Transportation Research Part D 106 (2022) 103236

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Socioeconomic impacts of resilience to seaport and highway transportation network disruption[☆]

Dan Wei [a,b,*], Adam Rose [a,b], Eyuphan Koc [c], Zhenhua Chen [d], Lucio Soibelman [c]

[a] Sol Price School of Public Policy, University of Southern California, United States
[b] Center for Risk and Economic Analysis of Threats and Emergencies, University of Southern California, United States
[c] Sonny Astani Department of Civil and Environmental Engineering, University of Southern California, United States
[d] City and Regional Planning, Knowlton School of Architecture, The Ohio State University, United States

ARTICLE INFO

Keywords:
Port disruptions
Transportation networks
Resilience to disasters
Socioeconomic impacts
Integrated transportation-economic model

ABSTRACT

An integrated transportation-socioeconomic model is developed to analyze the economic consequences of and resilience to seaport and associated transportation network disruptions. Since such disruptions can affect people in a region unequally, the model is constructed to analyze both aggregate economic impacts and impacts across socioeconomic groups. We illustrate the model's usefulness in a simulated earthquake scenario affecting the Ports of Los Angeles and Long Beach. Total GDP losses from port disruptions, highway transportation cost increases, and general building damages, working through regional and interregional supply-chains, are estimated at \$24.2 billion in the Port Region and \$30.2 billion in the U.S. as a whole. A combination of several resilience tactics is estimated to reduce GDP impacts by 41.3% in LA and 57.6% in the U.S. The distributional analysis indicates the extent to which lower-to-middle-income groups are more proportionally impacted by port disruptions and middle-to-higher-income groups are more impacted by building damages.

1. Introduction

Serving as critical portals of a nation's supply networks, seaports and their associated inland transportation infrastructure are especially vulnerable to major disruptions from a variety of causes. The economic impacts of these disasters can extend well beyond the on-site operations at the port complex, through supply-chain curtailments and delays in delivering imports and exports to their destinations.

Assessment of transportation system vulnerability and resilience has gained increasing attention, especially after incidents of port

☆ This research was supported by the California Department of Transportation and the Pacific Southwest Region University Transportation Center (PSR) through Grant 65A0674. We have benefited from the helpful suggestions and insights from the Project Panel for this study, as well as comments from an anonymous reviewer, on various versions of the report of the original research. We would like to thank UCLA's Taciroglu Research Group for sharing their seismic hazard simulation data and analysis results. We also like to thank Terrie Walmsley and Glyn Wittwer for answering questions in terms of the application of the TERM Model. We are especially grateful for the insightful comments from the three anonymous referees. We also appreciate the valuable research assistance of Juan Machado and Konstantinos Papaefthymiou. Any remaining errors and omissions are the responsibility of the authors alone. Moreover, the views expressed in this article represent those of the authors and not necessarily those of any of the institutions with which they are affiliated nor the institutions that funded the research.

* Corresponding author.

https://doi.org/10.1016/j.trd.2022.103236

Available online 9 April 2022

closures and related transportation network downtimes following major natural disasters in recent years (such as the impacts of Superstorm Sandy on the Port of New York/New Jersey and the entire transportation infrastructure of New York City and the surrounding region, Hurricane Irma to the Ports of Jacksonville and Miami, Hurricane Harvey to Port of Houston, and their drastic impact on trucking transportation). Many studies have analyzed the impacts (including both direct and indirect effects) stemming from transportation network disruptions in general, some of which focus specifically on port disruptions, and found them to be sizeable (Chang et al., 2000; Cho et al., 2001,2004; Werner, 2003; Tsuchiya et al., 2007; Gordon et al., 2004; Jung et al., 2009; Park et al., 2008; Pant et al., 2011; Rose and Wei, 2013; Xie et al., 2014; Zhang and Lam, 2015; Rose et al., 2018; Wei et al., 2020).

However, one of the major gaps in the literature is that most studies that estimate the economic impacts of such disruptions have not adequately accounted for the spatially-distributed and networked nature of the transportation systems. The functionality of individual components of transportation system (e.g., airport, seaport, bridge, etc.) is largely dependent on the status of the entire infrastructure network, which can be affected by large-scale disaster events such as earthquakes and hurricanes that result in spatially-distributed impacts. The focus of many studies is often on a single infrastructure component and thereby omits interdependency effects, such as the exacerbation caused by cascading failures, in today's networked transportation systems (Wei et al., 2018a, 2018b).[1] These methods also typically omit major sources of resilience of ports and highway networks – ways to decrease the negative impacts from interruptions of import and export flows through such tactics as input substitutions, use of inventories, conservation, and rescheduling of economic activities (Wei et al., 2020). To obtain a more comprehensive and practical understanding of the potential impacts on the local and regional economy, the networked nature of transportation systems and their post-disaster degradation has to be taken into account. Moreover, carefully simulated hazard scenarios with detailed spatial delineation of damages and response should be integrated into the economic impact analyses.

Furthermore, disasters and their impacts on critical infrastructure do not affect all people in a region equally. Studies have shown that economically disadvantaged groups typically suffer a higher proportion of income losses directly and indirectly from property damages and business interruptions caused by disasters than those in middle- and upper-income brackets (Mileti, 1999). Unfortunately, very few studies have analyzed these income distribution impacts (Masozera et al., 2007; Shaughnessy et al., 2010). Moreover, no studies to date have examined the income distribution impacts of more than a select few resilience tactics, which have the ability to reduce regional business interruption losses and have income distribution impacts of their own.

We have developed a synergetic approach linking a regional transportation model and a multi-regional computable general equilibrium (CGE) model (the TERM Model). This integrated model is also capable of analyzing the effects of port and transportation resilience. Moreover, we constructed and integrated a multi-sector income distribution matrix (MSIDM) into the modeling framework to analyze the economic losses stemming from disruptions of port operations and transportation network services, and the varying effects of resilience tactics across household income brackets. The application of the fully integrated model is demonstrated by using an earthquake scenario simulation that affects commodity flows at the twin Ports of Los Angeles and Long Beach and the related highway transportation network in the Los Angeles metropolitan region.

The paper is divided into eight sections. The background of the study is presented in Section 2, which summarizes the research gaps based on previous work in applying system-based analysis of transportation system resilience from both the transportation system analysis and economic impact analysis perspectives. Section 3 first presents the definitions and basic categories of economic resilience. The economic resilience tactics that are specifically applied to transportation system disruptions are then discussed. In Section 4, we introduce the individual modules of the integrated transportation-socioeconomic impact analysis model we developed. Section 5 introduces the disaster scenario case study. The results of the direct impacts are presented in Section 6. The economy-wide aggregate impacts and the distributional impacts of the disaster scenario are presented and interpreted in Section 7. We discuss the limitations of the current study and suggest areas for further research in Section 8. Section 9 summarizes major findings and policy implications of the study.

2. Background

2.1. Resilience assessment in transportation systems

Studies of transportation systems disruptions can generally be categorized into two broad methodological approaches: topological-based and system-based[2] approaches (Mattson and Jenelius, 2015). The first category only requires the topological structure, with

[1] Notable examples of exceptions that evaluate the economic impacts of disturbance to urban transportation network-based on detailed spatial transportation modeling include Cho et al. (2001), Tatano and Tsuchiya (2008), Cho et al. (2015), Koc et al. (2020), etc.

[2] Here, the term 'system-based' does not make a reference to a system-of-systems perspective, rather it is used to refer to the approach to the transport system that takes topology and demand simultaneously into account.

which disruption-related performance measures based on network efficiency are quantified, to be known. Such measures could be defined in terms of robustness, vulnerability, resilience, etc.[3] The efficiency metrics are quantities that can summarize the overall network state such as centrality (e.g., betweenness or closeness centrality), total shortest distance between pairs of nodes in the transportation system (or other indicators quantifying total cost in time or distance), size of the largest connected component, total changes in accessibility, etc. Topological studies mainly consider node or link removal scenarios, resulting either from random or strategic 'attacks' to the network. This approach is often subject to criticism along the dimensions of holism and realism, particularly in representing the physical infrastructure system as well as its characteristics with regard to demand and supply relationships.

System-based approaches work in a more holistic manner. The explicit modeling of network supply and demand, in addition to detailed information on the topological structure of the network, makes way for a comprehensive treatment of disruption-related effects on the system such as increased congestion due to reduced link capacity and lower redundancy. This method measures network efficiency losses in terms of the deteriorating conditions of traffic. Regardless of such advantages over topological approaches, criticisms of system-based studies focus on their extensive data needs and the requirement of calibrated models of network demand and supply, as well as requirements related to sophisticated software platforms (often GIS-based) accommodating various algorithms and methodological frameworks to simulate mobility (Koc et al., 2020).

Another task in this type of research is the assessment of the first-order damages (e.g., damage states for bridges) that arise from the disruption-causing event (Bocchini and Frangopol 2012). Specifically, if a formal assessment of the damages is to be implemented to determine the post-event condition of system components such as bridges or tunnels, detailed data-driven simulations are required (e.g., detailed infrastructure data inventories, open-source or proprietary simulation capabilities, etc.). Despite these challenges, system-based investigations offer a better opportunity to model for and simulate transportation system disruptions more comprehensively (in both realism and holism dimensions) while ensuring that desired granularity is achieved and, more significantly, they deem multi-disciplinary and stakeholder collaborations possible and allow the translation of findings in resilience research into more actionable insights for owners and operators of infrastructure.[4] This characteristic facilitates the design and deployment of the synergetic approach linking a regional transportation model and a multi-regional CGE model.

2.2. Limitations in system-based approach of transportation disruptions analysis

First, we note that formal hazard considerations determining loads and damage are rarely made in a comprehensive manner in previous research, with exceptions (including, for example, Cho et al. 2001, Koc et al. 2020). This leads to an underutilization of the detailed data inventories on transportation infrastructure that exist in the United States. Whether such considerations are included depends on the research objectives. Typically, in topological approaches, the objective is to find the 'most critical link' independent of the disruption causing event; thus, formal hazard considerations are often missing from this type of work. Another genre of topological studies investigates the type of attack (random, targeted, mixed) and its relationship to network resilience or node criticality, yet these studies usually focus on assumed attack strategies rather than naturally occurring hazard risks. However, when the objective is to evaluate network performance against hazard scenarios that can be characterized and estimated, the potential damage from the characterized event can be assessed and included in the resilience study. Khademi et al.'s (2015) review of this research area reveals that researchers mostly fall back on "what-if" assumptions to determine a damage and try to understand the corresponding impact on network performance. In this analysis, we adopt state-of-the-art earthquake simulations based on detailed structure-specific and site-specific calculations from earlier work (Koc, 2019a).

In the transportation systems analysis context, we observed that: 1) a key shortcoming for the works in this area is the use of heavily abstracted network models within a study region instead of leveraging the full availability of data and modeling tools in transportation engineering today, 2) a general lack of post-disaster travel demand data is hindering further advancements of research in this area, and 3) a lack of attention to various socioeconomic and sociotechnical issues such as transportation equity and environmental justice (e.g., air quality impacts) within the resilience scope.

In the case of (1), the level of abstraction expectedly varies from study to study; however, a commonality comes from the shortcomings in granular network modeling capabilities where the networks of today's metropolitan areas can be explicitly and holistically modeled (Koc et al., 2019b). According to Asakura (2007), in vulnerability and resilience assessments, the model constructed for a normal network state needs to be adjusted before being applied to the recovery network state. In terms of post-disaster travel demand data requirements (2), collecting empirical data is a limited option, because of the infrequent occurrence of disaster events. However, researchers have the option of resorting to existing travel demand models in efforts to analyze post-disaster travel behavior (see, e.g.,

[3] We offer the following brief definitions and distinctions of these terms. Vulnerability relates to the drawdown on the functionality of the system, whereas resilience, in terms of the narrow definition used in this analysis, relates to the efficient recovery from an initial drawdown. Robustness refers to the ability to withstand the shock (e.g., being non-sensitive against wrong design assumptions).Other relevant concepts from reliability engineering include flexibility and reconfigurability, which also play important role that influence the recovery path of disrupted system. As presented in more details later in the paper, one of the contributions of this study is to examine various reconfigurations of the highway traffic system following the shock. The main one is, however, how businesses reconfigure their production processes through the use of various resilience tactics.

[4] Broadly, understanding the economic impacts of transportation system disruptions could allow an owner/operator of infrastructure to analyze the need for investing in mitigation and resilience, this need could be justified in the eyes of other entities such as the local, regional or national governments, etc.

Chen et al., 2007).[5]

The lack of research on equity and environmental justice issues arising from transportation system disruptions (3) manifests itself in the narrow focus of studies on the travel cost-related aggregate or spatial effects of system disruptions. These large-scale events affect *users* of the system at varying levels.

For the economic impact analysis methods used in this field, most studies only carry out calculations of the direct impacts by simply tabulating property damage or lost business revenue. These works do not consider interindustry supply-chain effects or interregional economic diffusion effects.[6] Among the economic impact studies that apply different types of methodologies, Input-Output (I-O) modeling, in general, is a widely used approach (Pant et al., 2011; Okuyama and Santos, 2014; Rose et al., 2018). Furthermore, there exist some examples of state-of-the-art methods applied in this context, such as Computable General Equilibrium (CGE) and Spatial CGE (SCGE) models (Rose, 2015; Wei et al., 2020; Sue Wing et al., 2021). With regards to incorporation of the hazard and damage information, many works adopt simple assumptions related to the event causing the disruption, e.g., the hypothetical closure of a freight terminal over a period of time due to a simulated terrorist attack (MacKenzie et al., 2012; Park 2008). Such assumption-driven approaches do not utilize a comprehensive procedure of disaster assessment and associated damage estimation. To summarize, the state-of-the-art data, tools, and methods in hazard analyses are often not leveraged in most studies, particularly when economic impacts are simultaneously investigated (Wei et al., 2018b). Another major shortcoming in this area of work is (similar to the above) the failure in explicit and holistic modeling of the networked transportation system which leads to an oversimplified quantitative analysis of system functionality (Wei et al., 2018b). Abstraction of the network supply and travel demand as well as the dynamics of this pairing leads to a disconnect between the disciplines (engineering and economics) trying to advance the research in this area. In the case of the few studies that employ explicit network modeling, most examples aim exclusively at the quantification of the direct costs associated with transportation such as increased costs of travel or warehousing (see Xie and Levinson, 2011; Ashrafi et al., 2017; Vadali et al., 2015).

3. Economic resilience to transportation systems disruptions: ports and hinterland road networks

3.1. Economic resilience – definition and basic considerations

The important role of economic resilience has been highlighted in many studies of the economic impacts of disasters in the U.S. in the past two decades (see, e.g., Flynn, 2008; Rose et al., 2009; Martin and Sunley, 2015; Chen and Rose, 2018; Wei et al., 2020). The losses incurred by regional and national economies after major disasters are usually less than expected because of the significant potential of resilience of the economy at both the micro- and macro-levels. Resilience also helps explain how impacted regions can recover more rapidly than expected. There has been increasing attention to and emphasis on the concept of resilience for more than a decade, including major advances in the definition of economic resilience stemming from the work of Cutter (2016), Rose (2017), and others. In this study, we adopt a more narrow definition of resilience as relating to business continuity and recovery (see, e.g., Berke and Campanella, 2006), and thus exclude actions that are broadly classified into the category of mitigation, which usually take place before disaster occurrences. We do include various prior-event actions that help build capacity of resilience, however, such as enhancing stockpiles of critical materials, obtaining emergency electricity generators, developing and maintaining contingency plans, and conducting emergency response drills for better implementation once the disaster strikes (see, e.g., Wei et al., 2020).

Although the specific definitions of resilience can differ across disciplines, more commonalities than differences are found according to Alexander (2013), Cutter (2016), Rose (2017), and others. Below we first provide the general definitions of resilience, capturing the essence of the concept in many fields, followed by definitions that take into account economic considerations.[7] Following Rose and Liao (2005) and Rose (2017), we divide the definitions of resilience into the following two major categories:

- Static Resilience can be generally defined as the ability to maintain a high level of functionality in a system impacted by external shocks. *Static Economic Resilience* refers to the capability to use the remaining resources efficiently at a specific point in time. Therefore, it is in line with the core economic concept of efficient allocation of scarce resources, a condition worsened in disasters.
- Dynamic Resilience can be generally defined as the capability and speed by which a system recovers from external shocks. *Dynamic Economic Resilience* focuses on how resources can be utilized efficiently for repair and reconstruction over the recovery time period.

[5] Four categories of efforts, including reduction, readiness, response, and recovery, to reduce unreliability of a road network are presented in Nicholson (2007). Khademi et al. (2015) found that many studies isolate the analysis of the pre-disaster phase. Mattsson and Jenelius (2015) discuss the importance of evaluating the entire timeline of the disaster, as well as the benefit from multi-disciplinary collaborations.

[6] In operations research, many studies have considered propagation impacts of disruptions both forward and downward the supply-chains, as well as effects of supply-chain resilience measures (such as identifying high-risk suppliers and contracting with backup suppliers) using methods such as Bayesian network approach (Garvey et al., 2015; Hosseini and Ivanov, 2019; Hosseini and Ivanov, 2020) and agent-based modeling (Giannoccaro and Iftikhar, 2020; Li et al., 2021).

[7] We acknowledge that there are other general approaches and definitions of resilience. For example, one of the first such approaches was in the realm of systems analysis, where resilience has a more dynamic connotation closely related to the concepts of stability (for an extensive review of systems resilience we refer the reader to Hosseini et al., 2016). We also acknowledge the important contributions to resilience by ecologists such as Holling (1973) and Pimm (1984) to whose work our definitions of static and dynamic economic resilience are related. Finally, we note that our definitions of economic resilience are highly cited in transportation literature (see, e.g., Pant et al., 2015; Janic, 2015; Renne et al., 2020; Zhou and Chen, 2021).

Table 1
Summary of resilience tactics to port and highway transportation disruptions.

Supplier-Side Resilience Options	Customer-Side Resilience Options
Excess capacity: Bringing online capacity not in use at terminals experiencing little or no damages	*Use of inventories*: Stockpiling critical inputs
Ship re-routing: Redirecting vessels to alternative undamaged ports	*Conservation*: Implementing ways to utilize lower quantities of inputs per unit of output
Cargo prioritization: Prioritizing the unloading/loading of cargos, taking cargo values into consideration	*Input substitution*: Making use of goods similar to the ones whose output is disrupted
Effective management: Improving decision-making, stakeholder coordination, information sharing, and expertise in general	*Import substitution*: Transporting goods in supply shortages into the region from outside of it
Export diversion for import use: Obtaining goods originally intended for international market as substitutes for disrupted imports or goods produced domestically	*Production relocation.* Moving production activities to branch plants/ facilities located outside of disaster-affected regions.
Production recapture: Working extra hours/shifts to unload backlogged ships after ports reopen.	*Production recapture*: Working extra hours/shifts after the ports re-open to make up lost production
Effective road infrastructure asset management: Improvements in traffic flows	*Effective travel demand management*: implementing ways to decrease travel demand during recovery

Investment involves a time dimension in the decision process—resources that can be utilized for immediate consumption are invested in the reconstruction and recovery process aiming to restore productivity in the future.

In this study, the analysis is primarily focused on the role of *static* economic resilience from both the supplier and customer perspectives. However, *dynamic* economic resilience also comes into play in relation to variations in the restoration of highway capacity.

Important distinctions also exist between inherent and adaptive economic resilience (Rose and Liao, 2005; Tierney et al., 2007; Cutter, 2016). Inherent resilience relates to intrinsic capacity of resilience already existing within a system or the potentials to incorporate it prior to the disruptions by the enhancement of capabilities through “pre-positioning.” Some examples of inherent resilience include the existence and utilization of excess capacity and various forms of substitution options, such as rerouting ships, substituting between transportation modes, and geographic shifts of production activities. All of these coping strategies are in response to the functioning of the market system through price signals that influence decision-makings in reallocation of scarce resources. On the other hand, adaptive resilience is achieved by implementing tactics after the disruption strikes, such as conserving in ways previously not thought possible or modifying a technology.[8]

Economic resilience does not focus on property (including buildings and contents) damages, which typically occurs when the disruption commences, but instead highlights the loss reductions of the *flow of goods and services* resulting from the destruction of the *capital stock* of the port and associated highway network. The flow losses are typically measured as the reduction in production levels at the micro-level or as losses in gross domestic (regional) product (GDP or GRP) at the macro level, and are usually characterized as *business interruption* (BI). BI starts at the onset of the disaster, and typically continues throughout the entire process of individual business or system recovery (Rose, 2017).

The next step of evaluating the effects of resilience is to convert these definitions into an operational metric. For static resilience, the metric can be calculated as the percentage of BI avoided by implementing a specific resilience tactic, or a resilience strategy comprising a group of tactics, with respect to the maximum BI loss potentials from the disaster without implementing any tactic (Rose, 2017). This and other related metrics have been adopted in several studies to measure the effects of resilience (see, Rose et al. 2009; Rose and Wei, 2013; Xie et al., 2014).

3.2. *Economic resilience tactics applied to transportation system disruption*

Port resilience can be considered a special category of economic resilience (Rose and Wei, 2013; Wei et al., 2020). *Static* economic resilience to port disruptions refers to measures implemented by ports and businesses to effectively use remaining resources to maintain as much function as possible. Supplier-side resilience refers to a variety of tactics for keeping the port functioning. From the customer-side perspective, businesses affected both directly and indirectly by the interruption of imports or exports would not stand by passively, but could instead implement a broad set of coping measures.

Expanding on our prior research, we provide in Table 1 the definitions of various types of resilience tactics that can be adopted by either suppliers or customers relating to disruptions of ports and their hinterland transportation systems. The majority of these resilience tactics are derived formally from economic production theory (Rose and Liao, 2005; Dormady et al., 2019) and are codified

[8] Some major parallels exist between the definitions of economic resilience in this paper and those associated with supply-chain resilience. A prime example is the review and synthesis of the literature of the latter by Hosseini et al. (2019), in which those authors divide resilience into three major categories: absorptive capacity, adaptive capacity, and restorative capacity. The latter two are closely related to our static and dynamic resilience definitions, with the major difference being our distinction between inherent and adaptive resilience. Note also that we have focused our definitions on the micro level of individual ports, business, and transportation systems. However, our analysis is undertaken with a general equilibrium model and thus captures supply-chain linkages (see Rose and Liao, 2005 and Rose, 2015 for more details of the extension of our definitions to multiplier and general equilibrium effects, and hence to the economy as a whole).

Table 2
Hazard and vulnerability parameters.

PSH Source	2014 version of U.S. Conterminous Seismic Hazard Maps
Deagregation Return Period	975 years
Governing Fault	Palos Verdes
Moment Magnitude	7.3
Subsurface Rupture Length	90.37 km
Event type	Reverse-lip fault
Effects	Ground-shaking only
Intensity Measures for Damage Analysis	$SA_{0.3}$ and $SA_{1.0}$
GMPEs	Weighted average of the median SA values computed from 2013 GMPEs by Abrahamson et al., Boore et al., Campbell and Bozorgnia, Chiou and Youngs, and Idriss with weights for the first four equations set 0.22 and the last one set to 0.12 (Gregor et al., 2014).
Site Effects	Using the slope-based VS_{30} proxy method suggested by Wald et al. (2011).
Basin Effects	Neglected

in a U.S. National Academies of Sciences report (NRC, 2012). The authors have also been able to measure resilience through survey research (see, e.g., Rose et al., 2009; Dormady et al., 2018, 2021).[9] Dormady et al. (2021) have estimated the benefit-cost ratio of the two resilience tactics we apply as follows: Production Recapture – 1.5; Excess Capacity – 1.1.

4. Integrated transportation-socioeconomic impact analysis system

The integration of models on both transportation and economics fronts can provide rich insights for disaster resilience impact analysis. Hence, we have deployed a regional travel demand model that provides high-level spatial details of the disaster region and a CGE model that provides inter-sectoral and inter-regional linkages supplemented by a multi-sector income distribution matrix. In this section, we first describe each component of this integrated modeling system, followed by an overview of how they are linked, focusing especially on how the main outputs from one model are served as inputs into other models to create a holistic analysis of impacts of disaster scenarios.

4.1. Hazard damage assessment model

Hazard characterization and damage assessment results are adapted from a concurrent work, which discusses in detail the method used to select the specific seismic hazard scenario (a subsurface rupture length of 90.37 km for a 7.3-moment magnitude reverse-slip fault event) based on Probabilistic Seismic Hazard analysis (PSH), the calculation of the IMs resulting from the defined earthquake event by passing the source information to ground motion prediction equations (GMPEs), and the damage and recovery assessments of bridges (Koc et al., 2020). Additionally, the same seismic hazard scenario was simulated using FEMA HAZUS software to estimate damages to ports and the general building stock. Readers are referred to (Koc et al., 2020) for further discussion on the progression of calculations that lead to bridge damage state probabilities and restoration functions utilized to calculate the downtime associated with the simulated hazard used in this study. Hazard and vulnerability parameters are also summarized in Table 2. Fig. 1 summarizes results from hazard characterization and damage assessment with maps of the $SA_{1.0}$ resulting from the scenario event and the locations of the damaged bridges and traffic implications in terms of bridge downtimes.

4.2. Investigation of transportation resilience with the SCAG regional travel demand model

The regional travel demand model (RTDM) of the Southern California region, developed under the Regional Transportation Plan (RTP) by the Southern California Association of Governments (SCAG), is adopted as the transportation system analysis module of the integrated model (SCAG, 2019). The model is built and operated using the transportation planning software of TransCAD. It is validated using several types of travel data from independent sources, including automobile and truck travel counts, number of transit trips, Highway Performance Monitoring System (HPMS) data on Vehicle Miles of Travel, Freeway Performance Measurement System (PeMS) data on average speed, and other sources of travel survey data (Koc et al., 2020).

The results from damage assessment are integrated into the transportation model by manipulating its network topology to estimate

[9] One thing to note is that skills, capabilities, and attitudes of organizations can affect the actual implementation of the resilience tactics immediately after the disruption and throughout the recovery process. However, this consideration is beyond the scope of this study. The recovery functions used in HAZUS are largely based on expert surveys in which complexities such as organizational issues are not addressed.

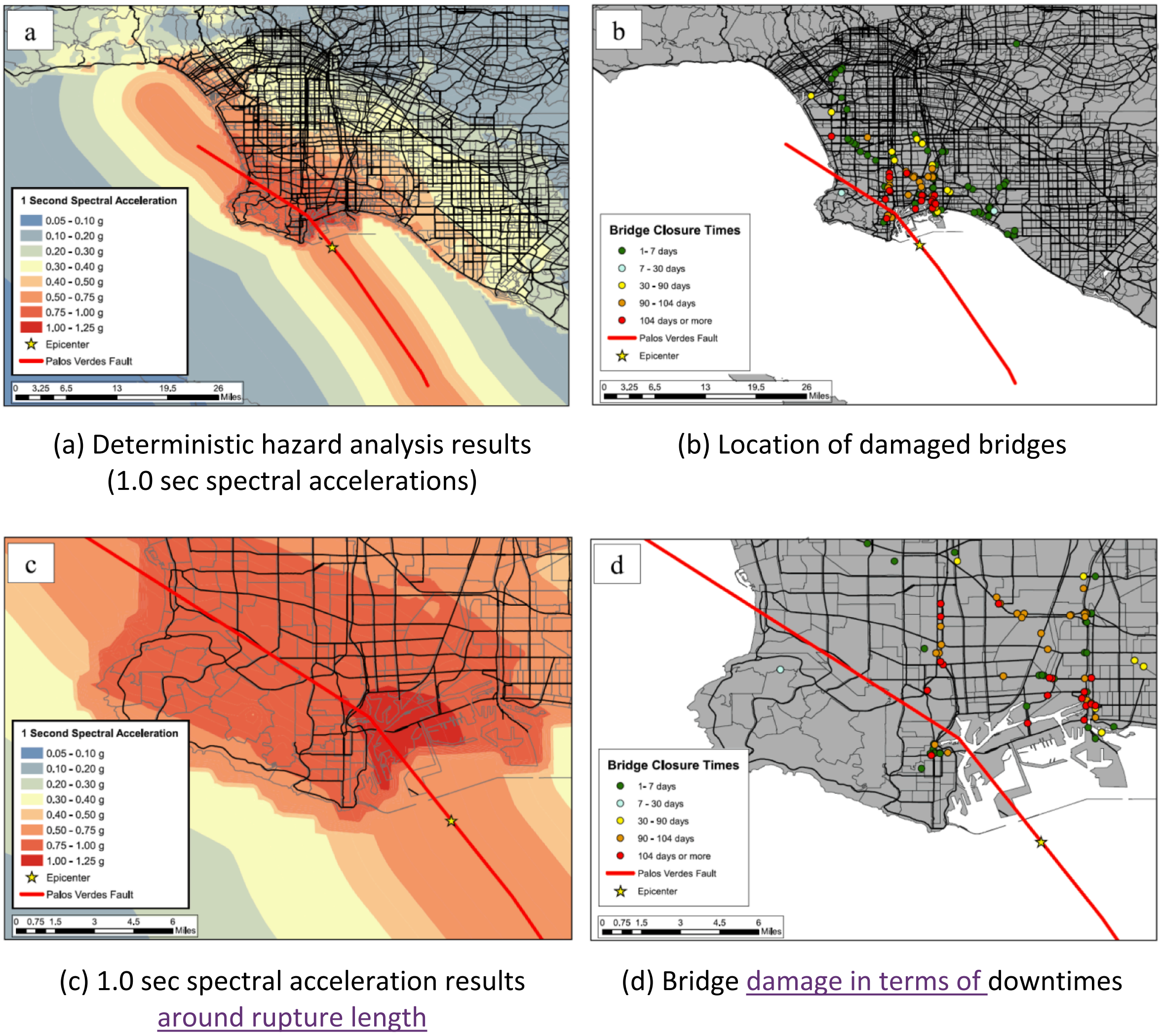

Fig. 1. Hazard characterization and damage assessment.

the degradation (the reader is referred to Koc et al., 2020, for details of the hazard analysis). For example, if a bridge is damaged[10] and cannot service traffic, the links and public transit routes going through the bridge are modeled closed until reconstruction is taken place. These post-disaster characterizations of the network capture the transportation disruption and the recovery in terms of network level functionality indicators, including VHT (Vehicle-Hours Traveled), VMT (Vehicle-Miles Traveled), delay, average speed, at the TAZ level.

4.3. The TERM multi-sector CGE model

We adapt the TERM multi-regional computable general equilibrium (CGE) model (Horridge et al., 2005, Wittwer, 2012) to estimate aggregate and sectoral economic impacts of the simulated earthquake scenario and the effectiveness of individual economic resilience tactics. CGE models are the state-of-the-art among applied general equilibrium modeling approaches used to study the economic impacts of disasters, including those affecting transportation systems (Rose, 2015; Rose et al., 2017; Chen et al., 2017; Chen and Rose, 2018; Wei et al., 2020; Zhou and Chen, 2021). They model the economy in terms of changes in behavior of businesses and consumers in

[10] Damage is considered binary based on a 75% post-event functionality threshold. Exact post-event functionality with respect to time is determined by HAZUS recovery functions. The 75% threshold was adopted from literature due to the lack of standardized data on the relationship between damage or functionality information and closure decisions made by inspectors (Gordon et al., 2004). This threshold assumption could be changed according to the agency/analyst operating with this framework. In reality, bridge inspectors visit the damaged site and make recommendations on closure.

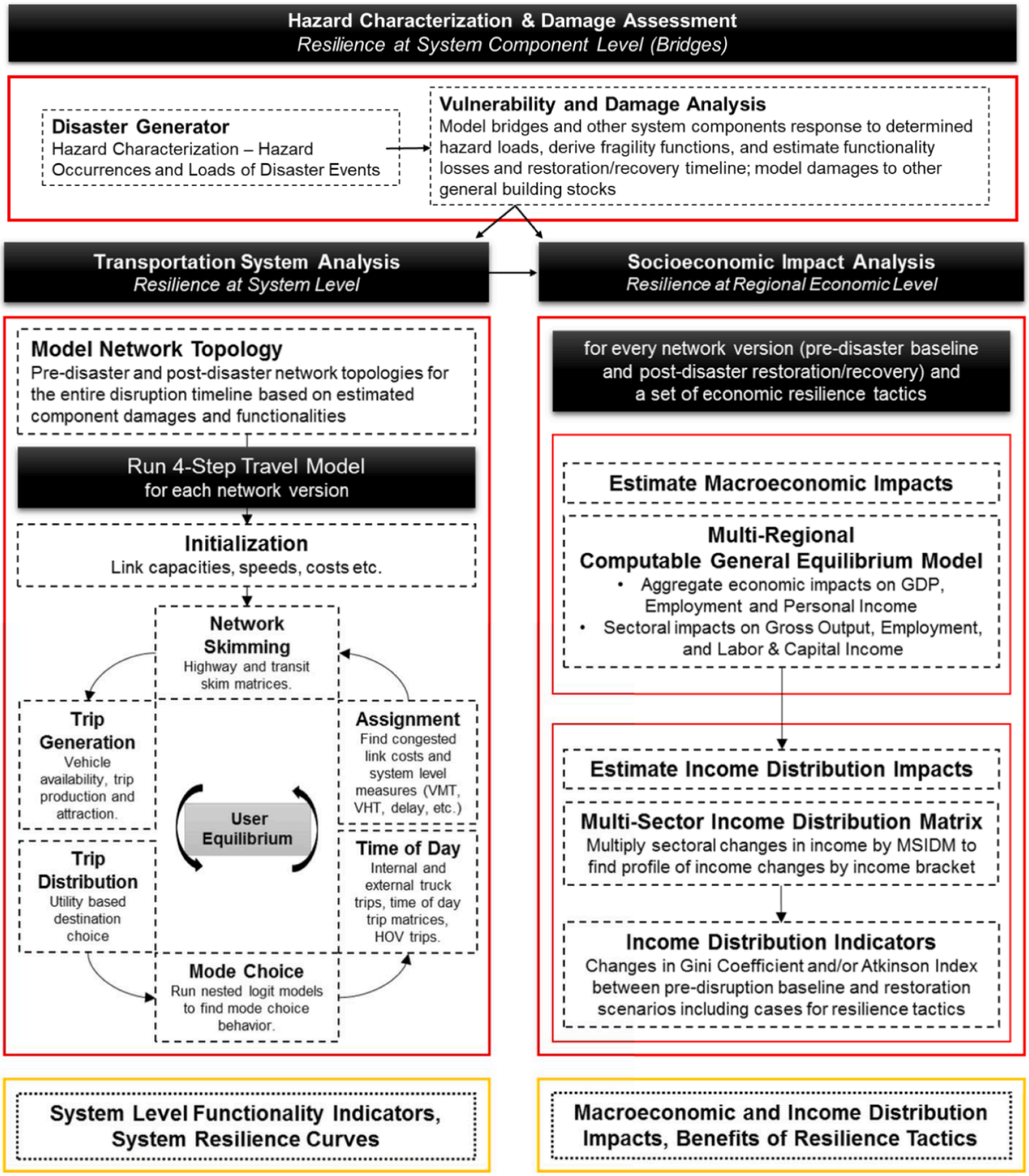

Fig. 2. Integration of transportation and economic models.

response to price signals, external shocks, and constraints of resources in the context of an integrated set of sectoral supply chains. The CGE formulation overcomes most of their limitation in related models, such as the input–output (I-O) analysis (Rose, 2015).

The TERM model uses a "bottom-up" approach, treating each of its regions as an individual and separate economy. It is assumed that producers maximize their profits by minimizing the costs of an aggregate of intermediate production inputs and primary factor inputs. This is characterized by the Constant Elasticity of Substitution (CES) production functions with the nested structure to allow for elasticity variations across input combinations. At the top level of the nesting structure, an aggregate of primary factor inputs is combined with an aggregate of intermediate inputs to produce the output. The aggregate of the intermediate inputs is also a CES composite of various types of commodities (some representing aggregate of commodities from various sources, with relatively low substitution possibilities). The aggregate of primary factor is in turn a combination of capital, labor, and land, with labor being a composite of labor of various skill levels. In each region, a representative household maximizes its utility by purchasing the optimal combinations of goods and services subject to its budget and preferences.

Our version of the TERM model is comprised of four regions and divides the economy into 97 sectors. The regions consist of Los

Angeles Metro Region[11], San Francisco Metro Region[12], the Rest of California, and the Rest of the U.S. Simulations were conducted with a short-run closure rule, under which wages were assumed rigid exogenously and employment adjusts endogenously.

4.4. Construction of the multi-sector income distribution matrix of California

In order to analyze the potential economic impacts stemming from disruptions of port and transportation networks and to evaluate the effects of resilience tactics across socioeconomic groups (specifically income groups), a Multi-Sector Income Distribution Matrix (MSIDM) for the state of California is constructed. The matrix provides the earnings profile according to nine income brackets for each producing sector in the economy, i.e., the proportion of the personal income (including both labor income and capital income) paid to each household income group by each economic sector (Rose et al., 1988; Li et al., 1999; Rose et al., 2012).

In 2018, total personal income in California was more than $2.4 trillion (BEA, 2019). The first major component is Wages and Salaries, which includes the total remuneration of employees. The total Employee Compensations, which were $1.35 trillion in 2018, are the sum of Wages and Salaries and Employer Contributions for Employee Pension and Insurance Funds. The total Proprietors' Income in 2018 was $249.6 billion.

The next major component of the personal income accounts is capital income, which amounted to $538.3 billion in California in 2018. These include dividends, interest payments, and rental income. The final major component of the personal income accounts is Personal Current Transfer Receipts, which were $341.2 billion in California in 2018. These mainly include payments from government welfare and benefit programs. The BEA Personal Income accounts for California were used as control totals when we constructed the individual income matrices in the following sections.

In this study, we adopt the nine household income brackets that are used in IMPLAN (the largest provider of regional input–output and social accounting data in the U.S.). The income distribution matrix for wages and salaries is constructed using the Occupation-Industry Employment matrix and the Occupation-Industry Wage matrix obtained from the BLS Occupational Employment Statistics (OES) (BLS, 2019a). IMPLAN data are used as the main data source to distribute proprietors' income, dividends, other property income, and transfers across sectors and income brackets (see Appendix A for more details).

The total personal income matrix is constructed by combining each individual matrix of various personal income components. We then calculated the total income distribution coefficient (structural) matrix for California by dividing the income value for each bracket in a given sector by the total income for that sector.

4.5. Model linkages

Fig. 2 shows how the various analytical models discussed in the previous sub-sections are integrated in this study.

Starting from the top of Fig. 2, hazard characterization and damage assessment results from a concurrent work (Koc et al., 2020), namely damage and recovery of bridges in the case of the simulated earthquake scenario, informed the transportation systems analysis. Additionally, the same scenario was simulated to estimate damages to other aspects of the built environments (i.e., General Building Stock) and ports. These hazard results inform both the transportation system analysis and the socioeconomic impact analysis. From left to right, Fig. 2 next presents the analytical framework of the transportation system model in terms of a 4-step travel demand model developed at the metropolitan-scale (see Koc et al., 2020 for a detailed description of the steps involved, including Network Skimming), Trip Generation and Distribution, Mode Choice, Time-of-Day Choice and Traffic Assignment. To arrive at the network performance indicators and resilience outcomes, the 4-step methodology is implemented for each of the network topology, including the versions of the pre-disaster baseline and the post-disaster degraded network. Traffic assignment results gathered across representative network versions along the disruption timeline set the stage to assess the functionality of network throughout the entire recovery path.

The linkages between the transportation model and the TERM CGE model have been established using the approaches discussed in Wei et al. (2020). This involves the use of estimated increase in transportation costs, reductions in commodity supply caused by port disruptions, and business interruptions caused by general building damages of the scenario earthquake, which are all inputs into the CGE model.

The next steps are to establish the linkage between the economic impact model (the TERM CGE Model) and the MSIDM. The first step is to calculate changes in income by bracket caused by building damages and degradation of the transportation system by multiplying the sectoral income changes by the MSIDM. We next estimate the overall changes in distribution of income in the study region by adding the changes in income across sectors by income bracket. The Gini coefficients for both the reference case and the resilience cases are calculated to evaluate whether inequality in income distribution has been increased or decreased under different disruption and resilience cases.

5. Disaster scenario and methods to estimate disaster damages

To illustrate the working of the integrated transportation-socioeconomic impact model, we use the results of a simulated scenario earthquake, an earthquake of magnitude 7.3 caused by a rupture of the Palos Verdes Connected fault system with an epicentral 1.4 km

[11] This region includes three southern CA counties: Los Angeles, Orange, and Riverside.

[12] This region includes nine northern CA counties: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma.

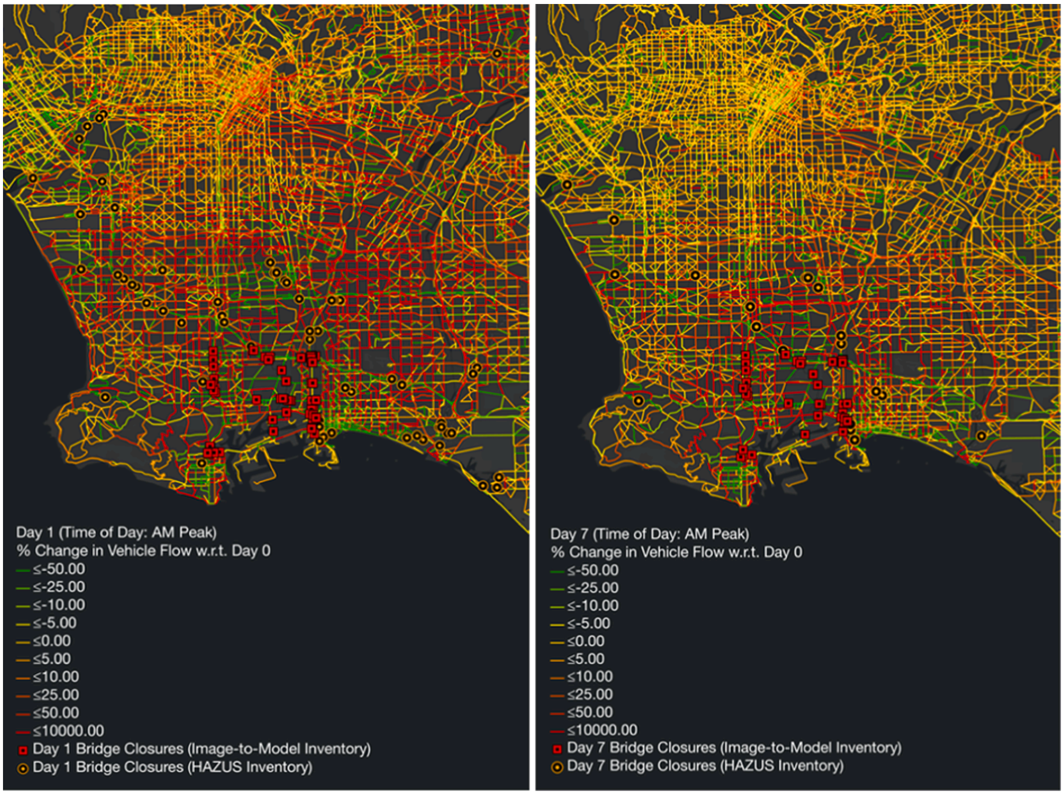

Fig. 3a. Changes in vehicle flow during AM peak time on day 1 and day 7 after the simulated earthquake event.

away from the San Pedro Bay ports as a case study.[13] This scenario event was identified by examining the probabilistic seismic hazards in the area for a 975-year return period, and the effects of the earthquake were limited to ground shaking only. The methodology used for additional hazard characterization and damage assessment for 1) bridges, 2) ports, and 3) general buildings is discussed in detail in Koc et al. (2020). In transportation systems analyses, bridges are regarded as the most critical segments of a road network due to the lower redundancy associated with them.

6. Direct impacts of the simulated earthquake scenario

6.1. Disruption and recovery of regional transportation

Based on HAZUS simulation results on damage state and replacement value of individual components of the transportation system, the repair and replacement costs of the highway transportation infrastructure are estimated to be over $300 million (in 2019 dollars). Six network versions in total (for Days 0, 1, 7, 30, 90, and 104 after the disaster event) were modeled for the simulated earthquake scenario. The solutions to the traffic assignment problem for each version were completed under fixed travel demand assumptions to quantify the disruption and recovery of transportation in the region. Simulation results indicate that 137 bridges are closed because of the earthquake damages on Day 1, and 62, 58, 45, and 19 bridges remain closed on Day 7, 30, 90 and 104, respectively. Every network version for the corresponding bridge closures, indicators of system level functionality, such as Total Travel Time (Vehicle-Hours-Traveled), Total Travel Distance (Vehicle-Miles-Traveled), and Delay, were quantified to investigate the disruption.

The simulation results indicate significant interruptions to regional mobility, especially for the transportation network on Day 1 (see Fig. 3a, which presents the percent changes in traffic flow on Day 1 and Day 7 after the scenario earthquake). Consequently, increases in total travel distance in terms of VMT on Days 1 and 7 after the earthquake for each TAZ are presented in Fig. 3b. In the first week after the earthquake event, about 850,000 h of increased travel time per day is estimated. This translates to a 6.52% reduction of TTT (Total Travel Time)-based functionality in the study region. Other than the quantitative results presented here and entered as inputs into the economic model, there are many ways that the detailed transportation simulation results could be utilized to inform

[13] Note that the seismic hazard scenario was originally characterized by the authors' collaborators at UCLA CEE's Taciroglu Research Group for a concurrent study on a comprehensive evaluation of resilience of transportation systems in metropolitan areas (Koc et al., 2020). The same reference provides detailed discussions on how a computer vision-enabled methodology is used to estimate damages to and restoration of bridges.

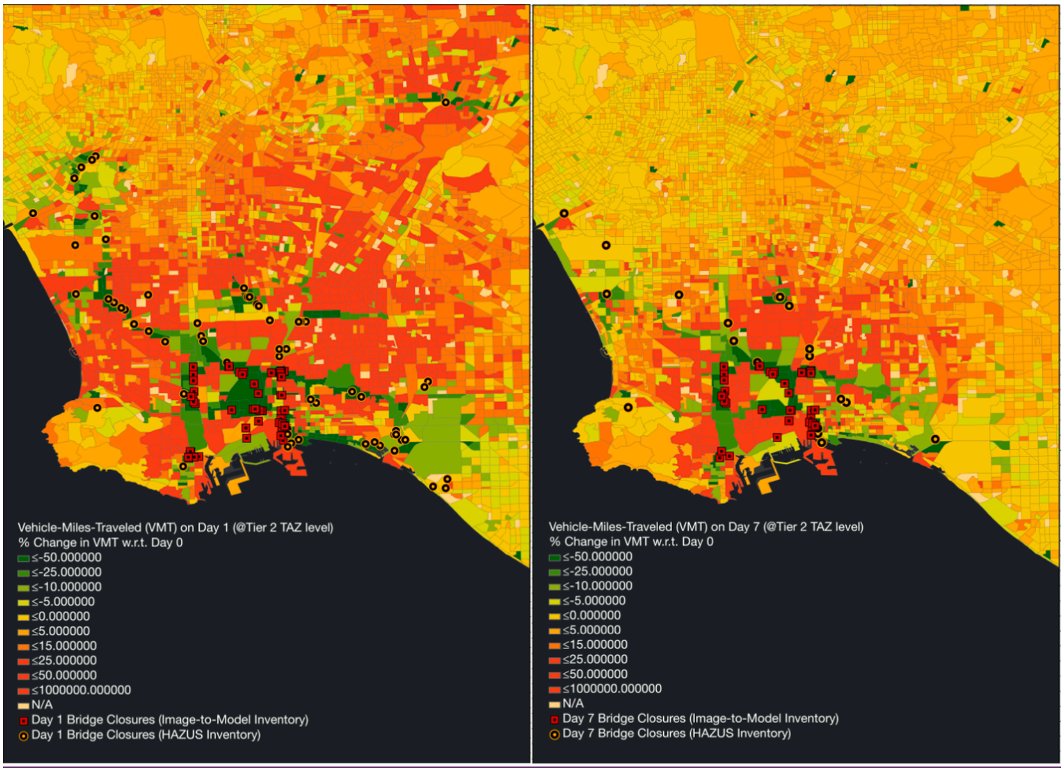

Fig. 3b. Changes in Vehicle-Miles-Traveled (VMT) during AM peak time on day 1 and day 7 after the simulated earthquake event.

operations and management of the road network under a disaster scenario. For example, Fig. 3b clearly shows the cascading disturbance in the transportation network towards west of the epicenter near POLA/POLB, primarily through I-405. A quick inspection of the root cause of this cascading effect reveals the damaged bridges along this highway corridor as critical network components that could be identified for a rapid restoration effort after the strike of the simulated earthquake or could be prioritized for seismic hardening or retrofitting in preparation of future disasters. We presented an example of such analysis below, which investigates the potential of prioritizing recovery effort to keep eight relatively less damaged bridges along I-405 open after the earthquake as a dynamic resilience tactic. More broadly, decision makers carrying out associated planning/modeling tasks for the owners/operators of road infrastructure can readily implement this integrated modeling framework or one they develop based on a similar perspective as they prioritize their resilience tactics to improve the performance of their networked infrastructure in the context of hazard risk.

In the simulation, Los Angeles County experiences the largest burden of this degradation, with a 11.81% decline in TTT-based functionality. The transportation disruption results, estimated at a much higher resolution (at the Traffic Analysis Zone level),[14] are aggregated up to regional breakdowns in the TERM Model. We use changes in TTT directly as the indicator of changes in transportation costs[15]. This is expressed as an average percent increase in transportation costs, which include labor costs that constitute the larger share, as well as fuel, operation, and maintenance costs, for the LA Metro Region as a whole, both within the Region and between LA Region and the rest of the state. For this TTT-based functionality, results for every network version are benchmarked to their baseline levels (see Table 3).

Since the simulations in the TERM Model are conducted on an annual basis, we first translated the transportation cost increases over the 105-day period presented in Table 3 to an overall percentage transportation cost increase per year. This is calculated as a 0.5271% increase in truck transportation cost within the LA Metro Region and a 0.26356% increase between the LA Metro Region and Rest of CA (on an annual basis).

We also simulated a hypothetical intervention to keep eight bridges open to service on the I-405 corridor from Day 1 (in the Reference Case, the service of these eight bridges is not restored until 7 days after the earthquake) to evaluate how the accelerated recovery of a critical component of the corridor in the highway transportation system can reduce the degree of transportation network

[14] >11,000 TAZs are used to model the travel demand in the SCAG region.

[15] TTD (Total Travel Distance)-based functionality indicates only marginal changes given the high redundancy in the dense urban network. High redundancy enables short detours, and TTD indicators change only marginally, while TTT indicators show a major disruption. In Los Angeles, the dense street networks result in this phenomenon. In other cities, such as San Francisco, closure of a few low redundancy links can result in significant decreases in TTD based functionality.

Table 3
Percentage increase in transportation costs for intraregional and interregional transportation between the LA metro region and the rest of CA.

FROM / TO	Days after Earthquake	LA METRO	REST OF CA
LA METRO	1–7	9.88	4.94
	7–30	1.34	0.67
	30–90	1.28	0.64
	90–104	1.04	0.52
	104–105	0.92	0.46

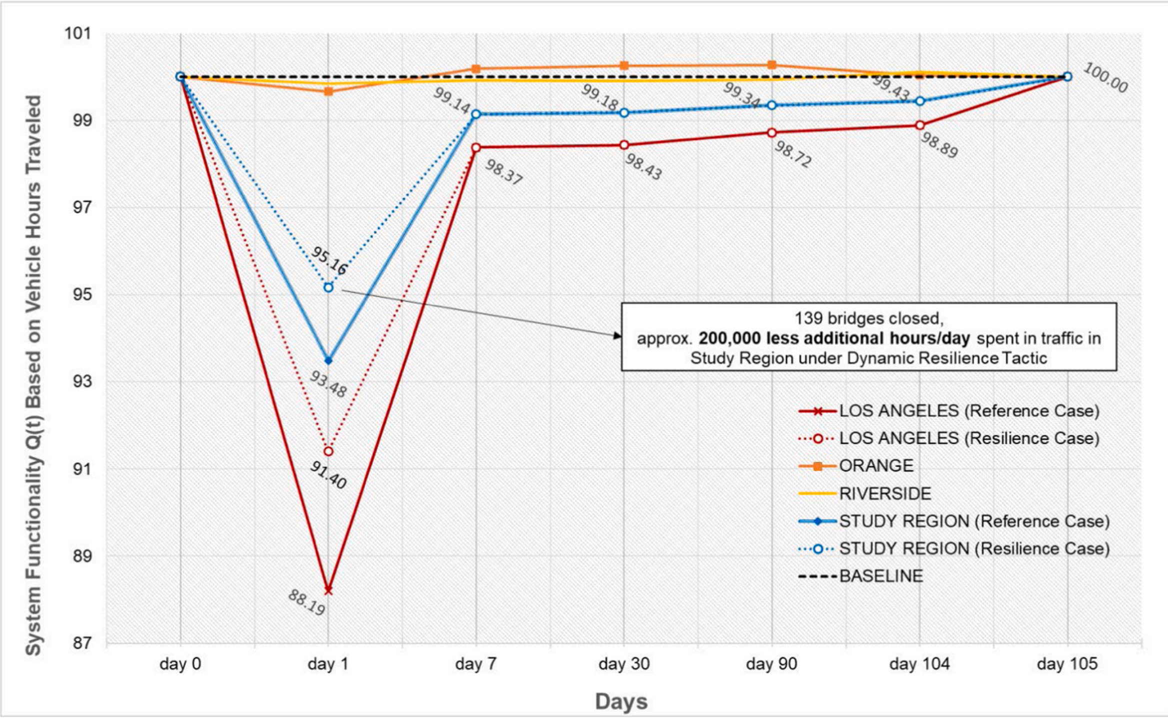

Fig. 4. Regional system functionality Q(t) (in VHT) before and after tactic to accelerate the opening of eight major bridges in week 1. Note: the system functionality measures are discrete in time (based on the simulation results of six network versions or key days in the aftermath of the scenario earthquake). Thus, the lines in the figure are simply drawn to join the various measurement points.

functionality decline during the first week in the aftermath of the earthquake. Such an intervention could entail the rapid installment of temporary support structures such as shoring systems that are often used in bridge construction.

The results in Fig. 4 indicate a significant improvement to system functionality for the resilience case of a more accelerated recovery of major bridges during Week 1: functionality loss in L.A. County is reduced by 3% and 220,000 h/day spent in traffic are saved with respect to the reference case.[16] As a result, the transportation cost increases in Days 1–7 are reduced from 9.88% to 7.27% within the LA region and from 4.94% to 3.63% between LA and the Rest of CA.

6.2. *Functionality loss and recovery at the ports of Los Angeles and long beach*

We also employed the HAZUS methodology to estimate the port's remaining functionality following the earthquake, as well as its recovery path (FEMA, 2013). HAZUS accommodates a database that provides detailed information on the berths at the ports. The total costs of repair and replacement of damaged port facilities are estimated to be over $210 million. The restoration at the port is simulated

[16] The Reference Case only considers inherent resilience of the transportation network, such as road redundancy. The Resilience Case considers an accelerated recovery of eight bridges in the main highway corridor, which help reduce the disturbance of the transportation network in the first week after the earthquake. Note, however, that we assume this strategy will not affect the speed of recovery of the other components on the highway corridors. Therefore, the degradation levels of the system are the same on the remaining simulated days (i.e., the solid and dotted lines overlap after Day 7 in Fig. 4).

Table 4
Real GDP impacts of port disruptions for the base case, reference case, and resilience case simulations. (in millions 2019 dollars and % reduction with respect to pre-disaster baseline levels).

	Los Angeles Metro	San Francisco Metro	Rest of CA	Rest of U.S.	U.S. Total	Loss Reduction Potential (for LA)	Loss Reduction Potential (for U.S.)
Base Case (no resilience)	−13,754.92 −1.71%	−5,912.57 −1.24%	−6,342.29 −1.12%	−52,900.52 −0.41%	−78,910.42 −0.54%		
Reference Case (With Inherent Resilience (IIR))	−1,763.81 −0.22%	−936.19 −0.20%	−739.53 −0.13%	−7,535.55 −0.06%	−10,975.09 −0.08%	87.18%	86.09%
Resilience Case (With Combined Resilience– IIR, Other Inherent, Adaptive Resilience)	−284.92 −0.04%	−64.06 −0.01%	−77.21 −0.01%	−331.96 0.00%	−758.15 −0.01%	97.93%	99.04%

based on the analysis of the damage state probability of the 171 port facilities under the earthquake scenario event, the repair and reconstruction time needed for different damage states, and the expected functionality levels of these facilities on selected key days after the strike of the earthquake until the recovery to 100% functionality. Since an industry classification scheme is not given for the port facilities in HAZUS, we used official facility maps published by the port authorities to manually classify the berths in the HAZUS inventory into main categories of cargos handled by the damaged facilities (containerized, breakbulk, dry bulk, liquid bulk, and automobiles). The HAZUS simulation results are presented in Appendix B. We then translate the reduction in port capacity into disruptions of import and export flows through the twin ports, measured as percentage reductions in import uses and export production by sector in each of the TERM regions.

6.3. General building stock damages in greater Los Angeles

The general building damages are calculated based on the HAZUS earthquake simulation results. The percent building damages are calculated by dividing the sum of dollar losses in building and contents by the total exposure values of building stocks. On average, business sectors in the LA Metro Region experience 1.4% to 6.21% property damages. The total costs of repair and replacement of the general building stock are estimated to be about $64 billion.

The percentage property damages from HAZUS occupancy classes are then mapped to TERM economic sectors. The weighted average recovery period by sector is calculated using the information on building damage states and the associated recovery time both obtained from HAZUS. Finally, the percent destruction of capital input is calculated on an annual basis based on the recovery time. Appendix C presents the percentage building damages by TERM model sector and the average recovery time for each sector based on HAZUS simulation results for various occupancy classes.

7. Socioeconomic impacts of the simulated earthquake scenario

7.1. Aggregate impacts of port disruptions

To simulate the macroeconomic impacts of port disruptions, we first translated reductions in port functionality into disruptions of import and export flows. The percentage reductions in import uses and export production by sector in each of the TERM regions are then calculated.

Like other CGE models, the TERM Model automatically captures the effects of three categories of inherent economic resilience that work through the price system. These are input substitution, import substitution, and regional production relocations (IIR).[17] Following the methodology developed in Wei et al. (2020), we estimate the loss reduction potential of the IIR by comparing the simulation results using the I-O analysis and the TERM simulation results of the port disruptions. The I-O analysis assumes fixed production coefficients (or a linear relationship between the changes in production inputs and changes in the output), and thus can be used as the Base Case with no resilience tactics incorporated. Table 4 first presents the GDP impacts of the Base Case (no resilience) and the GDP impacts obtained from the TERM simulations that take into consideration IIR (the Reference Case in Table 4).

The port disruptions are estimated to result in $1.76 billion GDP losses (0.219% reduction) in the LA Metro Region after the three major types of inherent resilience tactics are considered. The other regions in California, as well as the Rest of U.S., also experience GDP losses, but in smaller magnitudes in percentage terms because the LA Region is the final destination and direct user of nearly 50% of the import shipments through the Ports. The total losses in GDP are estimated to be about $11.0 billion for the U.S. as a whole, though this translates to less than a 0.1 percent decline.

[17] Input substitution refers to the use of similar goods as a replacement in the production process to the goods whose production and supply is interrupted directly and/or indirectly. Import substitution is the strategy to purchase goods and services in shortage from outside of the disaster impacted region. Regional production relocation can be achieved by shifting production activities to branch plants and facilities located outside of the disaster region.

The percentage loss reduction potential of the IIR resilience and of all resilience tactics considered for port disruptions in this study are presented in the last two columns of Table 4. A comparison of the Reference Case simulation results (presented in row 2) and the results from the I-O analysis (row 1) indicates that the IIR resilience automatically captured in the TERM model simulations can reduce 87.2% of the GDP impacts for the LA Metro Region and 86.1% at the national level.

We next run a simulation of other types of inherent and adaptive resilience tactics pertaining to port disruptions (see the last row of Table 4). The combined resilience can further reduce the GDP impacts to $0.28 billion for LA and $0.76 billion for the U.S., or a reduction of the potential GDP losses by almost 98% and over 99%, respectively, compared to the Base Case.

7.2. *Aggregate impacts of truck transportation cost increases and building stock damages*

The transportation cost increases over the 104-day recovery period, translating to a 0.5271% increase in truck transportation cost within the LA Metro Region and a 0.26356% increase between the LA Metro Region and the Rest of CA on an annual basis.

The GDP losses in the LA Metro Region are estimated to be $17.0 million. The Rest of California will only experience very slight GDP losses. The Rest of U.S. is estimated to have a small increase in GDP of $4.21 million, which can be explained by the effect of regional production shifts automatically captured by the TERM Model caused by a truck transportation cost increase (and thus an implicit production cost increase) in the LA Metro Region and the Rest of CA in comparison to the Rest of US. The resilience tactic of a more rapid opening of critical highway corridors during the first week after the seismic event is estimated to have a loss reduction potential of about 10% over the entire recovery period.

The simulated earthquake also results in destructions and damages to general building stock in the LA metro region, which in turn results in interruptions to the production of goods and services using the productive capital stock. The total GDP losses stemming from property damages are estimated to be nearly $23.4 billion (or a 2.8% reduction from the annual baseline level) in the LA Metro Region. The Rest of CA (excluding Northern California) is estimated to experience very slight GDP losses. The Rest of the U.S. is estimated to have an increase in GDP of $3.3 billion, which again can be explained by the effect of regional production shifts or locational substitution of economic activities caused by the simulated disaster.

After we take into consideration two major types of resilience tactics to cope with general building stock damages – the use of undamaged spare/excess capacity and production recapture – GDP losses decrease from $22.4 billion to $13.8 billion for the LA Metro Region and from $19.3 billion to $11.8 billion for the U.S. as a whole, a reduction of about 38% compared to the Reference Case, in which only the three major inherent resilience tactics (IIR) are taken into account.

When we compare the economic impacts of the three types of disruptions/damages of the earthquake scenario – port disruption, hinterland transportation cost increase, and general building damages – the impacts from general building damages account for over 92% of the total impacts in the LA Metro Region before resilience other than IIR is taken into account. The hinterland transportation system disruption results in the smallest impacts because of the high redundancy of the transportation network in the region. At the national level, impacts from general building damages account for about 63% of the total impacts (without resilience adjustments), while the port disruptions account for another one third of the total impacts. After the adjustment of the various resilience tactics, impacts from general building damages account for nearly 98% of the total impacts in the LA Metro Region and 94% for the U.S. This is because there are more effective resilience tactics businesses can implement to deal with port disruptions and supply chain shortages than are available in the case of physical damages to buildings and facilities.

7.3. *Combined economic impacts*

We also run a simulation in which we combine all three types of disruptions/damages together. This simulation is run for both the Reference Case and the Combined Resilience Case (see Table 5). The total GDP losses are estimated to be $24.2 billion (or a 3% reduction) in the LA Metro Region, and $30.2 billion in the U.S. as a whole (or a 0.21% reduction). After taking into account the effects of various resilience tactics, the total impacts are reduced to $14.2 billion in the LA Metro Region and $12.8 billion for the U.S. as a whole, or a loss reduction of 41.3% and 57.6%, respectively. The reason that total impacts are less at the national level than at the regional level in the Combined Resilience Case is that the Rest of the U.S. is expected to experience an overall increase in economic activities due to regional production shifts after the earthquake hits the LA area.

7.4. *Income distribution impacts*

Based on the simulation results from the TERM Model, we performed income distribution analyses for the LA Metro Region (the region affected most by the simulated earthquake scenario). The detailed income distribution impacts for port disruption, transportation cost increase, general building damage, and all three combined, are presented in Appendix D. The tables first present the distribution of personal income across income brackets in the baseline, followed by the income distribution impacts for both post-disruption simulation cases (Reference Case and Combined Resilience Case). For port disruptions, the percentage reductions in income are relatively higher for the lower- to middle-income groups in the Reference Case, but are relatively higher for the middle- to high-income groups in the Combined Resilience Case. For the transportation cost increase simulation, the percentage changes are relatively higher for some middle- and upper-income groups. For the building damage simulations, the middle- and higher-income groups in general experience relatively higher income losses in both the Reference Case and Resilience Case. This can be explained by the fact that a higher proportion of capital-related income is earned by higher-income groups.

Table 6 first presents the Gini coefficients for the income distribution in the baseline and various simulation cases. The changes in

Table 5
Real GDP impact of the combined disruptions/damages in the reference case and resilience cases (in millions 2019 dollars and % reduction with respect to pre-disaster baseline levels).

	Los Angeles Metro	San Francisco Metro	Rest of CA	Rest of U.S.	U.S. Total	Loss Reduction Potential(for LA)	Loss Reduction Potential (for U.S.)
Reference Case (With Inherent Resilience (IIR))	−24,207.64 −3.00%	−827.70 −0.17%	−855.49 −0.15%	−4,295.82 −0.03%	−30,186.64 −0.22%		
Combined Resilience Case (IIR, Other Inherent, Adaptive Resilience)	−14,200.35 −1.76%	−11.71 0.00%	−166.77 −0.03%	1,570.97 0.01%	−12,807.86 −0.09%	41.34%	57.57%

Table 6
Gini coefficient impacts.

Disruption Type	Baseline	Scenario Gini Coefficient	Change in Gini Coefficient	Gini Coefficient of the Income Loss
Port Disruption_Reference Case	0.465478	0.465614	0.000136	0.413109
Transportation Cost Increase_Reference Case	0.465478	0.465478	0.000000	0.490154
Building Damage_Reference Case	0.465478	0.463904	−0.001574	0.508171
Combined Disruptions_Reference Case	0.465478	0.464041	−0.001438	0.501768
Port Disruption_Resilience Case	0.465478	0.465473	−0.000006	0.471813
Transportation Cost Increase_Resilience Case	0.465478	0.465478	0.000000	0.490157
Building Damage_Resilience Case	0.465478	0.464243	−0.001235	0.508481
Combined Disruptions_Resilience Case	0.465478	0.464238	−0.001240	0.507328

the Gini coefficient relative to the baseline level are then presented. Finally, we compute the Gini coefficient for the income loss alone. The Gini coefficient increases in the port disruption Reference Case, which indicates that the disruption is borne slightly disproportionately by lower- and middle-income groups. The Resilience Case results in a Gini coefficient slightly lower than the baseline level, which is explained by the fact that the various resilience tactics are more effective in reducing impacts in the sectors that employ more people from the lower-income groups. For example, manufacturing sectors have a higher potential to use inventory and implement production recapture compared with service sectors such as healthcare, finance and insurance, or professional and business services. The Gini coefficients of the other cases decrease compared to the baseline level, indicating that the income losses stemming from transportation cost increases and general building damages are borne disproportionately by middle- and higher-income groups. This is because these groups earn a higher proportion of capital-related income and thus are expected to experience a higher proportion of income losses from capital stock damages. Since the impacts of general building damages account for over 90% of the total impacts in the LA Metro Region, the combined simulation of all three types of disruptions/damages also leads to lower Gini coefficients.

8. Limitations of current study and areas for future research

There are several limitations to the current study. First, the recovery of bridges in our integrated framework is largely based on HAZUS recovery functions that are derived from expert surveys. The difference in our case from a typical all-HAZUS methodology is the adoption of more advanced modeling through the image-to-model method for the bridges that are within the immediate periphery of POLA/POLB. For those bridges modeled based on HAZUS inventory, the assumption is that recovery will happen with estimated durations based on the Applied Technology Council evaluation of earthquake damage for California (ATC, 1985). No resource constraint is taken into consideration in the HAZUS modeling. Optimal resource allocations under resource constraints in the aftermath of disasters are important strategies to lead to faster recovery, which is an important topic for further investigation in future studies.

Second, the transportation system analysis in this study only focuses on the impacts on the road network (including both highways and surface roads) under disruptive events. It does not incorporate explicit analyses of intermodal substitutions between highway transportation and other transportation modes. Similarly, although inter-seaport substitutions (through ship diversions) are included in the port resilience analysis, rail as a resilience transportation substitution is not considered. Future studies can enhance these aspects by deploying multi-modal transportation infrastructure models.

Third, the current study models the disruption and recovery of the transportation network in the disaster region based on the assumption of fixed travel demand. This is a simplified assumption to make the current analysis, which has a primary focus on economic and distributional impacts of disaster resilience, manageable. In future work, changes in post-disaster travel demand should be taken into consideration. The change in travel demand can take place in both freight transportation and passenger travel flows. For the former, iterative simulation process can be constructed between the transportation and economic models, so that declines in production of goods and services caused by business interruptions estimated by the economic model can be fed back to the transportation model to re-calculate traffic assignment and trip distributions. The re-estimated system level functionality can then be used to further adjust the economic impact modeling, in an iterative fashion. As for passenger travel flows, behavioral response such as increased telecommuting due to reduced transportation network functionality can be modeled by altering the number of home-based-work trips in the travel demand model. The other possible option is to use the trip distribution (destination choice) and the mode choice modeling components in the travel demand model.

Fourth, there is a mis-match of the spatial resolutions of the transportation model at the Traffic Analysis Zone level and the economic model at the regional level. The main advancement of the current study is to aggregate and use the more accurate functionality losses estimated based on the high-resolution transportation model as inputs in the multi-regional economic consequence analysis model because these two types of models are typically utilized in isolation. Since transportation planning agencies are also interested in better understanding of distribution of impacts of disruptive events across more localized areas, including impacts to more socially and economically vulnerable communities and neighborhoods, method to allocate economic impacts to more granular analysis zones can be adopted in future analysis.

Finally, this study focuses on a single simulated disaster scenario. Our main purpose is to use this case study to illustrate how the integration of detailed models on transportation and economics fronts can provide rich insights in terms of the cost-effectiveness of resilience tactics to port and transportation system disruptions, and the economic aggregate and distributional impacts of the disruption before and after the implementation of the resilience tactics. Substantial uncertainty exists in disaster events, including factors such as type of incidents, intensity and magnitude of disruptions, recovery path and duration, among others. The results we present for this case study are sensitive to the values of these parameters. The owner/operator of port or other civil infrastructure could run a range of scenarios as they desire relating to their decision-making. The analytical framework established in this study can be adapted to estimate the disaster resilience impact in different contexts. Reduced-form models can be developed based on this analytical framework to enable decision-makers to alter key parameters of the disruption scenarios and obtain rapid simulation results as in the E-CAT (Economic Consequence Analysis Tool) decision support tool (Rose et al., 2017).

9. Conclusion

The increasing number of incidents of port closures and related transportation network downtimes following major disasters in recent years signify the importance of preparation and response. Integrated and operational models that combine considerations of structural engineering, transportation flows, economic linkages, and distributional implications can provide unique insights on the impacts of large-scale disasters, and the benefits associated with resilience during the recovery process. We contribute to the economic impact analysis of ports and their hinterland transportation infrastructure disruptions in two ways. First, we developed an integrated model that links a transportation network model with an economic impact analysis model in order to conduct a more holistic and accurate analysis of the impacts of and resilience to the transportation system disruptions. The functionality losses and recovery paths analyzed by the high-resolution transportation model greatly enhance the accuracy of the estimation of the average transportation cost increase both within the disaster directly impacted region and between the core impacted region and other regions, and thus enable us to model the spillover effects on the entire economy based on the sectoral specific dependence on transportation services. Second, to fill in an important gap in the port and transportation network disruption literature, we examine not only the impacts of such disruptions and the effectiveness of resilience tactics at the aggregate level, but also the income distribution impacts across socioeconomic groups for individual damage and disruption categories. Such analysis provides insights not only on the effectiveness of resilience tactics to reduce the aggregate economic losses, but also the potential to reduce distributional inequities. The application of the integrated model is demonstrated by using a simulated seismic event affecting commodity trade flows at the Port of Los Angeles and Port of Long Beach and the related inland freight transportation network in the Los Angeles Metro Region.

The integrated modeling system starts with a hazard characterization and damage assessment model that combines estimation of damage state probabilities and restoration functions to calculate the functionality downtimes of key components of the transportation network under the simulated earthquake scenario (Koc et al., 2020). Based on the damage assessment results, the four-step SCAG travel demand model is then used to generate transportation network functionality and performance indicators on key days throughout the entire recovery path. Damage assessment for ports and general building stocks was carried out using HAZUS. The results from the first two models are fed into the multi-regional TERM CGE model that estimates the aggregate and sectoral economic impacts of the simulated seismic scenario, with formal incorporation of modeling of a wide range of relevant static resilience tactics. A multi-sector income distribution matrix is constructed that uses the TERM model estimates on sectoral income changes to evaluate the equity implications of the disaster impacts and implementation of resilience tactics.

Our study confirms the findings of many other works that transportation network disruptions caused by disasters affecting a broad region can be sizeable, especially after the indirect and spillover effects through the supply-chain network and interconnected transportation infrastructure system are accounted. At the same time, various types of resilience tactics that can be implemented by both the suppliers and customers of the transportation (including port) services have the potential to significantly reduce business interruption losses. Our analysis results indicate that it takes 150 days for the ports to fully recover from the simulated seismic event. The total GDP impacts stemming from both import and export disruptions are estimated to be $11.8 billion in the LA Metro Region and $67.5 billion for the U.S. before we consider any resilience. These impacts are reduced to $1.5 billion and $9.4 billion, respectively, after the three major inherent economic resilience tactics (input substitution, import substitution, and inter-regional production relocations) estimated by the TERM CGE Model are taken into account. After we consider the other inherent and adaptive resilience tactics, the total impacts are further reduced to $0.24 billion in the LA Metro Region and $0.65 billion in the U.S. In addition, damages to the highway transportation system cause a 0.53% increase in truck transportation cost within the LA Metro Region and a 0.26% increase between the LA Metro Region and the Rest of CA (on an annual basis). The associated GDP losses are estimated to be only $15 million in the LA Metro Region because of the general high redundancy of the transportation network. The total GDP losses from damages to building stock are estimated to be $19.2 billion in the LA Metro Region, which is reduced to $11.8 billion after the adjustment for resilience. The GDP losses for the U.S. are $16.5 billion with no resilience, and $10.1 billion after the resilience adjustments. The lower impacts at the national level are due to the offsetting effect of regional production shifts from the earthquake-impacted region to elsewhere in the country. The combined simulation of all three types of disruptions/damages yields GDP losses of $12.1 billion for the LA Metro Region and $10.9 billion for the U.S. after we consider all the relevant resilience tactics. The loss reduction potential of resilience is 41.3% at the LA regional level and 57.6% at the national level.

New findings in this study contributing to the state-of-the-art knowledge of the literature are the distributional impacts of transportation disruptions and resilience, and thus providing insights on the potential to reduce disaster distributional inequities. The income distribution analyses for the LA Metro Region indicate that the income losses stemming from port disruptions are borne slightly disproportionately by lower- and middle-income groups. The Resilience Case for port disruptions results in a slightly lower Gini coefficient than the baseline level (indicating a more equitable distribution of income), which is explained by the fact that the various resilience tactics are more effective at reducing impacts in the sectors that employ more people from the lower-income groups. For example, manufacturing sectors have a higher potential of inventory uses and production recapture compared with service sectors such as healthcare, finance/insurance, and professional/business services. The Gini coefficients of the other cases decrease compared to the baseline level, which indicates that the income losses stemming from increased transportation cost and general building damages are borne disproportionately by middle- and higher-income groups. This can be explained by the fact that a higher proportion of capital-related income is earned by higher-income groups.

The authors also investigated adaptive resilience tactics relating to the transportation system and the corresponding improvements in functionality losses due to the initial disruption. The I-405 corridor was identified as a critical link that could be kept open due to the relatively lower levels of estimated damage in eight bridges located away from the epicenter of the scenario earthquake. This adaptive resilience tactic was shown to mitigate a significant amount (about 25%) of system functionality loss in the first week after the seismic event. Such calculations can provide important insights for decision-makers.

The results provide managerial insight in terms of estimates of aggregate and distributional losses from transportation disruptions and inform facility owners and operators the special values of resilience in reducing these losses. The disaggregation of these impacts and the corresponding resilience to them help distinguish the impacts between disruption of the port and earthquake damage to other structures, including the adjoining highway system. Moreover, the integrated and operational modeling framework developed in this study can be used by regional transportation and planning agencies for any relevant disaster scenario analysis to evaluate and prioritize resilience measures, including alternative restoration strategies of critical components (e.g., bridges) in the transportation network system in the aftermath of disasters. A framework like the one we developed would allow transportation agencies such as Caltrans to simulate extreme events and rank its assets like bridges in the order of individual economic impacts under alternative extreme event scenarios. This would allow them to compare the cost of upgrading (retrofit to increase resilience) each asset against the probability and costs of their failure during future extreme events. Such analyses would provide Caltrans valuable insights in terms of the utilization of their limited resources optimizing their asset upgrade strategies by identifying which assets should be prioritized to upgrade and in which order. Our analytical framework can also be used to provide technical support to define the best construction strategy. Using bridges as an example, after selecting the best ones to upgrade, Caltrans would be able to determine the best construction sequence/strategy (such as total vs. partial closures of certain bridges or segments of highways) that would minimize the economic impact on the local and regional economy in order to obtain community support for the projects.

Finally, actual resilience can differ from potential resilience modeled in this study. Given the various potential obstacles in practice, including restrictive regulations, market failures, and bounded rationality in decision-making, the presence of various resilience tactics does not necessarily lead to their optimal utilization. Our analysis provides useful insights to port authorities and terminal operators, businesses that depend on the services of the ports and the freight transportation network, and policymakers to identify and implement effective resilience measures and tactics and to establish or improve business emergency and continuity plans in preparation of unexpected disasters and disruptions.

CRediT authorship contribution statement

Dan Wei: Funding acquisition, Conceptualization, Methodology, Data curation, Writing – original draft, Writing – review & editing. **Adam Rose:** Funding acquisition, Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Eyuphan Koc:** Funding acquisition, Methodology, Data curation, Writing – original draft, Writing – review & editing. **Zhenhua Chen:** Methodology, Data curation, Writing - original draft, Writing - review & editing. **Lucio Soibelman:** Funding acquisition, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Construction of income distribution matrix

A.1. Employee compensation

To construct the income distribution matrix for wages and salaries, we first collected data from the BLS Occupational Employment Statistics (OES) (BLS, 2019a). The two main matrices we use are the Occupation-Industry Employment matrix and the Occupation-Industry Wage matrix. The industries are disaggregated at 4-digit NAICS level, and the occupation categories follow the 6-digit Standard Occupational Classification. For each occupation type of a given industry, BLS OES data report not only the annual average (mean) wages, but also wage rate in percentiles (10, 25, 50, 75, 90). One limitation of this data set was that the minimum and maximum wage percentiles are 10 and 90, respectively, and hence it does not readily provide information on the wage rate for the highest and lowest earners. In order to deal with this limitation, we estimated annual wage rates for an extended set of percentiles (1, 5, 20, 40, 60, 80, 95, 99) using linear interpolations following the methodology developed by Rose et al. (2012) and Prager (2013).

After we calculated the annual employee compensation by sector and occupation for each percentile (1, 5, 20, 40, 60, 80, 95, or 99), we multiply it by the number of employees in each percentile interval of this occupation in this sector to obtain the total employee compensations by percentile. Next, the total employee compensations by percentile and sector are allocated to the relevant household income brackets. The OES sectors are also mapped to the TERM CGE model sectors. Finally, we used the estimate of Total Employee Compensations in California in 2018, which was $1.346 trillion, as the control total to re-balance the entire Employee Compensation matrix we constructed.

A.2. Proprietors' income

The distribution of proprietors' income across sectors and income brackets is calculated based on IMPLAN data. In addition, IMPLAN also provides data on the amount of proprietors' income generated in each sector. We apply the distribution percentages across the nine income brackets to the total proprietors' income for each sector to obtain the distribution of proprietors' income across income brackets for each sector. The underlying assumption is that the proportional distribution of proprietors' income among the income brackets is the same across all sectors. Finally, we used the BEA estimate of total proprietors' income in California in 2018, which was $249.7 billion, as the control total to re-balance the entire proprietors' income matrix we constructed.

A.3. Capital income

IMPLAN also provides data on the distribution of the total Dividend Payments and Other Property Income (which mainly includes interest payments and rent income) across income brackets. In addition, IMPLAN also provides data on the amount of Other Property Income by sector. We first calculated the percentage distribution of Other Property Income across sectors, and then apply it to the total amounts of Dividend Payments and Other Property Income in each income bracket to obtain the distribution across sectors for each income bracket. The underlying assumption is that the proportional distribution of Dividend Payments and Other Property Income among the sectors is the same across all income brackets. Finally, we used the BEA estimate of total Dividends, Interest, and Rental Income in California in 2018, which was $538.3 billion, as the control total to re-balance the capital income matrix we constructed.

A.4. Personal transfer receipts

The final component of the personal income accounts is the personal transfer receipts (including social security benefits, medical benefits, veteran's benefits, and unemployment insurance benefits). IMPLAN provides data on the distribution of federal, state and local government transfer payments to each household income bracket. Similar as for the other components of the personal income accounts, we used the BEA estimate of total Personal Current Transfer Receipts in California in 2018, which was $341.2 billion, as the control total to re-balance the transfer income matrix we constructed. (See Tables A1 and A2)

Table A1
Multi-sector income distribution matrix for California, 2018. (millions of 2018$)

Sector	<10 k	10 k–15 k	15 k–25 k	25 k–35 k	35 k–50 k	50 k–75 k	75 k–100 k	100 k–150 k	>150 k	Total
01. Crops	17	158	3,284	4,056	1,648	1,497	1,991	1,606	6,194	20,451
02. Poultry & Eggs	0	3	38	48	23	24	36	29	114	315
03. Livestock	4	35	188	237	191	250	397	319	1,296	2,916
04. Other Livestock	1	3	14	17	17	22	35	28	114	251
05. Forestry, Fishing, & Hunting	2	20	26	38	131	198	243	186	756	1,601
06. Oil & Gas	9	45	54	75	207	353	550	441	1,581	3,315
07. Coal	0	0	0	1	2	5	3	2	4	18
08. Other Mining	4	10	15	62	213	465	294	216	311	1,589
09. Biomass electricity generation	1	6	7	10	25	41	67	60	208	426
10–11. Coal-fired and Gas-fired electricity generation	18	50	53	71	207	361	574	680	1,364	3,378
12. Hydroelectricity generation	1	5	5	7	21	41	68	87	150	386
13. Nuclear electricity generation	5	14	15	21	62	116	186	242	399	1,061
14. Renewable electricity generation	10	27	29	38	105	161	249	236	703	1,558
15. Electricity generation	5	15	16	21	61	105	165	192	399	979
16. Natural gas distribution	8	23	25	45	170	516	904	1,634	1,080	4,404
17. Water and sewage services	3	14	16	22	62	118	197	243	467	1,142
18. Residential Construction	64	313	493	1,250	3,343	6,603	6,417	5,301	11,173	34,957
19. Highway Construction	6	30	71	271	741	1,580	1,276	1,081	1,225	6,281
20. Other Non-Residential Construction	53	252	589	2,213	6,037	12,858	10,439	8,837	10,304	51,583
21. Highway Maintenance	6	28	61	214	583	1,229	1,026	866	1,140	5,152
22. Other Maintenance	24	116	254	903	2,456	5,190	4,308	3,638	4,680	21,569
23. Food Processing	33	99	886	2,243	2,667	2,638	1,647	1,383	3,239	14,835
24. Beverage & Tobacco Product Manufacturing	13	49	225	662	1,100	1,341	1,023	769	1,811	6,992
25. Textile & Textile Product Manufacturing	1	4	93	180	180	145	84	83	150	920
26. Apparel	2	10	373	554	294	311	283	313	509	2,649
27. Leather & Allied Products	0	0	12	45	24	9	4	5	11	110
28. Wood Product Manufacturing	3	8	106	346	410	331	164	136	246	1,749
29. Paper Mills	5	15	76	243	429	450	245	238	522	2,222
30. Printing & Related Support Activities	4	15	164	439	662	751	335	322	592	3,284
31. Petroleum Refineries	61	169	178	238	651	1,003	1,602	1,270	4,216	9,388
32. Other Petroleum & Coal Products	3	8	9	12	33	58	98	83	217	521
33. Chemicals	175	487	604	1,049	2,553	3,979	4,831	4,739	14,727	33,143
34. Rubber & Plastics	7	21	174	549	703	678	415	428	839	3,815
35. Non-Metallics	6	16	117	604	1,224	1,453	662	551	614	5,246
36. Primary Metal Manufacturing	2	2	35	177	279	260	120	100	87	1,063
37. Fabricated Metal Product	19	58	310	1,372	2,419	3,204	1,444	1,292	2,416	12,535
38. Agriculture Machinery	2	6	12	37	74	118	100	110	234	692
39. Industrial Machinery	1	3	37	185	343	568	373	505	643	2,659
40. Commercial Machinery	4	12	28	100	198	316	251	290	554	1,754
41. Ventilation, Heating & Air-Conditioning	1	4	9	31	62	100	81	92	181	563
42. Metalworking Machinery	1	5	15	60	116	189	142	173	293	995
43. Engines & Turbines	2	5	15	55	107	171	131	156	278	920
44. Other General Purpose Machinery Manufacturing	4	12	30	108	213	341	268	314	580	1,869
45. Computers	97	267	471	1,217	2,759	4,942	5,905	10,644	20,764	47,064
46. Computer Storage Devices	7	20	29	62	147	249	310	487	1,073	2,385
47. Computer Terminals & Other Peripheral Equipment	4	11	23	69	153	283	330	643	1,171	2,686
48. Communications Equipment	6	17	24	46	98	124	154	140	470	1,079

(continued on next page)

Table A1 (*continued*)

Sector	<10 k	10 k–15 k	15 k–25 k	25 k–35 k	35 k–50 k	50 k–75 k	75 k–100 k	100 k–150 k	>150 k	Total
49. Miscellaneous Electronic Equipment	27	73	103	200	423	536	666	606	2,028	4,661
50. Semiconductors & Related Devices	32	87	116	212	464	593	759	664	2,339	5,266
51. Electronic Instruments	8	21	28	53	115	146	184	164	565	1,284
52. Household Equipment, Appliances, and Component Manufacturing	4	12	20	42	84	105	123	121	366	878
53. Motor Vehicle and Parts Manufacturing	12	37	59	186	362	616	663	796	1,625	4,354
54. Aerospace Producr & Parts Manufacturing	18	50	131	609	1,087	1,955	1,878	2,612	3,978	12,319
55. Railroad Rolling Stock Manufacturing	0	0	1	6	10	18	16	24	32	106
56. Ship & Boat Building	0	1	7	42	71	133	120	183	228	786
57. Other Transport Equipment Manufacturing	1	2	4	16	29	51	50	67	110	327
58. Furniture & Related Product Manufacturing	2	9	150	472	598	558	294	240	470	2,793
59. Miscellaneous Manufacturing	21	59	206	745	1,279	1,839	1,383	1,820	3,275	10,626
60. Wholesale Trade	168	537	1,748	5,980	10,434	13,799	11,650	11,277	22,705	78,298
61. Air Transport	23	67	98	314	829	2,083	813	784	4,286	9,299
62. Rail Transport	2	6	7	9	61	319	230	166	175	976
63. Water Transport	5	16	37	41	115	205	214	164	448	1,247
64. Truck Transport	8	115	386	2,608	5,022	8,940	2,091	1,838	5,006	26,014
65. Transit and Ground Passenger Transport	7	36	160	736	1,212	889	452	343	1,259	5,093
66. Pipelines	0	2	2	4	18	41	55	56	64	242
67. Other Transportation	21	88	361	1,373	2,277	3,818	2,519	1,502	3,403	15,363
68. Warehousing	8	26	454	1,817	2,880	2,892	927	511	823	10,339
69. Retail Trade	109	543	14,099	23,812	21,508	14,635	9,874	8,232	20,770	113,580
70. Publishing Industries	89	249	310	543	1,434	2,787	3,740	5,547	12,041	26,741
71. Motion Picture & Sound Recording Industry	193	533	930	1,390	2,957	4,521	5,995	5,889	16,264	38,672
72. Broadcasting	58	369	494	767	2,001	3,113	4,806	4,202	14,064	29,875
73. Telecommunications	146	406	478	805	2,334	5,356	6,795	5,959	11,769	34,047
74. Information Services	4	10	29	97	400	1,141	1,937	4,477	7,487	15,581
75. Data Processing Services	1	5	14	60	170	584	940	2,190	3,658	7,623
76. Finance & Banking	232	672	1,152	3,683	8,878	15,548	15,050	17,851	41,160	104,226
77. Real Estate	807	2,622	3,951	7,169	15,264	19,639	25,482	20,864	72,803	168,600
78. Rental & Leasing Services	30	127	361	709	1,381	1,705	1,607	1,309	4,214	11,443
79. Lessors of Nonfinancial Intangible Assets	67	189	199	258	700	967	1,434	1,060	4,668	9,541
80. Professional, Scientific, Technical, Administrative, & Support Services	286	1,331	6,431	18,112	28,506	44,173	43,096	66,401	114,559	322,896
81. Waste management Services	8	23	117	359	822	1,105	896	358	741	4,430
82. Education Services	13	74	1,302	8,120	17,375	27,838	26,785	31,787	14,526	127,820
83. Health Care & Social Assistance	86	445	11,087	19,316	30,097	34,633	25,394	43,896	50,932	215,886
84. Arts, Entertainment & Recreation	51	245	2,247	3,488	3,576	4,256	3,990	3,121	9,099	30,074
85. Accommodations	21	70	1,450	3,291	3,051	2,130	1,168	941	1,973	14,095
86. Eating & Drinking Places	71	276	14,388	20,236	8,741	5,122	3,578	2,267	8,540	63,220
87. Other Services	−1	317	2,809	5,868	6,821	8,652	7,475	6,237	15,669	53,847
88. Owner-Occupied Dwellings	461	1,265	1,317	1,674	4,570	6,220	9,175	6,561	29,850	61,094
89. Government Enterprises	35	95	142	365	1,202	2,820	3,175	3,939	3,259	15,033
90. State & Local Government	9,229	24,878	15,481	13,834	23,560	34,338	34,865	36,254	29,481	221,919
91. Federal Government	15,277	41,406	25,560	20,684	31,027	34,537	31,426	20,617	50,210	270,743
Total	**28,343**	**79,882**	**117,735**	**190,410**	**277,948**	**371,097**	**344,198**	**375,087**	**691,027**	**2,475,727**

Table A2
Total personal income distribution coefficient matrix, 2018.

Sector	<10 k	10 k–15 k	15 k–25 k	25 k–35 k	35 k–50 k	50 k–75 k	75 k–100 k	100 k–150 k	>150 k	Total
01. Crops	0.001	0.008	0.161	0.198	0.081	0.073	0.097	0.079	0.303	1.000
02. Poultry & Eggs	0.001	0.009	0.122	0.151	0.073	0.077	0.113	0.092	0.361	1.000
03. Livestock	0.001	0.012	0.065	0.081	0.066	0.086	0.136	0.109	0.444	1.000
04. Other Livestock	0.002	0.013	0.054	0.069	0.067	0.089	0.140	0.110	0.456	1.000
05. Forestry, Fishing, & Hunting	0.002	0.013	0.016	0.023	0.082	0.124	0.152	0.116	0.472	1.000
06. Oil & Gas	0.003	0.013	0.016	0.023	0.063	0.107	0.166	0.133	0.477	1.000
07. Coal	0.003	0.008	0.011	0.037	0.123	0.260	0.179	0.133	0.247	1.000
08. Other Mining	0.002	0.006	0.009	0.039	0.134	0.292	0.185	0.136	0.195	1.000
09. Biomass electricity generation	0.003	0.014	0.017	0.023	0.060	0.095	0.158	0.142	0.488	1.000
10–11. Coal-fired and Gas-fired electricity generation	0.005	0.015	0.016	0.021	0.061	0.107	0.170	0.201	0.404	1.000
12. Hydroelectricity generation	0.004	0.012	0.014	0.019	0.056	0.106	0.175	0.225	0.390	1.000
13. Nuclear electricity generation	0.005	0.014	0.014	0.020	0.058	0.109	0.175	0.228	0.376	1.000
14. Renewable electricity generation	0.006	0.018	0.019	0.024	0.068	0.103	0.160	0.151	0.452	1.000
17. Electricity distribution	0.006	0.015	0.016	0.022	0.063	0.107	0.169	0.196	0.408	1.000
16. Natural gas distribution	0.002	0.005	0.006	0.010	0.039	0.117	0.205	0.371	0.245	1.000
17. Water and sewage services	0.003	0.012	0.014	0.019	0.054	0.103	0.173	0.213	0.409	1.000
18. Residential Construction	0.002	0.009	0.014	0.036	0.096	0.189	0.184	0.152	0.320	1.000
19. Highway Construction	0.001	0.005	0.011	0.043	0.118	0.252	0.203	0.172	0.195	1.000
20. Other Non-Residential Construction	0.001	0.005	0.011	0.043	0.117	0.249	0.202	0.171	0.200	1.000
21. Highway Maintenance	0.001	0.006	0.012	0.042	0.113	0.238	0.199	0.168	0.221	1.000
22. Other Maintenance	0.001	0.005	0.012	0.042	0.114	0.241	0.200	0.169	0.217	1.000
23. Food Processing	0.002	0.007	0.060	0.151	0.180	0.178	0.111	0.093	0.218	1.000
24. Beverage & Tobacco Product Manufacturing	0.002	0.007	0.032	0.095	0.157	0.192	0.146	0.110	0.259	1.000
25. Textile & Textile Product Manufacturing	0.001	0.004	0.101	0.196	0.196	0.158	0.091	0.090	0.163	1.000
26. Apparel	0.001	0.004	0.141	0.209	0.111	0.118	0.107	0.118	0.192	1.000
27. Leather & Allied Products	0.000	0.000	0.108	0.413	0.218	0.082	0.034	0.045	0.099	1.000
28. Wood Product Manufacturing	0.002	0.004	0.060	0.198	0.234	0.189	0.094	0.078	0.141	1.000
29. Paper Mills	0.002	0.007	0.034	0.109	0.193	0.203	0.110	0.107	0.235	1.000
30. Printing & Related Support Activities	0.001	0.004	0.050	0.134	0.202	0.229	0.102	0.098	0.180	1.000
31. Petroleum Refineries	0.007	0.018	0.019	0.025	0.069	0.107	0.171	0.135	0.449	1.000
32. Other Petroleum & Coal Products	0.005	0.015	0.017	0.023	0.064	0.111	0.188	0.160	0.416	1.000
33. Chemicals	0.005	0.015	0.018	0.032	0.077	0.120	0.146	0.143	0.444	1.000
34. Rubber & Plastics	0.002	0.006	0.046	0.144	0.184	0.178	0.109	0.112	0.220	1.000
35. Non-Metallics	0.001	0.003	0.022	0.115	0.233	0.277	0.126	0.105	0.117	1.000
36. Primary Metal Manufacturing	0.002	0.002	0.033	0.166	0.263	0.244	0.113	0.094	0.082	1.000
37. Fabricated Metal Product	0.001	0.005	0.025	0.109	0.193	0.256	0.115	0.103	0.193	1.000
38. Agriculture Machinery	0.003	0.008	0.017	0.053	0.108	0.170	0.144	0.159	0.338	1.000
39. Industrial Machinery	0.000	0.001	0.014	0.070	0.129	0.214	0.140	0.190	0.242	1.000
40. Commercial Machinery	0.002	0.007	0.016	0.057	0.113	0.180	0.143	0.166	0.316	1.000
41. Ventilation, Heating & Air-Conditioning	0.002	0.007	0.016	0.056	0.111	0.177	0.144	0.164	0.322	1.000
42. Metalworking Machinery	0.001	0.005	0.015	0.061	0.117	0.190	0.143	0.174	0.295	1.000
43. Engines & Turbines	0.002	0.006	0.016	0.059	0.116	0.186	0.143	0.170	0.302	1.000
44. Other General Purpose Machinery Manufacturing	0.002	0.006	0.016	0.058	0.114	0.183	0.143	0.168	0.310	1.000
45. Computers	0.002	0.006	0.010	0.026	0.059	0.105	0.125	0.226	0.441	1.000
46. Computer Storage Devices	0.003	0.008	0.012	0.026	0.062	0.104	0.130	0.204	0.450	1.000
47. Computer Terminals & Other Peripheral Equipment	0.001	0.004	0.009	0.026	0.057	0.105	0.123	0.239	0.436	1.000
48. Communications Equipment	0.006	0.016	0.022	0.043	0.091	0.115	0.143	0.130	0.435	1.000
49. Miscellaneous Electronic Equipment	0.006	0.016	0.022	0.043	0.091	0.115	0.143	0.130	0.435	1.000
50. Semiconductors & Related Devices	0.006	0.017	0.022	0.040	0.088	0.113	0.144	0.126	0.444	1.000
51. Electronic Instruments	0.006	0.016	0.022	0.041	0.089	0.114	0.144	0.128	0.440	1.000
52. Household Equipment, Appliances, and Component Manufacturing	0.005	0.014	0.022	0.048	0.096	0.119	0.140	0.138	0.417	1.000
53. Motor Vehicle and Parts Manufacturing	0.003	0.008	0.014	0.043	0.083	0.141	0.152	0.183	0.373	1.000
54. Aerospace Product & Parts Manufacturing	0.001	0.004	0.011	0.049	0.088	0.159	0.152	0.212	0.323	1.000
55. Railroad Rolling Stock Manufacturing	0.001	0.002	0.009	0.052	0.090	0.165	0.153	0.224	0.305	1.000
56. Ship & Boat Building	0.000	0.001	0.008	0.054	0.091	0.170	0.153	0.232	0.291	1.000
57. Other Transportation Equipment Manufacturing	0.002	0.005	0.011	0.048	0.087	0.155	0.152	0.205	0.335	1.000
58. Furniture & Related Producr manufacturing	0.001	0.003	0.054	0.169	0.214	0.200	0.105	0.086	0.168	1.000
59. Miscellaneous Manufacturing	0.002	0.006	0.019	0.070	0.120	0.173	0.130	0.171	0.308	1.000

(*continued on next page*)

Table A2 (*continued*)

Sector	<10 k	10 k–15 k	15 k–25 k	25 k–35 k	35 k–50 k	50 k–75 k	75 k–100 k	100 k–150 k	>150 k	Total
60. Wholesale Trade	0.002	0.007	0.022	0.076	0.133	0.176	0.149	0.144	0.290	1.000
61. Air Transport	0.002	0.007	0.011	0.034	0.089	0.224	0.087	0.084	0.461	1.000
62. Rail Transport	0.002	0.006	0.007	0.009	0.062	0.327	0.236	0.171	0.179	1.000
63. Waste Transport	0.004	0.013	0.030	0.033	0.093	0.164	0.172	0.132	0.360	1.000
64. Truck Transport	0.000	0.004	0.015	0.100	0.193	0.344	0.080	0.071	0.192	1.000
65. Transit and Ground Passenger Transport	0.001	0.007	0.031	0.144	0.238	0.175	0.089	0.067	0.247	1.000
66. Pipelines	0.001	0.006	0.010	0.016	0.076	0.170	0.228	0.229	0.264	1.000
67. Other Transportation	0.001	0.006	0.023	0.089	0.148	0.249	0.164	0.098	0.222	1.000
68. Warehousing	0.001	0.002	0.044	0.176	0.279	0.280	0.090	0.049	0.080	1.000
69. Retail Trade	0.001	0.005	0.124	0.210	0.189	0.129	0.087	0.072	0.183	1.000
70. Publishing Industries	0.003	0.009	0.012	0.020	0.054	0.104	0.140	0.207	0.450	1.000
71. Motion Picture & Sound Recording Industry	0.005	0.014	0.024	0.036	0.076	0.117	0.155	0.152	0.421	1.000
72. Broadcasting	0.002	0.012	0.017	0.026	0.067	0.104	0.161	0.141	0.471	1.000
73. Telecommunications	0.004	0.012	0.014	0.024	0.069	0.157	0.200	0.175	0.346	1.000
74. Information Services	0.000	0.001	0.002	0.006	0.026	0.073	0.124	0.287	0.481	1.000
75. Data Processing Services	0.000	0.001	0.002	0.008	0.022	0.077	0.123	0.287	0.480	1.000
76. Finance & Banking	0.002	0.006	0.011	0.035	0.085	0.149	0.144	0.171	0.395	1.000
77. Real Estate	0.005	0.016	0.023	0.043	0.091	0.116	0.151	0.124	0.432	1.000
78. Rental & Leasing Services	0.003	0.011	0.032	0.062	0.121	0.149	0.140	0.114	0.368	1.000
79. Lessors of Nonfinancial Intangible Assets	0.007	0.020	0.021	0.027	0.073	0.101	0.150	0.111	0.489	1.000
80. Professional, Scientific, Technical, Administrative, & Support Service	0.001	0.004	0.020	0.056	0.088	0.137	0.133	0.206	0.355	1.000
81. Waste Management Services	0.002	0.005	0.026	0.081	0.186	0.249	0.202	0.081	0.167	1.000
82. Education Services	0.000	0.001	0.010	0.064	0.136	0.218	0.210	0.249	0.114	1.000
83. Health Care & Social Assistance	0.000	0.002	0.051	0.089	0.139	0.160	0.118	0.203	0.236	1.000
84. Arts, Entertainment & Recreation	0.002	0.008	0.075	0.116	0.119	0.142	0.133	0.104	0.303	1.000
85. Accommodations	0.001	0.005	0.103	0.234	0.216	0.151	0.083	0.067	0.140	1.000
86. Eating & Drinking Places	0.001	0.004	0.228	0.320	0.138	0.081	0.057	0.036	0.135	1.000
87. Other Services	0.000	0.006	0.052	0.109	0.127	0.161	0.139	0.116	0.291	1.000
88. Owner-Occupied Dwellings	0.008	0.021	0.022	0.027	0.075	0.102	0.150	0.107	0.489	1.000
89. Government Enterprises	0.002	0.006	0.009	0.024	0.080	0.188	0.211	0.262	0.217	1.000
90. State & Local Government	0.042	0.112	0.070	0.062	0.106	0.155	0.157	0.163	0.133	1.000
91. Federal Government	0.056	0.153	0.094	0.076	0.115	0.128	0.116	0.076	0.185	1.000
Total	**0.011**	**0.032**	**0.048**	**0.077**	**0.112**	**0.150**	**0.139**	**0.152**	**0.279**	**1.000**

Appendix B. Functionality loss and recovery at POLA/POLB

Table B1 presents the percentage functionality loss in five different categories of cargo-handling terminals at Port of Los Angeles and Port of Long Beach on the selected key days after the strike of the earthquake until the recovery to 100% functionality.

Table B1
Percentage of port functionality and recovery estimates for different cargo-handling terminals.

Port of Los Angeles							
Facilities	**Day 1**	**Day 3**	**Day 7**	**Day 14**	**Day 30**	**Day 90**	**Day 150**
Container Terminals	51.57	66.47	71.96	72.96	75.74	87.19	100.00
Breakbulk	51.40	66.30	71.80	72.80	75.60	87.10	100.00
Dry Bulk	52.00	66.90	72.40	73.40	76.10	87.40	100.00
Liquid Bulk	51.48	66.38	71.86	72.88	75.64	87.14	100.00
Automobiles	53.40	68.25	73.70	74.70	77.30	88.20	100.00
Port of Long Beach							
Facilities	**Day 1**	**Day 3**	**Day 7**	**Day 14**	**Day 30**	**Day 90**	**Day 150**
Container Terminals	59.73	74.03	79.22	80.05	82.16	91.04	100.00
Breakbulk	60.00	74.26	79.41	80.21	82.32	91.15	100.00
Dry Bulk	58.91	73.34	78.54	79.39	81.56	90.72	100.00
Liquid Bulk	58.38	72.82	78.06	78.88	81.14	90.48	100.00
Automobiles	60.70	74.90	80.00	80.80	82.80	91.40	100.00

Appendix C. General building damage and recovery time

See Table C1.

Table C1
General building damage for LA metro region.

TERM Sector #	Short names	% Building & Content Loss	Average Recovery Time (Days)	% Capital Input Destruction on an Annual Basis
1	Crops	2.87%	60	0.47%
2	PoultryEggs			
3	Livestock			
4	OthLivestock			
5	ForestFrsHnt			
6	OilGas	5.07%	211	2.93%
7	Coal			
8	OtherMining			
9	BiomassGen	4.09%	251	2.81%
10	CoalsGen			
11	GasGen			
12	HydroGen			
13	NuclearGen			
14	RenewGen			
15	ElecDist			
16	NatGasDist			
17	WaterSewage			
18	ResidConstrt	3.37%	164	1.51%
19	OthConstruct			
20	HwyBrdgCons			
21	OthMaintain			
22	MRstreets			
23	FoodProc	5.29%	211	3.05%
24	BevTobManu			
25	Textiles	4.85%	211	2.80%
26	Apparels	4.81%	211	2.78%
27	LeathFtwr			
28	WoodProds	4.85%	211	2.80%
29	PulpPaperPbd			
30	Printing	4.81%	211	2.78%
31	PetrolRefine	5.29%	211	3.05%
32	OthPetrolCl			
33	Chemicals			
34	RubPlastic	4.81%	211	2.78%
35	NonMetMinPrd	5.07%	211	2.93%
36	PrimMetals			
37	FabriMetals	4.85%	211	2.80%
38	AgriMachinry			
39	IndustrMach			
40	CommrcMach			
41	AirConHeat			
42	MetalWkMach			
43	TurbnEngine			
44	OtherMach			
45	Computers	6.21%	266	4.53%
46	CmptrStorage			
47	ComptrTrmEtc			
48	CommunicEqp	4.81%	211	2.78%
49	MscElctEqp			
50	Semicondctr			
51	ElecInstrmnt			
52	HholdEqp			
53	MVPManu	4.85%	211	2.80%
54	AerospaceMan			
55	RlrdCars			
56	ShipsBoats			
57	OthTrnEqp			
58	Furniture	4.81%	211	2.78%
59	MiscManuf			
60	WholesaleTr	4.68%	217	2.78%
61	AirTrans	4.09%	251	2.81%
62	RailTrans			

(continued on next page)

Table C1 (*continued*)

TERM Sector #	Short names	% Building & Content Loss	Average Recovery Time (Days)	% Capital Input Destruction on an Annual Basis
63	WaterTrans			
64	TruckTrans	4.68%	217	2.78%
65	GrdPassTrans	4.09%	251	2.81%
66	Pipeline			
67	OthTransprt	4.85%	211	2.80%
68	Warehousing	4.68%	217	2.78%
69	RetailTr	4.22%	217	2.51%
70	Publishing	4.81%	211	2.78%
71	MovieSound	4.09%	251	2.81%
72	BroadcastSrv	4.51%	186	2.30%
73	Telecomm			
74	InfoSvce	4.09%	251	2.81%
75	DataProcScv			
76	FinancBank	3.92%	219	2.36%
77	RealEstate	4.09%	251	2.81%
78	RentLease			
79	AssetLessors			
80	PrfSciTchSrv			
81	WasteMgmt	4.54%	259	3.22%
82	Education	3.12%	223	1.91%
83	HealthSocAs	3.91%	249	2.63%
84	ArtsRecreat	4.51%	186	2.30%
85	Accommodatn	3.47%	247	2.35%
86	EatDrinkPlce	4.51%	186	2.30%
87	OthService	4.07%	217	2.42%
88	GovEnterprs			
89	StaLocGov	4.54%	259	3.22%
90	OwnOccDwell	4.08%	238	2.69%
91	FedGovt			
92	Holiday	4.51%	186	2.30%
93	FgnHol			
94	ExpTour			
95	ExpEdu	3.12%	223	1.91%
96	WT_EXP	4.09%	251	2.81%
97	AT_EXP			

Appendix D. Detailed income distribution impact results

See Tables D1-D4.

Table D1
Baseline income distribution and income changes in the port disruption simulation for the LA metro region (in millions 2019 dollars).

Income Bracket	Income Distribution			Income Changes relative to Baseline (M $)		Income Changes relative to Baseline (%)	
	Baseline	Port Disruption Base Case	Port Disruption Resilience Case	Port Disruption Base Case	Port Disruption Resilience Case	Port Disruption Base Case	Port Disruption Resilience Case
<10 k	3,474.1	3,470.5	3,472.2	−3.64	−1.87	−0.1048%	−0.0539%
10–15 k	9,993.2	9,981.3	9,987.6	−11.96	−5.58	−0.1196%	−0.0558%
15–25 k	20,527.7	20,461.1	20,511.8	−66.55	−15.90	−0.3242%	−0.0775%
25–35 k	37,426.9	37,290.4	37,392.5	−136.49	−34.40	−0.3647%	−0.0919%
35–50 k	56,675.1	56,495.4	56,620.7	−179.67	−54.38	−0.3170%	−0.0960%
50–75 k	77,908.2	77,686.9	77,838.1	−221.32	−70.11	−0.2841%	−0.0900%
75–100 k	74,636.7	74,459.5	74,573.8	−177.17	−62.89	−0.2374%	−0.0843%
100–150 k	80,606.5	80,413.0	80,541.8	−193.49	−64.71	−0.2400%	−0.0803%
150 k+	164,409.6	164,042.7	164,261.3	−366.88	−148.22	−0.2231%	−0.0902%
Total	525,658.0	524,300.8	525,199.9	−1,357.16	−458.05	−0.2582%	−0.0871%

Table D2
Baseline income distribution and income changes in the transportation cost increase simulation for the LA metro region (in millions 2019 dollars).

Income Bracket	Income Distribution			Income Changes relative to Baseline (M $)		Income Changes relative to Baseline (%)	
	Baseline	Transportation Cost Increase Base Case	Transportation Cost Increase Resilience Case	Transportation Cost Increase Base Case	Transportation Cost Increase Resilience Case	Transportation Cost Increase Base Case	Transportation Cost Increase Resilience Case
<10 k	3,474.1	3,474.1	3,474.1	−0.05	−0.05	−0.0015%	−0.0013%
10–15 k	9,993.2	9,993.1	9,993.1	−0.14	−0.13	−0.0014%	−0.0013%
15–25 k	20,527.7	20,527.3	20,527.3	−0.43	−0.38	−0.0021%	−0.0019%
25–35 k	37,426.9	37,426.1	37,426.2	−0.80	−0.72	−0.0021%	−0.0019%
35–50 k	56,675.1	56,674.0	56,674.1	−1.14	−1.03	−0.0020%	−0.0018%
50–75 k	77,908.2	77,907.0	77,907.1	−1.25	−1.13	−0.0016%	−0.0014%
75–100 k	74,636.7	74,635.1	74,635.3	−1.53	−1.39	−0.0021%	−0.0019%
100–150 k	80,606.5	80,604.9	80,605.0	−1.56	−1.41	−0.0019%	−0.0017%
150 k+	164,409.6	164,405.9	164,406.3	−3.66	−3.31	−0.0022%	−0.0020%
Total	525,658.0	525,647.4	525,648.4	−10.55	−9.55	−0.0020%	−0.0018%

Table D3
Baseline income distribution and income changes in the general building damages simulation for the LA metro region (in millions 2019 dollars).

Income Bracket	Income Distribution			Income Changes relative to Baseline (M $)		Income Changes relative to Baseline (%)	
	Baseline	Building Damage Base Case	Building Damage Resilience Case	Building Damage Base Case	Building Damage Resilience Case	Building Damage Base Case	Building Damage Resilience Case
<10 k	3,474.1	3,377.9	3,398.4	−96.20	−75.67	−2.7691%	−2.1780%
10–15 k	9,993.2	9,717.5	9,776.4	−275.76	−216.84	−2.7595%	−2.1699%
15–25 k	20,527.7	19,961.7	20,083.6	−566.02	−444.08	−2.7573%	−2.1633%
25–35 k	37,426.9	36,265.9	36,516.9	−1,161.03	−910.02	−3.1021%	−2.4314%
35–50 k	56,675.1	54,770.7	55,181.9	−1,904.45	−1,493.25	−3.3603%	−2.6347%
50–75 k	77,908.2	75,260.2	75,831.4	−2,648.01	−2,076.80	−3.3989%	−2.6657%
75–100 k	74,636.7	71,997.2	72,564.3	−2,639.49	−2,072.35	−3.5365%	−2.7766%
100–150 k	80,606.5	77,818.8	78,417.5	−2,787.64	−2,188.98	−3.4583%	−2.7156%
150 k+	164,409.6	157,795.0	159,211.6	−6,614.55	−5,197.95	−4.0232%	−3.1616%
Total	525,658.0	506,964.8	510,982.0	−18,693.14	−14,675.92	−3.5561%	−2.7919%

Table D4
Baseline income distribution and income changes in the combined disruptions/damages simulations for the LA metro region (in millions 2019 dollars).

Income Bracket	Income Distribution			Income Changes relative to Baseline (M $)		Income Changes relative to Baseline (%)	
	Baseline	Combined Simulation Base Case	Combined Simulation Resilience Case	Combined Simulation Base Case	Combined Simulation Resilience Case	Combined Simulation Base Case	Combined Simulation Resilience Case
<10 k	3,474.1	3,374.3	3,396.6	−99.81	−77.52	−2.8729%	−2.2313%
10–15 k	9,993.2	9,705.6	9,770.9	−287.58	−222.35	−2.8778%	−2.2250%
15–25 k	20,527.7	19,895.6	20,067.7	−632.10	−460.04	−3.0792%	−2.2411%
25–35 k	37,426.9	36,130.8	36,482.5	−1,296.16	−944.39	−3.4632%	−2.5233%
35–50 k	56,675.1	54,593.2	55,127.9	−2,081.94	−1,547.22	−3.6735%	−2.7300%
50–75 k	77,908.2	75,043.0	75,762.3	−2,865.25	−2,145.98	−3.6777%	−2.7545%
75–100 k	74,636.7	71,822.9	72,502.2	−2,813.79	−2,134.48	−3.7700%	−2.8598%
100–150 k	80,606.5	77,629.4	78,353.6	−2,977.10	−2,252.84	−3.6934%	−2.7949%
150 k+	164,409.6	157,432.8	159,065.7	−6,976.73	−5,343.91	−4.2435%	−3.2504%
Total	525,658.0	505,627.5	510,529.2	−20,030.47	−15,128.73	−3.8106%	−2.8781%

References

Alexander, D., 2013. Resilience and Disaster Risk Reduction: An Etymological Journey. Nat. Hazards Earth Syst. Sci. 13 (11), 2707–2716.

Zhou, L., Chen, Z., 2021. Are CGE models reliable for disaster impact analyses? Econ. Syst. Res. 33 (1), 20–46.

Applied Technology Council (ATC). 1985. ATC-13 Earthquake Damage Evaluation Data for California. ATC, Redwood City, CA. https://www.atcouncil.org/pdfs/atc13.pdf.

Asakura, Y., 2007. Requirements for transport network flow models used in reliability analysis. Int. J. Crit. Infrastruct. 3, 287–300.

Ashrafi, Z., Shahraki, H., Bachmann, C., 2017. Quantifying the Criticality of Highway Infrastructure for Freight Transportation. Transp. Res. Rec. 2610, 10–18.

Berke, P., Campanella, T., 2006. Planning for Postdisaster Resiliency. The ANNALS of the American Academy of Political and Social Science 604 (1), 192–207.
Bocchini, P., Frangopol, D., 2012. Restoration of Bridge Networks after an Earthquake: Multicriteria Intervention Optimization. Earthquake Spectra 28 (2), 427–455.
Bureau of Economic Analysis (BEA), 2019. Quarterly Personal Income by State: Personal Income by Major Component (SAINC4). https://apps.bea.gov/iTable/iTable.cfm?reqid=99&step=1#reqid=99&step=1.
Bureau of Labor Statistics (BLS), 2019a. Occupational Employment Statistics. https://www.bls.gov/oes/tables.htm.
Chang, S.E., Shinozuka, M., Moore II., J.E., 2000. Probabilistic Earthquake Scenarios: Extending Risk Analysis Methodologies to Spatially Distributed Systems. Earthquake Spectra 16 (3), 557–572.
Chen, Z., Rose, A., 2018. Economic Resilience to Transportation Failure: A Computable General Equilibrium Analysis. Transportation 45 (4), 1009–1027.
Chen, Z., Rose, A., Prager, F., Chatterjee, S., 2017. Economic Consequences of Aviation System Disruptions: A Reduced-Form Computable General Equilibrium Analysis. Transp. Res. A 95, 207–226.
Chen, A., Yang, C., Kongsomsaksakul, S., Lee, M., 2007. Network-based accessibility measures for vulnerability analysis of degradable transportation networks. Networks and Spatial Econ. 7, 241–256.
Cho, S., Gordon, P., Moore, J.E., Richardson II, H.W., Shinozuka, M., Chang, S.E., 2001. Integrating Transportation Networks and Regional Economic Models to Estimate the Costs of a Large Earthquake. J. Regional Sci. 41 (1), 39–56.
Cho, J.K., Gordon, P., Moore, J.E., Pan, Q., Park, J.Y., Richardson, H.W., 2015. TransNIEMO: Economic Impact Analysis Using a Model of Consistent Inter-Regional Economic and Network Equilibria. Transp. Planning and Technol. 38, 483–502.
Cho, S., Gordon, P., Richardson, H.W., Moore II, J.E., Shinozuka, M., 2004. Analyzing Transportation Reconstruction Network Strategies: A Full Cost Approach. Rev. Urban and Regional Development Studies 12 (3), 212–227.
Cutter, S., 2016. The landscape of disaster resilience indicators in the USA. Nat. Hazards 80, 741–758.
Dormady, N., Roa-Henriquez, A., Rose, A., 2019. Economic Resilience of the Firm: A Production Theory Approach. Int. J. Prod. Econ. 208, 446–460.
Dormady, N., Rose, A., Rosoff, H., Roa-Henriquez, A., 2018. Estimating the Cost-Effectiveness of Resilience to Disasters: Survey Instrument Design & Refinement of Primary Data. In: Ruth, M., Reisemann, S.G. (Eds.), Handbook on Resilience of Socio-Technical Systems. Edward Elgar, Cheltenham.
Dormady, N., Rose, A., Morin, B., Roa-Henriquez, A., 2021. "The Cost-Effectiveness of Economic Resilience," under review at the International Journal of Production Economics.
Federal Emergency Management Agency (FEMA), 2013. Hazus-MH 2.1 Technical Manual: Earthquake Model. Washington, DC: Federal Emergency Management Agency.
Flynn, S., 2008. America the Resilient: Defying Terrorism and Mitigating Natural Disasters. Foreign Affairs 87, 2–8.
Giannoccaro, I., Iftikhar, A., 2020. Mitigating Ripple Effect in Supply Networks: the Effect of Trust and Topology on Resilience. Int. J. Prod. Res. https://doi.org/10.1080/00207543.2020.1853844.
Gordon, P., Moore II, J.E., Richardson, H.W., Shinozuka, M., An, D., Cho, S., 2004. Earthquake Disaster Mitigation for Urban Transportation Systems: An Integrated Methodology that Builds on the Kobe and Northridge Experiences. In: Okuyama, Y., Chang, S. (Eds.), Modeling Spatial and Economic Impacts of Disasters. Springer-Verlag, Berlin Heidelberg, Germany.
Gregor, N., Abrahamson, N.A., Atkinson, G.M., Boore, D.M., Bozorgnia, Y., Campbell, K.W., Chiou, B.S.J., Idriss, I.M., Kamai, R., Seyhan, E., Silva, W., 2014. Comparison of NGA-West2 GMPEs. Earthquake Spectra 30 (3), 1179–1197.
Holling, C., 1973. Resilience and stability of ecological systems. Annu. Rev. Ecol. Syst. 4, 1–23.
Horridge, M., Madden, J., Whittwer, G., 2005. The impact of the 2002–2003 drought on Australia. J. Policy Model. 27, 285–308.
Hosseini, S., Ivanov, D., 2019. A new resilience measure for supply networks with the ripple effect considerations: A Bayesian network approach. Ann. Oper. Res. https://doi.org/10.1007/s10479-019-03350-8.
Hosseini, S., Ivanov, D., 2020. Bayesian networks for supply chain risk, resilience and ripple effect analysis: A literature review. Expert Syst. Appl. 161 (2020), 113649.
Hosseini, S., Ivanov, D., Dolgui, A., 2019. Review of quantitative methods for supply chain resilience analysis. Transp. Res. Part E 125, 285–307.
Hosseini, S., Barker, K., Ramirez-Marquez, J., 2016. A review of definitions and measures of system resilience. Reliab. Eng. Syst. Saf. 145, 47–61.
Janic, M., 2015. Modelling the Resilience, Friability and Costs of an Air Transport Network Affected by A Large-Scale Disruptive Event. Transp. Res. Part A 71, 1–16.
Jung, J., Santos, J.R., Haimes, Y.Y., 2009. International Trade Inoperability Input-Output Model (IT-IIM): Theory and Application. Risk Anal. 29, 137–154.
Khademi, N., Balaei, B., Shahri, M., Mirzaei, M., Sarrafi, B., Zahabiun, M., Mohaymany, A.S., 2015. Transportation network vulnerability analysis for the case of a catastrophic earthquake. Int. J. Disaster Risk Reduct. 12, 234–254.
Koc, E., Cetiner, B., Lee, J., Nutakki, A., Soibelman, L., Taciroglu, E., 2019a. System-based resilience assessment of networked transportation systems in metropolitan areas: Case of Greater Los Angeles. Proceedings of the 2019 ASCE International Conference on Computing in Civil Engineering.
Koc, E., Cetiner, B., Soibelman, L., Taciroglu, E., 2019b. System-Based Vulnerability and Resilience Assessment in Mega-Scale Transportation Systems: Towards Data and Model-Driven Methodologies. ASCE International Conference on Computing in Civil Engineering (accepted).
Koc, E., Cetiner, B., Rose, A., Soibelman, L., Taciroglu, E., Wei, D., 2020. CRAFT: Comprehensive Resilience Assessment for Transportation Systems in Urban Areas. Adv. Eng. Inf. 46, 101159.
Li, Y., Chen, K., Collignon, S., Ivanov, D., 2021. Ripple Effect in the Supply Chain Network: Forward and Backward Disruption Propagation, Network Health and Firm Vulnerability. Eur. J. Oper. Res. 291 (3), 1117–1131.
Li, P., Rose, A., Eduardo, B., 1999. "Construction of an Input-Output Income Distribution Matrix for the U.S." In: Hewings G., Sonis M., Madden M., Kimura Y. (eds) Understanding and Interpreting Economic Structure. Springer-Verlag Berlin Heidelberg: Germany.
MacKenzie, C.A., Barker, K., Grant, F.H., 2012. Evaluating the consequences of an inland waterway port closure with a dynamic multiregional interdependence model. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans 42 (2), 359–370.
Mattsson, L., Jenelius, E., 2015. Vulnerability and resilience of transport systems-a discussion of recent research. Transp. Res. Part A 81, 16–34.
Martin, R., Sunley, P., 2015. On the Notion of Regional Economic Resilience: Conceptualization and Explanation. J. Econ. Geography 15 (1), 1–42.
Masozera, M., Bailey, M., Kerchner, C., 2007. Distribution of Impacts of Natural Disasters across Income Groups: A Case Study of New Orleans. Ecol. Econ. 63 (2–3), 299–306.
Mattson, L.G., Jenelius, E., 2015. Vulnerability and resilience of transport systems - A discussion of recent research. Transp. Res. Part A: Policy and Practice 81, 16–34.
Mileti, D.S., 1999. Disasters by Design: A Reassessment of Natural Hazards in the United States. Joseph Henry Press, Washington, DC.
National Research Council (NRC), 2012. Disaster Resilience: A National Imperative. Washington, DC: National Academies Press.
Nicholson, A.J., 2007. Road network unreliability: impact assessment and mitigation. Int. J. Crit. Infrastruct. 3, 346–375.
Okuyama, Y., Santos, J.R., 2014. Disaster Impact and Input-Output Analysis. Econ. Syst. Res. 26 (1), 1–12.
Pant, R., Barker, K., Grant, F.H., Landers, T.L., 2011. Interdependent Impacts of Inoperability at Multi-modal Transportation Container Terminals. Transp. Res. Part E: Logistics and Transp. Rev. 47 (5), 722–737.
Pant, K., Barker, T.L., 2015. Dynamic impacts of commodity flow disruptions in inland waterway networks. Transp. Res. D 89, 137–149.
Park, J.Y., 2008. "The Economic Impacts of a Dirty-Bomb Attack on the Los Angeles and Long Beach Port: Applying Supply-Driven NIEMO." J. Homeland Security and Emergency Manage. 5(1): 1–20, Article no. 21.
Park, J.Y., Gordon, P., Moore II, J., Richardson, H., 2008. The State-by-State Economic Impacts of the 2002 Shutdown of the Los Angeles-Long Beach Ports. Growth and Change 39, 548–572.
Pimm, S.L., 1984. The Complexity and Stability of Ecosystems. Nature 307, 321–326.
Prager, F., 2013. The Economic and Political Impacts of U.S. Federal Carbon Emissions Trading Policy across Households, Sectors and States. University of Southern California. PhD Dissertation. Price School of Public Policy.
Renne, J., Wolshon, B., Murray-Tuite, P., Pande, A., 2020. "Emergence of Resilience as a Framework for State Departments of Transportation (DOTs) in the United States," Transportation Research Part D: Transport and Environment 82: 102178.

Rose, A., 2015. Macroeconomic Consequences of Terrorist Attacks: Estimation for the Analysis of Policies and Rules. In: Mansfield, C., Smith, V.K. (Eds.), Benefit Transfer for the Analysis of DHS Policies and Rules, Cheltenham. Edward Elgar, UK.
Rose, A., 2017. “Benefit-Cost Analysis of Economic Resilience Actions,” in S. Cutter (ed.) Oxford Research Encyclopedia of Natural Hazard Science, New York: Oxford.
Rose, A., Liao, S., 2005. Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions. J. Regional Sci. 45 (1), 75–112.
Rose, A., Wei, D., 2013. Estimating the Economic Consequences of a Port Shutdown: The Special Role of Resilience. Econ. Syst. Res. 25 (2), 212–232.
Rose, Z., Stevens, B., Davis, G., 1988. Natural Resource Policy and Income Distribution. John Hopkins University Press, Baltimore.
Rose, A., Wei, D., Paul, D., 2018. Economic consequences of a disruption of oil imports: The role of seaports in U.S. energy security. Energy Policy 115, 584–615.
Rose, A., Wei, D., Prager, F., 2012. Distributional Impacts of Greenhouse Gas Emissions Trading: Alternative Allocation and Recycling Strategies in California. Contemporary Econ. Policy 30 (4), 603–617.
Rose, A., Oladosu, G., Lee, B., Beeler Asay, G., 2009. The Economic Impacts of the 2001 Terrorist Attacks on the World Trade Center: A Computable General Equilibrium Analysis. Peace Economics, Peace Science, and Public Policy 15, Article 6.
Rose, A., Prager, F., Chen, Z., Chatterjee, S., Wei, D., Heatwole, N., Warren, E., 2017. Economic Consequence Analysis of Disasters – The E-Cat Software Tool. Springer, Singapore.
Shaughnessy, T.M., White, M.L., Brendler, M.D., 2010. The Income Distribution Effect of Natural Disasters: An Analysis of Hurricane Katrina. J. Regional Analysis & Policy 40 (1), 84–95.
Southern California Association of Governments (SCAG). 2019. “Regional Transportation Plan.” http://rtpscs.scag.ca.gov/Pages/default.aspx.
Sue Wing, I., Wei, D., Rose, A., Wein, A., 2021. “Economic Consequences of the HayWired Earthquake Scenario – Digital and Utility Network Linkages and Resilience,” in U.S. Geological Survey Scientific Investigations Report 2017–5013–R–W, The HayWired Earthquake Scenario—Societal Consequences, https://pubs.er.usgs.gov/publication/sir20175013V3.
Tatano, H., Tsuchiya, S., 2008. A Framework for Economic Loss Estimation due to Seismic Transportation Network Disruption: A Spatial Computable General Equilibrium Approach. Nat. Hazards 44, 253–265.
Tierney, K., 2007. Businesses and disasters: Vulnerability, impacts, and recovery. In: Rodríguez, H., Quarantelli, E.L., Dynes, R.R. (Eds.), Handbook of Disaster Research. Springer, Heidelberg, Germany, pp. 275–296.
Tsuchiya, S., Tatano, H., Okada, N., 2007. Economic Loss assessment due to Railroad and Highway Disruptions. Econ. Syst. Res. 19 (2), 147–162.
Vadali, S., Chandra, S., Shelton, J., Valdez, A., Medina, M., 2015. Economic Costs of Critical Infrastructure Failure in Bi-national Regions and Implications for Resilience Building: Evidence from El Paso-Ciudad Juarez. Res. Transp. Business and Manage. 16, 15–31.
Wald, D.J., McWhirter, L., Thompson, E., Hering, A.S., 2011, August. A new strategy for developing Vs30 maps. In Proceedings of the 4th IASPEI/IAEE International Symposium: Effects of Surface Geology on Seismic Motion, Santa Barbara, CA.
Wei, D., Chen, Z., Rose, A., 2020a. Evaluating the Role of Resilience in Recovering from Major Port Disruptions: A Multi-Regional Analysis. Papers in Regional Science 99 (6), 1691–1722.
Wei, F., Koc, E., Soibelman, L., Li, N., 2018a. Disaster economics and networked transportation infrastructures: status quo and a multi-disciplinary framework to estimate economic losses. In: Smith, I., Domer, B. (Eds.), Advanced Computing Strategies for Engineering. EG-ICE Springer.
Wei, F., Koc, E., Soibelman, L., Li, N., 2018b. Disturbances to Urban Mobility and Comprehensive Estimation of Economic Losses. Polytechnica 1, 48–60.
Wei, D., Koc, E., Rose, A., Chen, Z., Soibelman, L., 2020b. Socioeconomic Dimensions of Resilience to Seaport and Highway Transportation Network Disruptions. Final Report to the California Department of Transportation.
Werner, S.D., 2003. “Current Developments and Future Directions for Seismic Risk Analysis of Highway Systems”, Sixth U.S. Conference and Workshop on Lifeline Earthquake Engineering (TCLEE).
Wittwer, G., 2012. Economic Modeling of Water: The Australian CGE Experience. Springer, Heidelberg.
Xie, F., Levinson, D., 2011. Evaluating the Effects of the I-35W Bridge Collapse on Road-users in the Twin Cities Metropolitan Region. Transp. Planning Technol. 34, 691–703.
Xie, W., Li, N., Wu, J., Hao, X., 2014a. Modeling the economic costs of disasters and recovery: analysis using a dynamic computable general equilibrium model. Nat. Hazards Earth Syst. Sci. 14, 757–772.
Xie, W., Li, N., Li, C., et al., 2014b. Quantifying cascading effects triggered by disrupted transportation due to the Great 2008 Chinese Ice Storm: implications for disaster risk management. Nat. Hazards 70, 337–352. https://doi.org/10.1007/s11069-013-0813-9.
Zhang, Y., Lam, J., 2015. Estimating the Economic Losses of Port Disruption due to Extreme Wind Events. Ocean Coast. Manag. 116, 300–310.