the defined sector categories, compared against the default values in (Hallegatte 2014).

Overproduction parameters

We refine overproduction parameters τ_α and α_{max} (Figure 3a, Figure 3c). First, we reduce τ_α from 12 months to 6 months for Manufacturing and Beverages + Foods sectors, drawing insights from the accelerated deployment of production recapture strategies following events like the 2016 Kumamoto Earthquake (S&P Global 2016a; S&P Global 2016b; Maruya et al. 2017). We reduce τ_α from 12 months to 1 month for Services sectors. Services typically carry little inventory compared to other sectors, and can adapt rapidly due to high teleworking potential compared to non-services industries (OECD 2021). For Utilities sectors, where responsiveness to consumer demand is critical, we reduce τ_α to 3 days to reflect agility in adjusting production continuously to match demand, many times throughout the day (e.g., energy utilities). Finally, we lower α_{max} from 125% to 110% across all sectors to better align with empirical industrial productivity indices (IIPs) following the 2011 Tohoku Earthquake (Kajitani et al. 2013; Ministry of Economy, Trade and Industry (METI) 2018).

Inventory parameters

In most cases, we maintain the default values of inventory parameters τ_s and n_s (Figure 3b, Figure 3d), except for Utilities and Services sectors, where we reduce τ_s from 30 days to 3 days. This implies that Utility sectors can rapidly replenish their inventories when productive capital remains undamaged. Similarly, for Services sectors, we reduce τ_s from 30 days to 14 days to reflect rapid adaptability. Finally, we reduce n_s from 90 days to 30 days for Services sectors, because Services sectors carry little inventory compared to other sectors.

Heterogeneity parameter

Finally, we reduce the heterogeneity parameter ψ from 0.8 to 0.7 for all sectors to reflect recent studies of post-shock substitutional elasticity (Figure 3e). Fujiy et al. (2022) suggests that elasticities (the degree to which consumers or producers can switch between different goods or services in response to changes in prices or availability) are slightly higher (between 0.38 and 0.41) than previously reported in Atalay (2017). Such an increase implies that production reductions (that arise when inventories are insufficient) are softened, due to increased flexibility. As a result, ψ should decrease to reflect increased input substitutability.

R-ARIO BEHAVIORAL PARAMETER SENSITIVITY ANALYSIS

In this section, we describe a Sobol sensitivity analysis (Saltelli et al. 2010) to quantify the influence of R-ARIO behavioral parameters on the predicted indirect loss. We apply this approach for the parameters assigned to the $N_{cat} = 7$ sector categories defined in Figure 3.

First, we select sampling bounds for the behavioral parameters based on the upper and lower bounds in Figure 3. Sobol sampling is used to efficiently cover the sample space.

Next, we generate samples of the behavioral parameters. Each sample of parameters $\mathbf{X}^{(k)}$ is a $N_{cat} \times 5$ matrix, accounting for the five types of behavioral parameters:

$$\mathbf{X}^{(k)} = \begin{bmatrix} \psi_1^{(k)} & n_{s,1}^{(k)} & \tau_{s,1}^{(k)} & \alpha_{max,1}^{(k)} & \tau_{\alpha,1}^{(k)} \\ \psi_2^{(k)} & n_{s,2}^{(k)} & \tau_{s,2}^{(k)} & \alpha_{max,2}^{(k)} & \tau_{\alpha,2}^{(k)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \psi_{N_{cat}}^{(k)} & n_{s,N_{cat}}^{(k)} & \tau_{s,N_{cat}}^{(k)} & \alpha_{max,N_{cat}}^{(k)} & \tau_{\alpha,N_{cat}}^{(k)} \end{bmatrix} \tag{7}$$

where k is an index indicating the sample number, ranging from 1 to N_{sim}.

When using the proposed behavioral parameters introduced in the previous section, $N_{cat} = 7$, resulting in a total of 35 variables in the sensitivity analysis. For sample k, we run the R-ARIO model and record and the $Loss$ (total indirect loss across the economy) .

Using the ensemble of N_{sim} samples along with the recorded output, we estimate Sobol indices $S_{1,i}$ and $S_{T,i}$ for each of the $N_{cat} \times 5$ variables. Each index uses an i subscript to denote one of the 35 variables in the analysis (e.g., α_{max} for the Manufacturing category).

$S_{1,i}$, the first-order Sobol index, measures the contribution in output variance associated with modifying a variable in isolation:

$$S_{1,i} = \frac{\mathbb{V}ar[\mathbb{E}_{\mathbf{X}_{\sim i}}[Loss|X_i]]}{\mathbb{V}ar[Loss]} \tag{8}$$

where X_i is R-ARIO behavioral parameter variable i (associated with a specific parameter-category pair) and $\mathbf{X}_{\sim i}$ denotes the set of all variables except X_i .

$S_{T,i}$, the total-order Sobol index, measures a variable's first- and higher-order influence on predicting the model output. Unlike $S_{1,i}$, $S_{T,i}$ measures higher (or total-order) influence that accounts for all levels of interaction:

$$S_{T,i} = \frac{\mathbb{E}_{\mathbf{X}_{\sim i}}[\mathbb{V}ar_{X_i}[Loss|\mathbf{X}_{\sim i}]]}{\mathbb{V}ar[Loss]} \tag{9}$$

The inequality $0 \leq S_{1,i} \leq S_{T,i} \leq 1$ must hold for all cases, in addition to:

$$\sum_i S_{1,i} < 1 \tag{10}$$

Finally, we use values of $S_{1,i}$ and $S_{T,i}$ to rank each variable. Any variables that heavily influence indirect losses will have high index values. Such variables should be prioritized for subsequent behavioral parameter refinement efforts.

It is important to note that variables at the sector category level are used here and in the case study to illustrate this method. Sector-level analyses can be obtained by expanding $\mathbf{X}^{(k)}$ to consider $N_s \times 5$ variables, where N_s is the number of sectors.

CASE STUDY: 2016 KUMAMOTO EARTHQUAKE

An analysis of the 2016 Kumamoto Earthquakes in Japan is used here to demonstrate the R-ARIO model, identify key drivers of indirect loss, and compare predicted recovery times obtained from variants of the model. We begin with an overview of the study region and disaster, followed by a summary of model inputs, implementation, and analysis results. Finally, we discuss the application of a variance-based sensitivity analysis on the selected behavioral parameters.

Overview of study region and disaster

Kumamoto, one of Japan's 47 prefectures, is located on the southern island of Kyushu and is home to 1.3% of the country's population. The prefecture's capital, Kumamoto City, is a key economic hub and is home to over 40% of the prefecture's 1.7 million residents (Figure 4). In 2016, Kumamoto's GDP was approximately 6 trillion yen, accounting for just over 1% of Japan's total GDP.

The Kumamoto Earthquake sequence occurred along the Futgawa-Hinahgu fault in the Kumamoto prefecture, beginning with a M_w 6.2 foreshock on April 14th, followed by a M_w 7.0 mainshock two days later. Multiple significant aftershocks in the following days caused additional destruction. Damage and fatalities from the foreshock were concentrated in Mashiki Town, a small suburb north of the fault zone. The mainshock exacerbated the damage in Mashiki and extended the radius of influence to nearby Kumamoto City. Two hundred seventy-three confirmed casualties have been reported (Kumamoto Cabinet Office 2016).

Over 198,000 homes in the prefecture experienced some form of damage, with over 20% experiencing collapse (Kumamoto Prefecture 2022). As a result, over 60% of losses reported by the Office of the Cabinet stemmed from housing. Commerce and industrial assets sustained significant damages, causing cascading supply chain disruption across Japan. Damage to buildings and infrastructure in the prefecture produced losses of roughly 3.79 trillion yen as of September 14th, 2016 (Kumamoto Cabinet Office 2016).

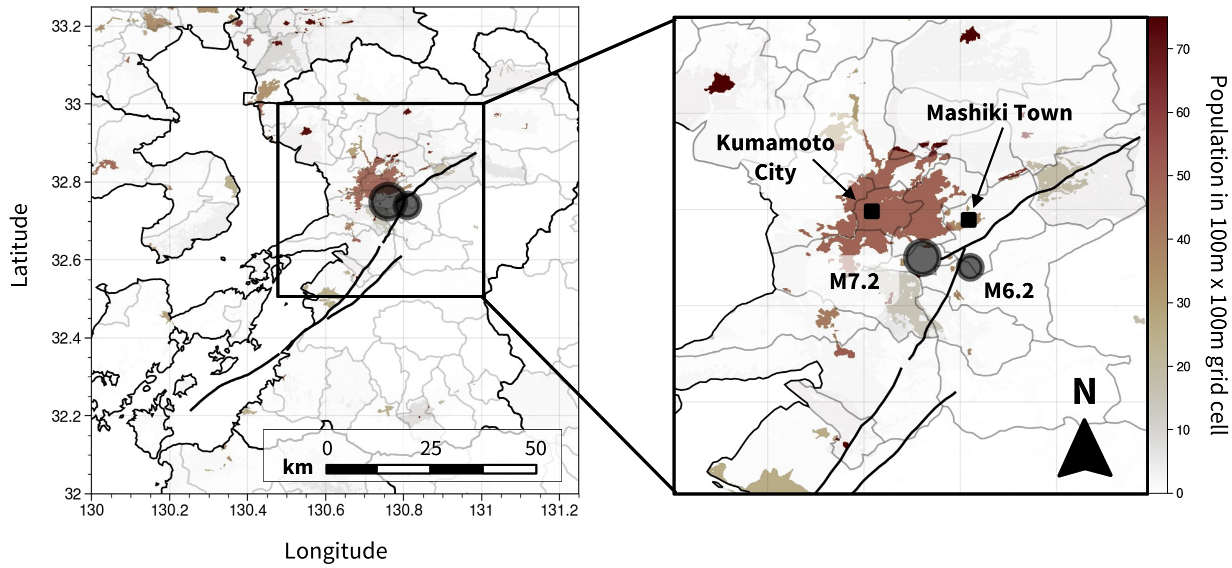

Fig. 4. Epicenters of major earthquakes (indicated by circles) and population density in the Kumamoto Prefecture (indicated by shading), along with fault traces for the Futagawa-Hinagu fault zone.

Assemble inputs

Next, we describe the assembly of the necessary input data for the R-ARIO model (Table 1). This data falls into four categories: pre-disaster economic data, monetary losses due to direct damage, repair time curves, and ARIO behavioral parameters.

Pre-disaster economic data

We assemble the input-output table and key economic metrics (e.g., value added, total final demand, exports, imports, and local demand) for Kumamoto from official prefectural data (Kumamoto Prefecture 2020) for the 2015 fiscal year. The input-output table, consisting of 37 productive sectors, is visually represented in the electronic supplement, Figure S1. We compute sector-level fixed assets using replacement costs provided by Sompo Inc. (Table S1).

Direct losses

We derive sector-specific direct losses by aggregating building-level claims data supplied by Sompo Inc (Table S2). Total building damage losses across all sectors are 1.76 trillion Yen, and further details regarding the treatment of losses can be found in the electronic supplement. We assume that 75% of reconstruction demand from these losses are distributed to the construction sector, and the remaining 25% are distributed to manufacturing sectors, consistent with past studies (e.g., Hallegatte 2008; Markhvida and Baker 2023)

Reconstruction time curves

Sector-specific reconstruction time curves are used to determine the rate of reconstruction at each time step in the R-ARIO model. We develop each curve using building-level reconstruction times, which are estimated using a proprietary model by Sompo Inc. These times are strictly limited to repairs and do not include impediments to reconstruction progress. Upon converting building-level reconstruction data into sector-level reconstruction trajectories, we observe that the time to 95% reconstruction is achieved within six months. Trajectories for each sector are illustrated in the electronic supplement, Figure S2.

Behavioral parameters

The proposed set of behavioral parameters in Figure 3 is employed for the case study. We tabulate assigned sector categories for each of the 37 productive sectors in the electronic supplement, Table S3. The impact of the refined set, relative to the default ARIO parameters introduced in Hallegatte (2014), is described in the next section.

R-ARIO model results

In this section, we describe the R-ARIO-predicted post-earthquake indirect loss, value added dynamics, and reconstruction over time at various resolutions. Next, we explore the influence of the R-ARIO model on recovery time and quantify the influence of the proposed behavioral parameters on predicted indirect loss.

Post-earthquake economic loss and recovery at the economy-level

To examine the impact of the R-ARIO model refinements, we simulate regional economic recovery using several variants of the model, as listed below:

- **Dynamic Reconstruction + explicit Housing losses + Behavioral Parameter Refinement (DR+H+BPR)**: this is the complete R-ARIO model proposed in this study.
- **Dynamic Reconstruction + explicit Housing losses (DR+H)**: this is the R-ARIO model introduced in this paper, but it uses the Hallegatte (2014) behavioral parameters rather than the proposed refined sector-level behavioral parameters.
- **Baseline**: this is equivalent to the original ARIO model.

Indirect losses predicted by the DR+H+BPR model over the first 30 days amount to roughly 88 billion, which is within reported estimates by the Cabinet Office during the same period (81 to 113 billion yen) (Takeda and Inaba 2022). The DR+H and Baseline model predictions are also within this range, at 91 and 101 billion yen, respectively. Indirect loss estimates over an analysis period of five years following the earthquake, aggregated at the economy level, are shown in Figures 5c-e for each case, along with the associated post-earthquake dynamics in value added (Figure 5b), and productive capital recovery trajectory (Figure 5a).

Figure 5a shows the predicted capital recovery, accounting for economic constraints that impede repairs of productive capital. Recovery is rapid during the first year following the disaster. The DR+H and DR+H+BPR models — which both incorporate dynamic reconstruction — follow very similar trajectories and exhibit higher rates of recovery, particularly in the first few months. Across all three models, more than 50% of damaged capital recovers within the first six months of the initial shock, and 95% recovers within 2 years. Both the DR and DR+BPR models predict a shorter time to 95% recovery of 1.25 years, compared to 1.60 years for the Baseline model. The dynamic reconstruction assumption can account for the swift progress made during the first month of recovery (reconstruction time curves for Kumamoto sectors generally exhibited rapid reconstruction initially), while the baseline model is forced to leverage a constant reconstruction rate that cannot capture this progress.

Figure 5b depicts the recovery of value added. All three models predict an identical initial 19% drop in prefectural value added. However, the recovery trajectories differ among the models. Value added recovers rapidly in the first year, with the DR+H+BPR model returning to pre-disaster values the quickest at 0.7 years, followed by the DR+H model at 1.0 year, and finally the Baseline model at 1.5 years. Due to assumed overproduction, value added continues to increase beyond the pre-disaster baseline. The median trajectories peak at 2.03%, 2.00%, and 1.59% of pre-earthquake value added for the DR+H+BPR, Baseline, and DR+H models, respectively. Beyond the peak, value added descends and eventually converges to pre-disaster values. As observed with recovery times, DR+H+BPR peaks the quickest, followed by DR+H, and Baseline. Among the three models, only the Baseline model exhibits a non-monotonic recovery due to supply-side constraints that impede recovery around the six-month mark.

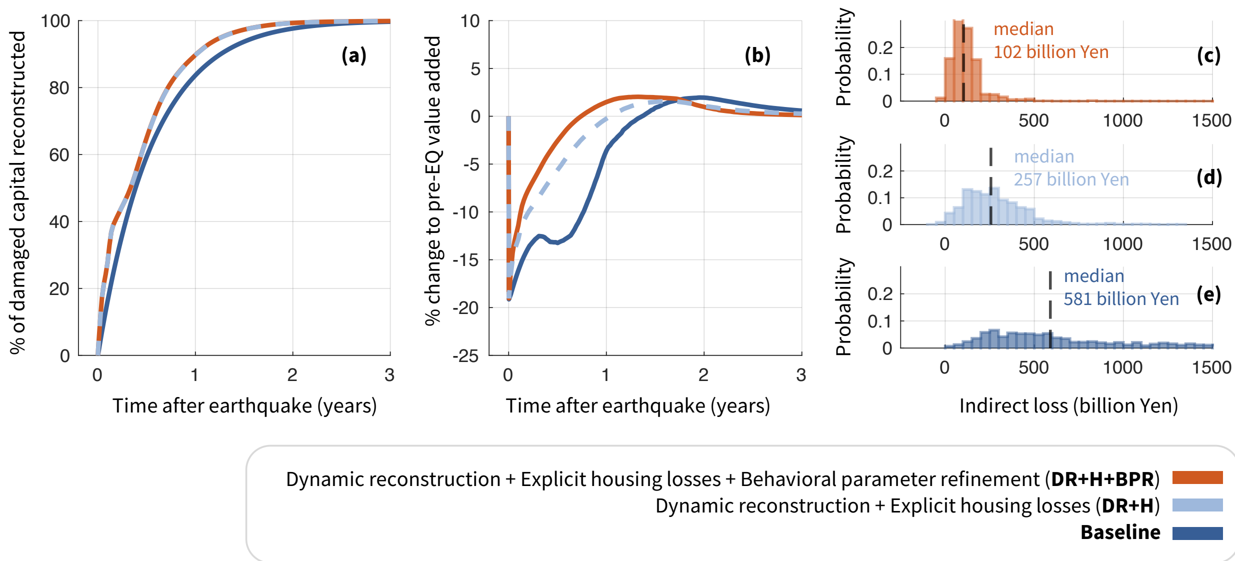

Fig. 5. Results for each of the three models, based on a set of 1000 simulations and a 5-year recovery window. Panels (a) and (b) represent the 50th percentile recovery trajectories of productive capital and value added, respectively. The histograms in (c), (d), and (e) illustrate the indirect losses for different variants of the R-ARIO model. Dashed lines indicate the 50th percentile value in each case.

Figures 5c-e illustrate the total predicted indirect loss over the analysis period. By integrating each realization of value added across time, a corresponding realization of total indirect loss at the economy level can be obtained. Among the three models, DR+H+BPR predicts the lowest median indirect loss over the entire recovery period, at approximately 102 billion yen. In contrast, the DR+H and Baseline models, which lack behavioral parameter refinement, predict substantially higher median indirect losses of 257 billion yen and 581 billion yen, respectively. The higher losses predicted by the DR+H and Baseline are due in part to longer τ_α values associated with the default ARIO behavioral parameter settings. Notably, the significant median indirect loss predicted by the Baseline model is due to its much longer period of non-recovery compared to the other two models. Overall, including behavioral parameter refinement reduces the predicted median indirect loss over the recovery period by 155 billion yen when compared to the DR+H model (i.e., the difference between median losses in 5c and d).

Sector-level economic recovery

The results in Figure 5 can be disaggregated by sector to reveal recovery attributes not visible at the aggregate economy level. For each sector, we extract building recovery, production capacity, production, demand, and value added over time. Figure 6 shows Construction sector results to demonstrate relationships between demand, production capacity, and value added over time. As part of this example, we examine the single realization associated with the median indirect loss shown in Figure 5.

Figure 6a shows that capital is nearly reconstructed within two years of the disaster. This resembles the economy-level productive capital recovery trajectory in Figure 5a.

Figure 6b shows trends in production and demand. Immediately following the disaster, demand for the Construction sector dramatically increases. This sharp increase in demand is expected because 75% of all reconstruction demand is assigned to the Construction sector. During this same period, the sector loses over 20% of its pre-disaster production capacity, constraining production, and hence, ability to fulfill demand. Production capacity is restored to its pre-disaster level 0.7 years after the disaster, but it still

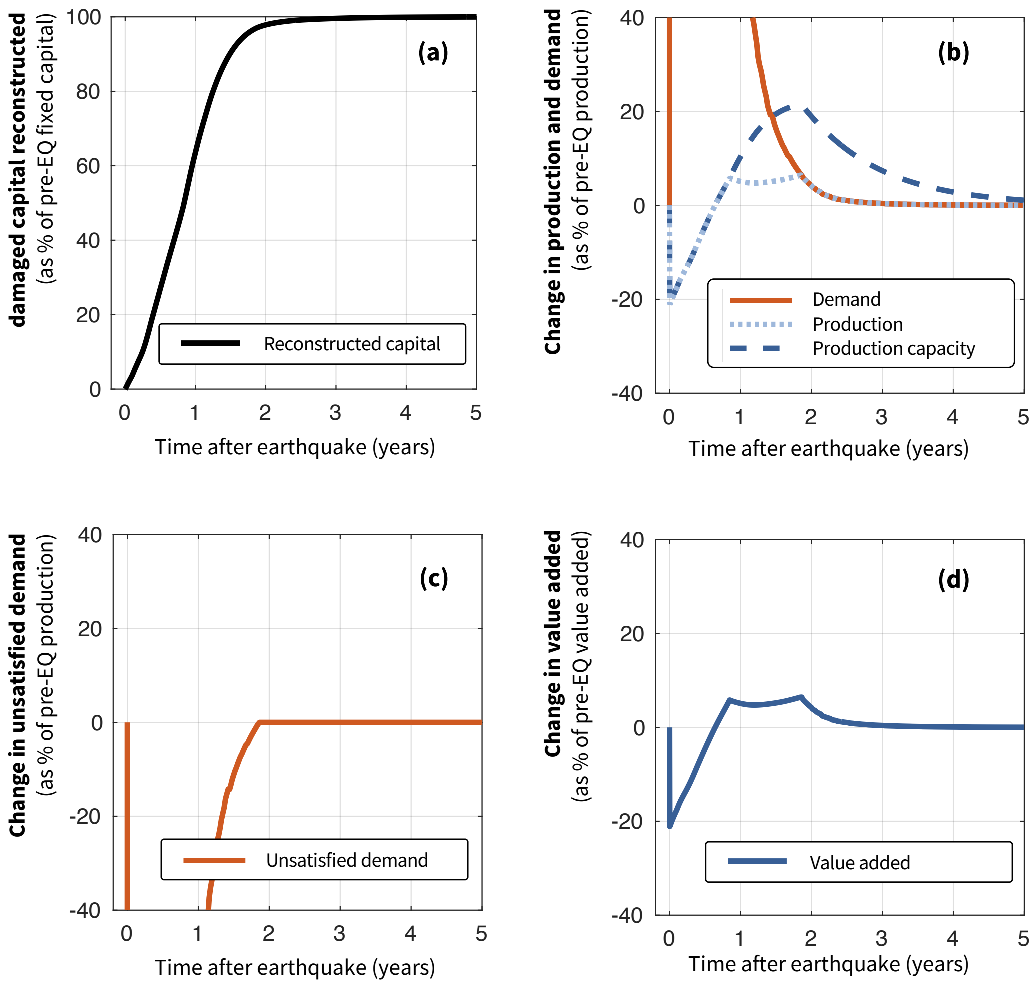

Fig. 6. Results for a single ARIO realization (associated with the 50th percentile indirect loss in Figure 5c) for the Construction sector.

fails to meet demand and begins transitioning into overproduction. An extra capacity equivalent to 20% of pre-disaster production is gradually added to the sector roughly 1.6 years after the disaster. Interestingly, while capacity grows to meet elevated demand, actual production (light blue curve) cannot keep up and production plateaus at roughly 5% over baseline production due to supply-side constraints. During this plateaued period of production, demand is rapidly decaying and the Construction sector's actual production can fulfill all demand by year 2 (the orange and light blue curves merge). Demand returns to pre-earthquake levels (along with production) shortly after. Production capacity, by comparison, is significantly slower to return to baseline.

Figure 6c shows the amount of unsatisfied demand (the difference between the demand and production curves in Figure 6b) over the entire recovery period. By the end of the year 2, the demand unsatisfied returns to 0, indicating that all demand can be fulfilled by production beyond this point.

Finally, the value added trajectory (Figure 6d) quantifies the changes in value added over time, and is used to calculate the indirect losses of the sector (through integration of trajectory over the entire recovery period). Value added takes the sharpest loss immediately following the disaster, decreasing by an amount equivalent to over 20% of its pre-disaster value. Due to the rapid initiation of overproduction, value added is restored to its pre-earthquake value added within 0.7 years of the initial drop. The time to recover value added takes roughly 35% of the time to recover all physical capital shown in Figure 6a. This trend, whereby sectors achieve quicker recovery of lost value added compared to recovery of damaged productive capital, is observed for nearly all sectors in the Kumamoto economy. Value added peaks at roughly 0.8 years after the earthquake, plateaus for an additional year, then gradually decreases to its pre-earthquake value before year three. Other sector-specific trajectories, including uncertainty bounds, can be found in the electronic supplement, Figures S4-S9.

Sector-level losses

We integrate sector-specific value added curves for each of the 37 sectors to quantify the absolute total loss, and the losses as a fraction of the pre-earthquake value added, broken down by direct and indirect sources. Results for each sector can be found in the electronic supplement, Figure S10. To simplify presentation, we sum the sector-level 50th percentile indirect losses for each of the seven categories proposed in Figure 3.

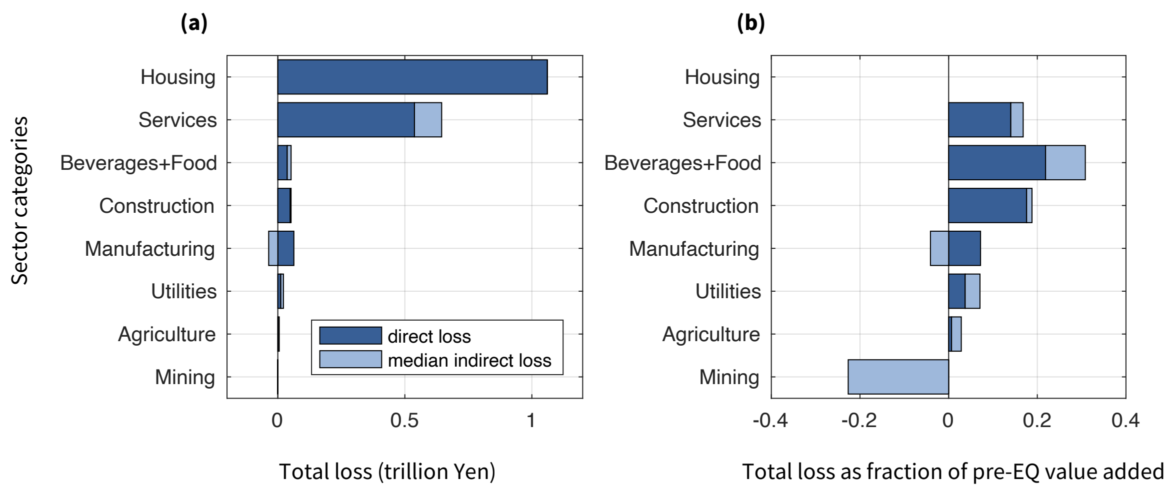

Fig. 7. 50th percentile direct and indirect losses across the seven economic sector categories (plus housing) in terms of absolute monetary value in trillion yen (left) and fraction of pre- disaster value added.

Figure 7 shows the direct and indirect losses per sector category, in absolute values and as a fraction of the total value added across all sectors within a category. The 50th percentile indirect loss across the economy (102 billion yen) is small relative to total losses (1.7 trillion yen). In absolute monetary terms, the Services category incurs the greatest indirect loss across all categories, followed by the Beverages + Food and Utilities categories. Interpreting these results within the context of the economic recovery yields a number of insights.

The Construction category's indirect loss (both in absolute terms and as a fraction of its pre-earthquake value added) is relatively low compared to other categories. This relatively small loss stems from the substantial gains due to overproduction (e.g., that of the kind observed in Figure 6b). Such overproduction is expected, since the demand for reconstruction following the disaster is substantial. When integrating the value added trajectory to obtain the indirect loss, the initial shock is barely significant enough to counteract large gains from overproduction.

The Manufacturing category (e.g., iron + steel, production machinery, plastic products + rubber products sectors) experiences a net gain in value added due to strong overproduction across several sectors, as 25% of the reconstruction demand goes to manufacturing sectors. Across a handful of Manufacturing sectors, the gain from overproduction counteracts the initial drop in value added.

The Mining category (which consists solely of the mining sector) also experiences a net gain in value added. This result is attributed to a gentle initial drop in value added, and a notably extended duration of overproduction. The mining sector is implicitly critical to the reconstruction of economic capital, since it is the primary supplier to the electricity, gas, and heat sector (within the utilities category), which supplies a significant number of manufacturing sectors (per the I-O table in the electronic supplement). The Mining category is among the few sectors to incur zero direct damage in the analysis inputs, which influences the observed net gain.

Influence of ARIO model on recovery time

Previous sections illustrated how ARIO-predicted recovery in value added, production, and productive capital can be disaggregated at the individual sector level. These sector-level trajectories can be used to extract time-to-recovery statistics, such as the time to restore lost value added. Such measures can then be used to compare recovery performance across sectors. Figure 8 provides a comparison of time-to-recovery metrics for the seven sector categories, plus housing. All reported metrics are based on 50th percentile recovery trajectories across an ensemble of 1000 simulations. Times represented at the sector category level are estimated by averaging times across all sectors within a category.

For each sector, we extract the R-ARIO-predicted times to recover 95% of the lost value added, production, and productive capital. Across most categories, the median value added is restored to pre-earthquake levels within one year. The Manufacturing and Agriculture categories are the quickest and slowest to recover, at 0.5 and 1.2 years, respectively. Recovery of production is nearly identical to that of value added across all categories. Times to recover value added and production for housing are set to zero in Figure 8, since housing is not a productive sector.

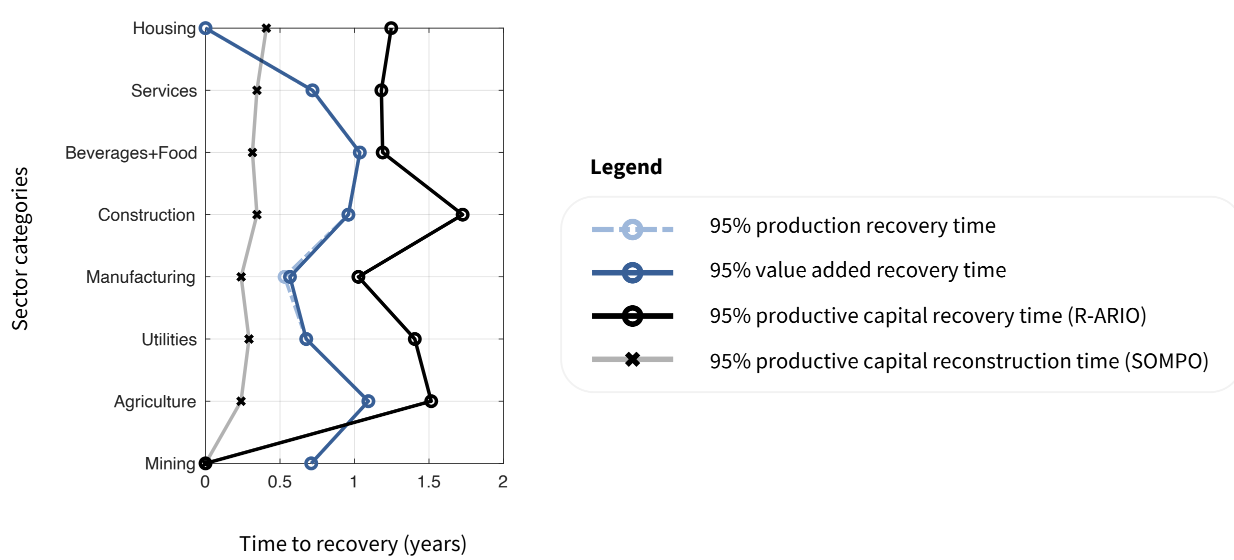

Fig. 8. R-ARIO-predicted time to recover 95% of lost production, R-ARIO-predicted time to recover 95% of lost value added, R-ARIO-predicted time to recover 95% of damaged productive capital, and time to reconstruct 95% of damaged capital based on user-provided reconstruction time curves. In all four cases, sector category averages are shown.

The R-ARIO-predicted time to recover 95% of damaged productive capital accounts for supply and reconstruction constraints. Across all sector categories with damaged capital (i.e, not the Mining category), Manufacturing sectors experience the swiftest recovery of productive assets on average, at roughly one year.

The reconstruction time data used to generate reconstruction time curves (and hence, the dynamic reconstruction rates used in the R-ARIO model for individual sectors) is generated using a proprietary catastrophe model by Sompo Inc. While these repair time curves are useful for enabling dynamic reconstruction rates, they do not take into account supply chain disruptions, or the capacity of the construction sector to fulfill post-disaster reconstruction demand. Past studies, such as Markhvida and Baker (2023), have demonstrated that the resulting sector- and community-level repair times generated by similar models (e.g., HAZUS (Federal Emergency Management Agency (FEMA) 2020)) can be significantly lower than the recovery time estimates made by the ARIO model.

Figure 8 compares R-ARIO-predicted productive capital recovery times and Sompo-provided reconstruction times. The average time to repair 95% of damaged capital is 0.28 years, per Sompo-provided reconstruction time data (which do not include supply or reconstruction delays). The R-ARIO model predicts significantly longer average recovery times, at 1.1 years. The longer estimate provided by the R-ARIO model is consistent with documented reports of capital recovery, particularly housing. One year after the Kumamoto Earthquake, thousands of households were still residing in temporary housing (Takeda and Inaba 2022).

ARIO model parameter sensitivity

Next, we perform a Sobol sensitivity analysis to understand the relative importance of sector-specific behavioral parameters on the predicted indirect losses shown in Figure 5. We compute $S_{1,i}$ and $S_{T,i}$ using equations 8 and 9, respectively. The results, displayed in Figure 9, show several features of the analysis. The behavioral parameter variables relating to inventory (particularly n_s) significantly influence the indirect losses. While this finding is consistent with the ARIO sensitivity studies in Markhvida and Baker (2023) and Hallegatte (2014), our results unveil new sector-specific insights.

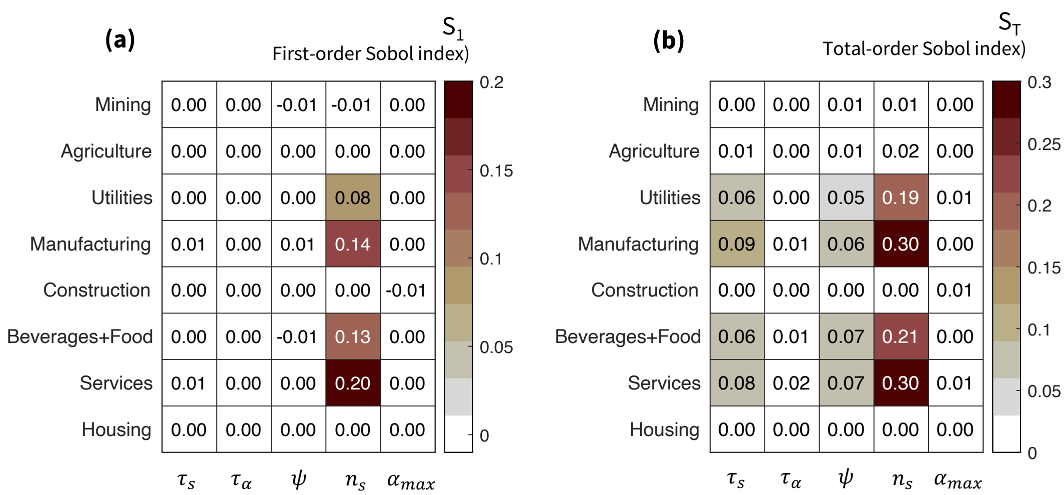

Fig. 9. (a) First-, and (b) total-order Sobol indices across the seven sector categories and behavioral parameters, measured with respect to the R-ARIO-predicted indirect loss across the prefecture.

Figure 9a shows that not all category-specific behavioral parameter variables for n_s exhibit the same modeling importance. For example, the n_s parameter variables for Manufacturing, Services, and Beverages + Food sectors are significantly more important than for those of other categories, and explain 20%, 14%, and 13% of the total first-order variance of the indirect loss, respectively.

When higher order effects are considered (Figure 9b), the importance of n_s holds, and sector category rankings based on $S_{1,i}$ hold true for $S_{T,i}$. Interestingly, inventory parameter τ_s and heterogeneity parameter ψ, which have near-zero first-order indices, have more significant $S_{T,i}$ values. Similar to n_s, both τ_s and ψ parameter settings for Manufacturing, Services, and Beverages + Food sectors have high importance. The τ_s parameters yield slightly higher $S_{T,i}$ values than ψ in most cases.

Across 35 variables in this analysis, the top 3 variables when ranked using first- and total-order indices are associated with the n_s behavioral parameter. Across all settings of n_s, the value assigned to Services category is the most significant in both first- and total-order contexts. While this result motivated our careful scrutiny of the n_s parameter for the Services category, the results in this section suggest that priority for future refinements should be considered for the Manufacturing and Beverages + Food categories as well.

CONCLUSIONS

This paper presented R-ARIO, a refined ARIO model to simulate post-disaster economic recovery. The R-ARIO model incorporates (i) explicit modeling of housing losses separate from productive capital losses, (ii) dynamic reconstruction rates based on sector-specific reconstruction time curves, and (iii) sector-level modeling of behavioral parameters. We proposed a refined set of parameters across seven sector categories that address inter-sector differences, in accordance with available empirical observations and recent studies on post-disaster business adaptation. These parameters reflect inter-sector differences and can accommodate context-specific changes based on new evidence. The enhancements aim to improve indirect loss estimation, capture temporal differences in reconstruction demand, and enable uncertainty quantification, sensitivity studies, and refinement at the sector level.

We applied the R-ARIO model to explore economic recovery following the 2016 Kumamoto Earthquake in Japan. The R-ARIO model estimates aggregate indirect losses at 5.4% of the median total (direct + indirect) loss, which amounts to 1.86 trillion yen. Indirect losses predicted by the R-ARIO model over the first 30 days following the disaster align closely with the 81 to 113 billion yen range estimated by the Cabinet Office. Over a longer five-year analysis period, the R-ARIO model predicts a median indirect loss of 102 billion yen. When sector-level behavioral parameter modeling is omitted (and older default parameters are used in place of the proposed set) this loss more than doubles to 257 billion yen. The dynamic reconstruction assumption is responsible for properly modeling the high rate of recovery within the first month following the disaster, which previous constant reconstruction rate assumptions cannot capture. Furthermore, explicit and separate modeling of housing losses prevents distortion of economic recovery caused by injecting significant direct damage into the real estate sector.

We evaluated sector-level indirect loss estimates to unveil trends across specific sector categories. Overall, the Services category generated the largest portion of indirect losses in absolute monetary terms, followed by the Beverages + Food and Utilities categories. The Construction category incurs low indirect loss (as a fraction of pre-earthquake value added) following the earthquake due to the compensating effect of overproduction. On the other hand, the Manufacturing category and the Mining category both experience net gains in value added, due to strong overproduction to support reconstruction that counteracts initial sector-level shocks. In terms of recovery time, the value-added recovers within a year for most sectors, with the Manufacturing category recovering the quickest (0.5 years on average) and Agriculture the slowest (1.2 years on average). The average time to recover lost production is nearly identical to the time to recover value added for all productive sector categories. When comparing R-ARIO-predicted times to restore lost productive capital with user-provided reconstruction time curves, we found that the R-ARIO model extends the average time to 95% recovery of productive capital (across all sector categories) from 3.5 months to 13.5 months. The longer estimate provided by the R-ARIO model, which includes supply chain impacts that impede repairs, is more consistent with documented reports of recovery, particularly housing.

Finally, we applied a global sensitivity analysis to evaluate the relative importance of specific behavioral parameters in the Kumamoto case study. The inventory parameter n_s for Manufacturing, Services and

Beverages+Food categories explains 20%, 14%, and 13% of the total first-order variance in predicted indirect losses, respectively. These trends hold for the total-order variance as well. While inventory parameters are most important overall, there is significant variability in importance between categories. Therefore, efforts to refine behavioral parameters should focus on the subset of variables with significant influence on indirect loss. The results of the sensitivity study can be used to inform mitigation strategies at the sector level. Influential behavioral parameters can be used to identify sector-specific interventions that target economy-level indirect loss reduction.

It is important to note, however, that the results in this paper are subject to limitations associated with the R-ARIO model. First, like other I-O models, the R-ARIO model assumes static productive capacity and no input substitution, which is unlikely to be realistic over longer time horizons. Second, the model assumes post-disaster recovery trajectories return to their pre-earthquake baselines, which also may not hold over longer recovery periods. Finally, indirect loss estimates are influenced by the assumed reconstruction demand distribution, which is a user-defined assumption. Future research should explore the influence of labor constraints on reconstruction, particularly those attributed to housing losses, which are significant in this case study. Further validation of the model beyond the initial 30-day indirect loss estimates comparison to reported values is also necessary.

Despite the challenges inherent in refining macroeconomic models, the proposed R-ARIO model supports the development of integrated disaster risk management policies in the following ways. First, it can inform the design of disaster risk financing strategies by providing a more comprehensive understanding of both direct and indirect losses across industries, allowing for a more accurate assessment of government and private sector liabilities, as well as the impact on government revenue(World Bank 2021). Second, by capturing the dynamic interplay between housing recovery and the economy, the R-ARIO model facilitates evaluations of the indirect impact of housing risk reduction programs or recovery strategies on other industries and vice versa. Lastly, the model offers a way to assess the broader benefits (both direct and indirect) of disaster mitigation and risk reduction programs. This aligns with the "Triple Dividend" framework (Tanner et al. 2015) by highlighting not only the avoided losses but also co-benefits such as enhanced economic resilience.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request. Source code for the R-ARIO implementation used in the study is available at github.com/0marissa/SR-ARIO.

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SUPPLEMENTAL MATERIALS

Figs. S1–10 and Tables S1-3, are available online as part of an electronic supplement in the ASCE Library (ascelibrary.org).

REFERENCES

Atalay, E. (2017). “How Important Are Sectoral Shocks?.” *American Economic Journal: Macroeconomics*, 9(4), 254–280 Publisher: American Economic Association.

Barrot, J.-N. and Sauvagnat, J. (2016). “ Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks *.” *The Quarterly Journal of Economics*, 131(3), 1543–1592.

Botzen, W. J. W., Deschenes, O., and Sanders, M. (2019). "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies." *Review of Environmental Economics and Policy*, 13(2), 167–188.

Federal Emergency Management Agency (FEMA) (2020). "Hazus Earthquake Model Technical Manual." *Report no.*, Washington, DC:.

Fujiy, B. C., Ghose, D., and Khanna, G. (2022). "Production Networks and Firm-level Elasticities of Substitution.

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

Guan, D., Wang, D., Hallegatte, S., Davis, S. J., Huo, J., Li, S., Bai, Y., Lei, T., Xue, Q., Coffman, D., et al. (2020). "Global supply-chain effects of covid-19 control measures." *Nature human behaviour*, 4(6), 577–587.

Hallegatte, S. (2008). "An Adaptive Regional Input-Output Model and its Application to the Assessment of the Economic Cost of Katrina." *Risk Analysis*, 28(3), 779–799.

Hallegatte, S. (2014). "Modeling the Role of Inventories and Heterogeneity in the Assessment of the Economic Costs of Natural Disasters: Modeling the Role of Inventories and Heterogeneity." *Risk Analysis*, 34(1), 152–167.

Haywired (2019). "Economic Consequences of the HayWired Scenario—Digital and Utility Network Linkages and Resilience." *Scientific Investigations Report*. Series: Scientific Investigations Report.

Kajitani, Y., Chang, S. E., and Tatano, H. (2013). "Economic Impacts of the 2011 Tohoku-Oki Earthquake and Tsunami." *Earthquake Spectra*, 29(1_suppl), 457–478.

Koks, E. E., Carrera, L., Jonkeren, O., Aerts, J. C. J. H., Husby, T. G., Thissen, M., Standardi, G., and Mysiak, J. (2016). "Regional disaster impact analysis: comparing input–output and computable general equilibrium models." *Natural Hazards and Earth System Sciences*, 16(8), 1911–1924 Publisher: Copernicus GmbH.

Kumamoto Cabinet Office (2016). "Digital Archives of Kumamoto Disasters, <https://www.kumamoto-archive.jp/en/about>.

Kumamoto Prefecture (2020). "Kumamoto Prefecture Industry Association Table - Kumamoto Prefecture Homepage, <https://www.pref.kumamoto.jp/soshiki/20/50333.html>.

Kumamoto Prefecture (2022). "Damage from the Kumamoto Earthquake [Report 326]." *Report no.*, <https://www.pref.kumamoto.jp/uploaded/attachment/242582.pdf>.

Liu, Y., Li, Y., Wang, G., Gao, G., and Chen, Y. (2023). "Quantifying multi-regional indirect economic losses: An assessment based on the 2021 rainstorm events in China." *Frontiers in Earth Science*, 10, 1057430.

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. and Baker, J. W. (2023). "Modeling future economic costs and interdependent industry recovery after earthquakes." *Earthquake Spectra*, 1–24.

Markhvida, M., Walsh, B., Hallegatte, S., and Baker, J. (2020). "Quantification of disaster impacts through household well-being losses." *Nature Sustainability*, 3(7), 538–547.

Maruya, H., Torayashiki, T., and International Research Institute of Disaster Science, Tohoku University 468-1 Aramaki-Aza-Aoba, Aoba, Sendai, Miyagi 980-0845, Japan (2017). "Damage of Enterprises and Their Business Continuity in the 2016 Kumamoto Earthquake." *Journal of Disaster Research*, 12(sp), 688–695.

McDonald, N. J. and McDonald, G. W. (2020). "Towards a dynamic equilibrium-seeking model of a closed economy." *Systems*, 8(4), 42.

Ministry of Economy, Trade and Industry (METI) (2018). "Historical Data, Indices of Industrial Production, <https://www.meti.go.jp/english/statistics/tyo/iip/b2010$_result - 2.html$>.

OECD (2021). “Measuring telework in the COVID-19 pandemic.” *OECD Digital Economy Papers 314* (July). Series: OECD Digital Economy Papers Volume: 314.

Okuyama, Y. (2007). “Economic Modeling for Disaster Impact Analysis: Past, Present, and Future.” *Economic Systems Research*, 19(2), 115–124.

Okuyama, Y. (2022). “A few good models for economic analysis of disasters: can your model handle the truth?.” *Handbook on the Economics of Disasters*, 30–49.

Petak, W. J. and Elahi, S. (2000). “The Northridge Earthquake, USA and its economic and social impacts.” IIASA, Laxenburg Austria (July).

Ranger, N., Hallegatte, S., Bhattacharya, S., Bachu, M., Priya, S., Dhore, K., Rafique, F., Mathur, P., Naville, N., Henriet, F., Herweijer, C., Pohit, S., and Corfee-Morlot, J. (2011). “An assessment of the potential impact of climate change on flood risk in Mumbai.” *Climatic Change*, 104(1), 139–167.

Rose, A. and Guha, G.-S. (2004). “Computable general equilibrium modeling of electric utility lifeline losses from earthquakes.” *Modeling spatial and economic impacts of disasters*, Springer, 119–141.

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.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., and Tarantola, S. (2010). “Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index.” *Computer Physics Communications*, 181(2), 259–270.

S&P Global (2016a). “Japanese production recovers in aftermath of Kumamoto earthquake; IHS forecasts full recovery to take until Q4.” *S&P Global*, <https://www.spglobal.com/mobility/en/research-analysis/japanese-production-recovers-in-aftermath-of-kumamoto-earthquake-ihs-forecasts-full-recovery-to-take-until-q4.html> (April).

S&P Global (2016b). “S&P Global: Japanese vehicle output rises 1.7% y/y during May, exports up 4.6% y/y.” *S&P Global*, <https://www.spglobal.com/mobility/en/research-analysis/japanese-vehicle-output-rises-17-yy-during-may-exports-up-46-yy.html> (June).

Takeda, K. and Inaba, K. (2022). “The damage and reconstruction of the Kumamoto earthquake: an analysis on the impact of changes in expenditures with multi-regional input–output table for Kumamoto Prefecture.” *Journal of Economic Structures*, 11(1), 20.

Tanner, T., Surminski, S., Wilkinson, E., Reid, R., Rentschler, J., and Rajput, S. (2015). “The triple dividend of resilience: realising development goals through the multiple benefits of disaster risk management.

Wang, C., Wu, J., He, X., Ye, M., and Liu, Y. (2018). “Quantifying the spatial ripple effect of the Bohai Sea ice disaster in the winter of 2009/2010 in 31 provinces of China.” *Geomatics, Natural Hazards and Risk*, 9(1), 986–1005.

Wang, D., Guan, D., Zhu, S., Kinnon, M. M., Geng, G., Zhang, Q., Zheng, H., Lei, T., Shao, S., Gong, P., et al. (2021). “Economic footprint of california wildfires in 2018.” *Nature Sustainability*, 4(3), 252–260.

Wei, D., Chen, Z., and Rose, A. (2020). “Evaluating the role of resilience in reducing economic losses from disasters: A multi-regional analysis of a seaport disruption.” *Papers in Regional Science*, 99(6), 1691–1722 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/pirs.12553.

Wein, A. and Rose, A. (2011). “Economic Resilience Lessons from the ShakeOut Earthquake Scenario.” *Earthquake Spectra*, 27(2), 559–573.

World Bank (2021). *Financial Risk and Opportunities to Build Resilience in Europe*. World Bank.

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.

Zhang, Z., Li, N., Xie, W., Liu, Y., Feng, J., Chen, X., and Liu, L. (2017). “Assessment of the ripple effects and spatial heterogeneity of total losses in the capital of China after a great catastrophic shock.” *Natural Hazards and Earth System Sciences*, 17(3), 367–379.