Disaster Economics and Networked Transportation Infrastructures: Status Quo and a Multi-disciplinary Framework to Estimate Economic Losses

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Abstract. In recent years, the frequency and severity of catastrophic events triggered by natural hazards have increased. Meanwhile, man-made hazards, such as terrorist attacks, and their impacts on infrastructure systems have gained increasing attention. These hazards (both natural and man-made) can cause catastrophic physical damage to transportation infrastructure systems that are essential to the wellbeing of the society. Moreover, the direct economic losses (e.g., physical damage to infrastructure) diffuse and expand continually through the disruption of economic activities between different regions and industries, resulting in enormous and complex indirect losses. A comprehensive investigation of total losses, including direct and indirect losses, requires the use of economic impact analysis models. However, most of the economic impact analysis methods and models introduced in the existing literature fail to incorporate the spatially distributed and networked nature of transportation infrastructures. To achieve a comprehensive and a realistic understanding of the economic impacts caused by the disturbances to the transportation infrastructure, the spatial distribution and the networked nature of transportation systems has to be accounted for, and realistic and locally relevant hazard scenarios must be incorporated into the economic analyses. This paper first provides a detailed account of the status-quo in economic modeling associated with impact analysis of transportation disturbances to identify the gaps in this domain. Next, focusing on the commuting related economic impacts of transportation disturbances as an example, the paper introduces a multidisciplinary framework designed to demonstrate an understanding on how to address the gaps. Preliminary results from a Los Angeles case study are presented.

Keywords: Disasters · Economic impact analysis · Transportation
Interindustry economics

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1 Introduction

Natural and man-made hazards disturb transportation systems that are essential to the wellbeing of the society at an increasing rate and severity to cause extensive physical damage. Direct economic losses resulting from physical damages diffuse and expand continually through economic activities between different regions and industries, resulting in enormous indirect losses. Research on transport-related economic losses caused by the Niigata-Chuetsu earthquake shows that 40% of total losses occurred in the Kanto region and other non-ignorable losses reached remote regions such as Okinawa [1]. In this context, understanding the economic impacts of hazards beyond the direct losses and studying the inter-industry and inter-regional diffusion of the impact is critical. A comprehensive investigation of total losses (including direct, indirect and induced costs) requires the use of tools from interindustry economics in the form of economic impact analysis models.

Many researchers have been trying to estimate economic losses due to natural and man-made hazards using models for economic impact analysis. Among varieties of models that have been used the Input-Output models (IO) and the Computable General Equilibrium (CGE) models are the most common approaches. In a pioneering study, Cochrane [2] applied IO models to estimate disaster losses. Hallegatte [3] introduced adaptive behaviors into IO models and proposed the Adaptive Regional Input-Output model. Park et al. [4] and Park et al. [5] constructed demand-driven and supply-driven regional Input-Output models based on IMPLAN and CFS data, and applied them to evaluate the U.S. economic losses of various types of infrastructure disruptions caused by hypothetical terrorist attacks. Rose [6] and Rose and Liao [7] estimated the regional economic impacts of water supplies disruptions using a CGE model, and considered resilience measures. Some researchers also integrated other non-economic methods, such as Inoperability Input-Output Model [8]. However, the literature in hazards and economic impact analysis mostly focuses on individual infrastructure components (e.g. a bridge instead of the road network) and almost always fails to incorporate the spatially distributed and networked nature of civil infrastructures into the impact assessment. This is a major shortcoming of the works in this domain, as individual infrastructure components depend on the well-being of the network to carry out the desired functions. Thus, e.g. if one studies the impact of a hazard on a port and does not consider the post event condition of the inland highway network supporting the port's functionality, the analysis cannot provide insight into the totality of impacts induced on the supply chains going through the port. Only a handful of studies attempted to estimate the economic impacts of disturbances to spatially distributed and networked transportation systems. In addition, a predominant number of these studies assumed - hypothetically or based on hazard information - the failure of a small subset of infrastructure components and did not study the full spectrum of the potential impacts, i.e. functionality losses that spread well beyond a small subset of infrastructures, due to a locally relevant natural or man-made hazard.

To achieve a comprehensive and a realistic understanding of the economic impacts caused by the disturbances to the transportation systems, (1) the spatial distribution and the networked nature of transportation systems has to be accounted for, and (2) realistic and locally relevant hazard scenarios must be incorporated into the economic analyses. Surveying the literature, we provide a detailed account of the status-quo in economic modeling associated with the impact analysis of transportation disturbances to identify the gaps in this domain. We also introduce an exemplary and a multidisciplinary framework developed to demonstrate an understanding on how to begin addressing these gaps. The framework consists of an integration of engineering and economic domains, and incorporates hazard-specific features to investigate the earthquake risk and the potential impacts on commuting in the Greater Los Angeles Area. Direct impact indicators (in terms of commuting times and distances) are selected in order to represent the performance of the urban transportation network and how commuting based mobility can be disrupted due to simulated functionality losses. These indicators are coupled with economic impact analysis.

2 Literature Review

To draw a picture of the status-quo of this domain at the interface of economics and engineering, a literature review was conducted. To find the articles studying economic impact analysis and specifically focusing on transportation disturbances, Web of Science was accessed. Initially, various combinations of the keywords or keyword groups such as 'economic losses', 'hazard', 'disaster', 'disruption', 'transportation', 'economic impact analysis', 'supply chain disruption' were used to list the previous works in the area.

During the search process, a cut-off date was not used as we did not identify an earlier review with a similar scope. From the results of the search, articles that are authored in languages other than English were excluded. Note that our review did not include the articles that exclusively used engineering approaches to study transportation disturbances as well, i.e. studies that do not intend to analyze economic impacts were excluded. These include works that focus on, among many other branches of engineering, transportation safety, traffic engineering and optimization, infrastructure management, and so on. Lastly, articles from the field of economics that study direct and indirect economic losses due to man-made or natural hazards were excluded from the review if they investigated the impacts on several industries without clearly specifying the extent of losses in transportation related sectors [9–11]. The attempts at the initial keyword-based search helped us reveal 23 papers that satisfy our criteria. Studying the citation network of these 23 papers, 17 additional papers were discovered and added to the review inventory. Among these studies, 34 are published in peer-reviewed journals, 5 of them are published in conference proceedings and one is a technical report.

We present a categorization and elaborate on the reviewed studies based on this categorization. Originating from the motivation of this paper, the reviewed studies were categorized according to the following three dimensions: *(1) Scope of Network Modeling and Analysis*, to distinguish studies that achieve explicit transportation network modeling and analysis from the ones that do not attempt the same; (*2) Scope of Hazard Impact Information*, to identify studies that base their hazard impact information on simple assumptions, reported or reviewed impacts, or on realistic simulations of locally relevant hazards, or studies that simply do not have hazard information; *(3) Scope of Economic Modeling*, to identify the spectrum of economic impact analysis methods and tools utilized in reviewed studies. The remainder of this section is structured with respect to the first two dimensions of this categorization scheme.

2.1 Category 1: Papers that Use Simple Assumptions for Hazard Impacts (Direct Losses) and Do not Use Explicit Network Modeling

Among the reviewed studies, most have not used explicit transportation network modeling and analysis, and only used simple assumptions for the treatment of hazard impacts. Oztanriseven and Nachtmann [12] applied a Monte Carlo simulation model to estimate the potential losses of waterway disruptions on the MKARNS (McClellan–Kerr Arkansas River Navigation System), and calculated related holding cost, penalty cost and transportation cost. Other studies tried to quantify the indirect economic impacts of disruptions with initial losses spreading over numerous sectors. Lian and Haimes [13] applied a DIIM (dynamic inoperability input-output model) to estimate the economic impacts of a potential terrorist attack in Virginia which results in the inoperability of truck transportation, broadcasting and telecommunications and utilities sectors, at a level of 20%, 50% and 60%, respectively. It is essential to note that, in the case of terrorist attacks, it is hard to simulate the hazard realistically due to the innate randomness of these events. This leaves the researchers with simplistic assumptions about the damages to the infrastructure. Li et al. [14] examined the economic impacts of a hypothetical flooding scenario in London through an input-output analysis with initial losses in labor, service and other sectors. Park et al. [15] proposed NIEMO (national interstate economic model) and the supply-side NIEMO with a succeeding study [16] and applied the models to evaluate port closure scenarios. However, the final demand losses were estimated based on the reduction of imports and exports without any realistic hazard simulation. Park [16] also conducted demand-side and supply-side models on hypothetical port shutdown scenarios and looked at potential substitution effects estimated by econometric simulation models.

Other researchers estimated the economic impacts of supply chain disruptions without leveraging explicit network models. Wei et al. [17] estimated the direct and indirect supply-chain-related losses of Chinese white alcohol industry caused by several earthquakes in Sichuan using IIM (Inoperability Input-Output model). Gueler et al. [18] built a coal delivery network including coal mines and power plants and calculated the total transportation cost of partial or full disruption of the Ohio River as a transportation mode. Tan et al. [19] and Zhang and Lam [20] investigated the direct and total import/export related losses of port disruptions based on a Petri Net model for the Shenzhen port, respectively, in which they illustrated the flow of the supply chain of printer business of HP through the Shenzhen port.

Rose and Wei [21] estimated the total economic impacts of a 90-day seaport shutdown scenario based on supply-driven and demand-driven IO models. Santos and Haimes [22] estimated the economic impacts of airline transportation sector disruption caused by terrorism using IIM. Pant et al. [23] applied an MRIIM (multi-regional inoperability input-output model) to assess the economic losses of a two-week shutdown of the Port of Catoosa without considering disturbances to commodity flows transported through other ports. Thekdi and Santos [24] introduced a modified DIIM to quantify the economic impacts of sudden-onset port disruptions with scenario-based methods. Irimoto et al. [25] quantified the economic losses caused by regional and international transport links interruptions based on inter-regional and trans-national IO models, respectively. Tatano and Tsuchiya [1] used a SCGE (spatial computable general equilibrium model) to estimate the economic impacts of transportation infrastructure disruptions caused by Niigata-Chuetsu earthquake of 2004. The economic losses were calculated based on a simple assumed two-period disruption scenario. Ueda et al. [26] proposed a SCGE model to estimate the economic damage caused by railway traffic interruption due to earthquake. In the model, the price of transport services was set at 1 to 10 times higher than usual. In his study presenting a conceptual framework only, Thissen [27] pointed out that additional costs on transportation and commuting could have larger economic impacts on the society due to permanent increase in transport cost caused by increased security measures. The author proposed a SAGE (spatial applied general equilibrium model) and analyzed how the surging transportation costs would affect the production and labor market. However, the author did not deploy his framework on a case study.

2.2 Category 2: Papers that Use Reported/Reviewed Hazard Impacts (Direct Losses) and Do not Use Explicit Network Modeling

Only a few studies managed to introduce the impacts of past disasters (based on reported or reviewed disaster information) on transportation networks into economic models. Jaiswal et al. [28] estimated the direct and landslide risk (in monetary value) in a transportation line in Southern India by simple math approach. Catastrophic events of the recent past drew a lot of research attention. Kajitani et al. [29] investigated the 2011 Tohoku earthquake and tsunami to summarize the disaster related losses and estimated the capacity losses. MacKenzie et al. [30] examined the production related losses of the same event based on a multi-regional input-output model. Tokui et al. [31] calculated the indirect economic losses caused by supply chain disruptions using modified forward linkage model (a revised input-output model) based on self-estimated direct damages to economic sectors; however, the process of finding the damage ratios was not discussed in elaborate detail. These studies investigating the losses from the 2011 Tohoku earthquake and tsunami do not particularly focus on transport systems; however, disturbance to transportation is treated as a major source of economic loss. Xie et al. [32] used a CGE model and estimated the indirect economic impacts of 15.6% decrease in road freight service inputs to other sectors, which was triggered by transportation disruption due to the Great 2008 Chinese Ice Storm. Yu et al. [33] estimated the economic losses based on an IIM model when the transportation sector of Luzon, Philippines experienced a 15% of inoperability according to World Bank estimates.

2.3 Category 3: Papers that Use Realistic Simulated Hazard Impacts (Direct Losses) but Do not Use Explicit Network Modeling

Only two studies in the review inventory calculated the economic losses based on realistic simulated hazard impacts but without explicit network modeling. Zhang and Lam [34] estimated the probability of port disruptions based on climate analysis and then calculated the transportation related losses by a simple math approach. Rose et al. [35] used CGE and IO models to quantify the total economic impacts of port cargo disruptions caused by the SAFRR tsunami scenario which is based on extensive prior research.

2.4 Category 4: Papers that Use Simple Assumptions for Hazard Impacts (Direct Losses) but Use Explicit Network Modeling

Only a handful of studies estimated the impacts of transportation disruptions with explicit network modeling. Xie and Levinson [36] estimated the traffic related losses caused by the increase in travel time triggered by the collapse of the I-35 Bridge on the Mississippi river. However, they did not take the ripple effect across the national highway system caused by the bridge collapse into account. Omer et al. [37] proposed the NIRA framework (networked infrastructure resiliency assessment) and applied it on estimating the resilience of a regional transportation network-transportation corridor between Boston and New York City. Economic losses for Hartford-New York City Link under different levels of disruptions were calculated based on simple indicators such as average cost per hour per person. Ashrafi et al. [38] measured the costs of highway closures based on commodity values and the increase in time cost, however, the authors only investigated a single link disruption and could not accommodate commodity types due to data shortage. It is worth mentioning that only transportation related costs were calculated in these papers, as a result, the accounting of the ripple effects across other industries caused by network disruptions was missing.

On the other hand, some studies leveraged advanced economic models and managed to capture the ripple effects in the economy. Tsuchiya et al. [39] formulated an SCGE-transportation integrated model and applied it to estimate the economic losses due to links disconnection in hypothetical earthquake scenarios. However, they assumed that there is no congestion and travel times were estimated based on shortest paths. Kim and Kwon [40] built an integrated model consisting of a sub-transport model and a SCGE model and applied it to assess the impacts of traffic accessibility disruptions and production losses due to nuclear and radiation accidents in Japan. A multi-disciplinary group of researchers combined transportation network analysis with the National Interstate Economic Model (NIEMO), and evaluated the economic impact of disruptions on major elements of the highway network (bridges and tunnels) based on commodity flow data [41, 42]. However, the selection of disrupted bridges was not based on hazard considerations and was largely hypothetical being based on auxiliary metrics such volume of truck traffic crossing the bridge, number of alternative routes available, etc. Moreover, TransNIEMO is computationally expensive due to data acquisition and reconciliation, which limits the extensive application of the model.

2.5 Category 5: Papers that Use Reported/Reviewed Hazard Impacts (Direct Losses) and Use Explicit Network Modeling

Some researchers were able to gather data on past hazards to investigate impacts on transport networks. Mesa-Arango et al. [43] estimated the economic impacts of highway segments closure due to severe floods based on FAF3 data and historical disruptions records. Torrey [44] quantified the volumes of trucks and the amount of travel delay based on public data in order to estimate the impacts of congestions on trucking industry by region, metropolitan, state and national levels. However, both studies considered transport related operational costs by simple math operations and did not investigate the problem from inter-industry economics perspective. On the other hand, Tirasirichai and Enke [45] applied a regional CGE model to evaluate the indirect economic losses induced by increasing travel costs due to increased travel costs caused by damages to highway bridges. The increased travel costs data was based on earlier studies [46, 47]. However, the indirect losses were calculated on a set of random elasticity values, which are essential values to calibrate and identify all other parameters.

2.6 Category 6: Papers that Use Realistic Simulated Hazard Impacts (Direct Losses) and Use Explicit Network Modeling

Lastly, very few studies estimated the economic impacts of transportation infrastructure disruptions in a comprehensive way that incorporates explicit network modeling, and realistically simulated and locally relevant hazard impacts. Cho et al. [48] integrated seismic, transportation network, spatial allocation and economic models, and applied their methodology on the Elysian Park earthquake scenario. Studying the same scenario, Gordon et al. [49] estimated the structural damage, business interruptions, network disruption and bridge repair costs of the earthquake based on an integrated, operational model. Sohn et al. [50] estimated the final demand losses and increased transport costs of 1812 New Madrid earthquake based on functionality losses in the transportation network, final demand loss function, and an integrated commodity flow model. Postance et al. [51] combined disaster simulation and network modeling by quantifying increased travel time based on susceptible road segments and disruption scenarios. The scenarios were identified through a susceptibility analysis. However, economic losses in this study are measured by an increase travel time multiplying national user generalized cost without considering ripple effects across other industries.

Based on all of the above, we draw the following conclusions from our literature review. The existing economic impact analysis methods are sophisticated to the extent that transportation disturbances due to natural and man-made hazards can be investigated in a comprehensive way. However, most of the literature in this area does not leverage explicit transportation network models. This shortcoming undermines the spatially distributed nature of and the interdependencies that exist within today's transport systems. Moreover, hazards that create the disturbances are not incorporated into the investigation in a systematic way, where researchers often use simplistic assumptions to fill the gap of missing hazard impact information that is locally relevant to the study area. Having identified these gaps in the literature, we propose a framework in the next section to demonstrate a multi-disciplinary understanding on how to begin addressing these gaps.

3 Economic Impact Analysis of Commuting Disturbances

Here we introduce a multidisciplinary framework that was developed to demonstrate possible approaches to address the gaps identified in the literature. It is essential to note that the primary focus of this paper is the economics facet of the larger framework, however, we broadly introduce the other facets as well. The framework was designed to investigate the economic impacts of a potential earthquake event in the Greater Los Angeles Area. It takes advantage of public domain hazard simulation software to estimate damage states and restoration timelines for the bridge inventory[1] of a metropolitan area. The results from earthquake hazard simulations are used to construct the degraded versions of the network given the restoration information, to mimic the recovery of a transportation network following an earthquake[2].

In addition, the version of the framework introduced in this paper only focuses on the impact on commuting (home-workplace-home trips taken on a daily basis) in the study area and its economic consequences. Commuting is a rarely studied facet in economics of transportation disturbances compared to some other services provided by these networks (e.g., movement of freight goods). Leveraging fine grain public domain data on commuters and an open source routing engine, the framework calculates commuting costs (in terms of driving times and distances) for all of the commuters that use the metropolitan transportation network to access their workplaces. First, routing is done for the undamaged network (business-as-usual) to establish a pre-event baseline for comparing the increasing commuting costs on the degraded, i.e. damaged network versions. These costs are converted to monetary values and become inputs to the economic impact analysis. Figure 1 illustrates the conceptual framework.

The economic impact analysis facet of the framework takes increasing commuting costs as its input. Note that, during network analysis, it is assumed that commuters will maintain trips to their workplaces as usual, i.e. the earthquake event does not cause loss of employment, migration of labor or businesses, etc. This constant trip demand assumption is widely used in literature [52]. However, the commuting trips become costlier due to the hazard-related disturbance to transportation. We assume that increasing costs of commuting will be fully passed on to the consumers. Therefore, increasing costs result in increasing prices for the outputs of every sector that uses transportation services as an input. This increasing price effect throughout the economy and leads to a shrinkage in consumer expenditures. Decreasing consumer expenditure has a direct inhibiting impact on final demand. Consequently, the reduction in final demand results in a loss of total economic output in the region. Quantifying the loss of economic output over the

[1] We assume that most critical components of the transportation network are its bridges. This is well established by the literature in transportation safety.

[2] Earthquakes present a different opportunity for economic impact analysis than some of the other hazards. This is due to the advanced ability of scientists to forecast the impact of these events which gives way to policy initiatives directed to mitigation [50].

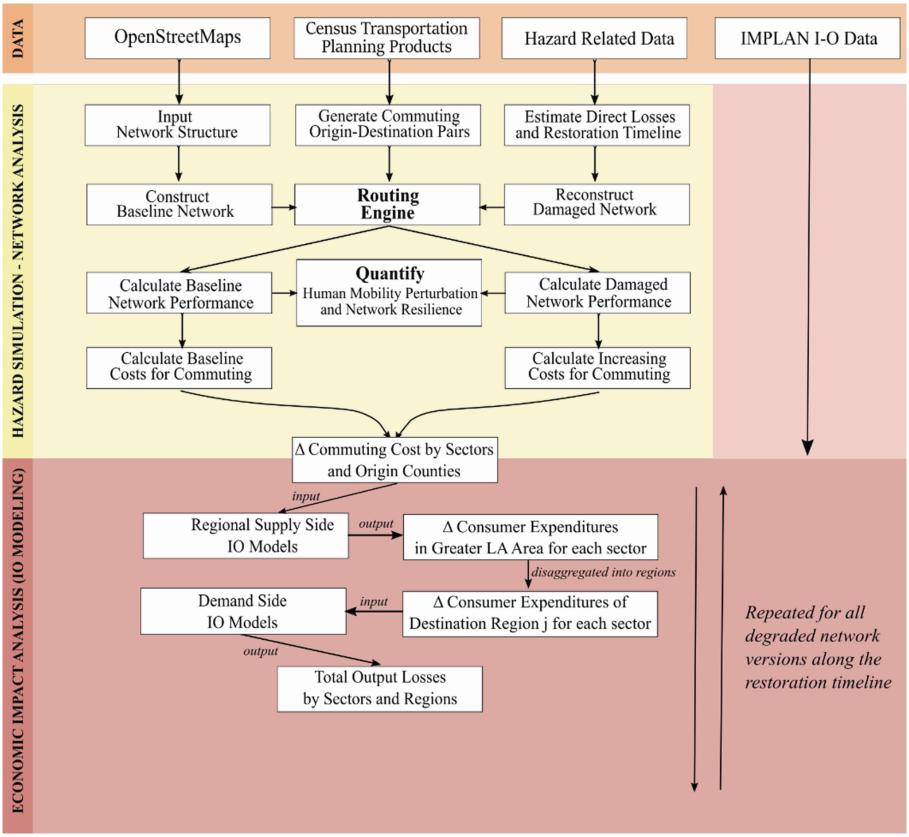

Fig. 1. Illustrating the conceptual framework.

restoration timeline of the network for its multiple degraded versions will allow us to estimate the total economic impact due to the earthquake related disturbance of commuting.

There are multiple ways for traffic network disruptions to induce increases in commuting costs. One of the ways is through the increase in operation costs. Commuters that have to travel on suboptimal routes due to the loss of functionality in the transportation network will travel over longer distances for longer durations. Increasing consumption in fuel, maintenance, repair, etc. follows from this adverse effect. In addition, for businesses that are paying mileage reimbursements to their employees, it will be costlier to provide the same benefit given a disrupted network. The mileage reimbursements are usually paid in terms of a constant dollar amount per unit distance traveled (e.g., $0.5/km). Last but not least, that people spending more time driving means they tend to spend less time on income generating or leisure activities. Here, there would be time-money tradeoff effects.

To estimate the economic cost of commuting disturbance, two factors need to be examined, namely the increase in travel distance and travel time. The economic cost of increasing travel distance can be estimated using average operation and reimbursement costs. However, the cost of travel time is difficult to quantify as it is a non-market intangible item and related to many factors [53]. There is still no universally accepted approach to quantify the cost of travel time. However, in this study, the average tradeoff value of time is used to represent the market price value of travel time.

We primarily focus on these two effects in our framework. Originating from these two effects, the economic impact of the commuting disturbance can be estimated based on supply-side and demand-side Input-Output models. As restoration advances with time, e.g. as bridges are opening to traffic, the economic impact of the hazard will diminish with time. In our future work, we will use the results of this step-wise approach as an economic resilience indicator that couples with engineered network resilience.

3.1 Estimating Costs of Increasing Travel Distance and Time

We quantify the direct impact indicators in the form of increasing travel times and distances through network analysis. The increasing traveling costs are distributed among economic sectors based on the Census data on commuters regarding the industries that employ them.

Assume that there are M regions and N industries, and assume i, j (i, j = 1, 2, … M) denote the origin and destination regions, respectively. Finally, we denote production sectors with k (k = 1, 2, … N).

Economic costs of increasing travel distance are quantified as follows:

$$\Delta TDC_{ij}^{k} = TRC_{ij}^{k} + \Delta TOC_{ij}^{k} \tag{1}$$

where

ΔTDC_{ij}^{k} is the cost of increasing travel distance (referenced to business-as-usual baseline network) from origin region[3] i to destination region j for sector k.

ΔTRC_{ij}^{k} is the increase in total reimbursement cost paid by employers to commuters traveling from origin region i to destination region j for sector k.

ΔTOC_{ij}^{k} is the increase in total operation cost from origin region i to destination region j, in which higher fuel consumption is the biggest part.

ΔTOC_{ij}^{k} is calculated simply by multiplying the total driving distance summed up for all commuting trips from i to j by the average cost of driving. The former comes from our network analysis and the latter is a statistic offered by the Bureau of Transportation Statistics[4].

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[3] The economic region in the full deployment of the framework will be the regions in Los Angeles that we have the input-output table for.

[4] These values are published annually by Bureau of Transportation Statistics. Average cost of driving includes fuel, maintenance, and tires. Available online at: www.rita.dot.gov/bts.

For increasing travel time, the cost would be:

$$\Delta TTC_{ij}^{k} = \Delta TT_{ij}^{k} \times ATC_{ij}^{k} \tag{2}$$

where

ΔTTC_{ij}^{k} is the total cost of increasing travel time from origin region i to destination region j for sector k.

ΔTT_{ij}^{k} is the increase in total travel time summed up for commuting trips from region i to j referenced to the baseline total.

ATC_{ij}^{k} is the average tradeoff value of time. This is to account for the time spent by commuters in driving instead of income generating or leisure activities.

In this way, the total cost of increasing travel distance and time:

$$\Delta TC_{ij}^{k} = \Delta TDC_{ij}^{k} + \Delta TTC_{ij}^{k} \tag{3}$$

where

ΔTC_{ij}^{k} is the increase in total travel cost from origin region i to destination region j for sector k.

3.2 Estimating the Impact Through Interindustry Economics: Supply-Side IO Model

In 1958, Ghosh [54] proposed the supply-driven IO model. It has fixed allocation coefficients similar to the Leontief Input-Output model [55]. Following its inception, the model received criticism regarding its plausibility [56], however, Dietzenbacher [57] proposed a way to address this problem by interpreting the Ghosh model as a price model.

The designed framework uses a supply-side IO model to estimate the impact of increasing commuting costs in the regional economy. It should be noted that the impact of price inflation (caused by increasing transportation costs) on consumer expenditure cannot be treated independently for every region as consumers may spend their money on goods and services in any region in the Greater Los Angeles Area. Therefore, we take the Greater Los Angeles Area as a single region and use a supply side IO model to estimate the decreased consumer expenditures. To be specific, the inflation in sector k's goods and services caused by increasing travel costs in all regions results in decreasing consumer expenditures in the Greater Los Angeles Area. In the supply-side IO model, increasing travel costs are aggregated in order to estimate the whole impact on consumer expenditure in the Greater Los Angeles Area.

The total increasing travel cost for sector k by all regions is aggregated as following:

$$\Delta TC^{K} = \sum_{i=1}^{M} \sum_{j=1}^{M} \Delta TC_{ij}^{k} \tag{4}$$

The decreasing consumer expenditure is calculated as following:

$$\Delta CE^{K} = \Delta TC^{k} \times (I - B)^{-1} \tag{5}$$

where

ΔTC_{ij}^{k} is the total price inflation for sector k due to increasing commuting costs.
ΔCE^{K} is the decrease in total consumer expenditure for sector k after price inflation effect.

$(I - B)^{-1}$ is the output inverse matrix and B is the direct output coefficients matrix of the Greater Los Angeles Area.

In the short term, it is assumed that producers will not be closed or new ones will not be established but the existing producers will change their production quantity. Therefore, the impact of reduced consumer expenditure on total output losses for each region is not the same given different output levels for each region. Then the decreased expenditures will be reallocated to each region.

The reallocation process of decreasing consumer expenditures is as following:

$$\Delta CE_{j}^{k} = c_{j}^{k} \times \Delta CE^{K} \tag{6}$$

where

ΔCE_{j}^{k} is the total decreased consumer expenditure in region j for sector k.

c_{j}^{k} is the consumer expenditure ratio of region j to the whole area.

Next, we use a demand side IO model to estimate the economic impacts based on reductions in final demand.

3.3 Estimating the Impact Through Interindustry Economics: Demand-Side IO Model

Demand-side IO models have been proposed and widely-used to assess the economic impact of reduction in final demand. Here, we make the assumption that there is no substitution effect and consumer expenditures have direct impacts on final demand. This assumption was proposed and used in TransNIEMO [42]. Then, the total output losses can be calculated based on NIEMO, a demand-driven Input-Output model. This demand-side version of NIEMO is useful to analyzing the backward linkage impacts. In our framework, we estimate total output losses with an approach similar to [15] as follows.

Using the decreasing consumer expenditures from the supply-side, we use a demand-side Input-Output model to estimate the total output loss for sector k due to the losses in final demand in destination region j.

$$\Delta \mathrm{X}_{j}^{k} = (I - A)_{j}^{-1} \times \left(-\Delta CE_{j}^{k}\right) \tag{7}$$

where

ΔX_j^k is the decrease in total output in destination region j for sector k.

$(I - A)_j^{-1}$ is input inverse matrix and A is direct input coefficients matrix in destination region j.

Based on that, the total impacts of commuting disturbances can be summed up by regions and by sectors.

The total impacts by regions are:

$$\sum\nolimits_{k=1}^{N} \Delta X_j^k \tag{8}$$

And the total impacts by sectors are:

$$\sum\nolimits_{j=1}^{M} \Delta X_j^k \tag{9}$$

In this way, the total output losses induced by increasing commuting costs due to transportation infrastructure disruptions can be calculated. Sectors and regions that are more easily affected by network disturbances can be identified. Prevention measures can be taken and limited resources can be distributed wisely to mitigate the general economic impacts. Note that, this economic impact estimation methodology will be carried out for all the degraded versions of the transportation network. This will enable us to observe the economic recovery along with the recovery in the road network.

4 Case Study: Quantifying Economic Impacts of Increasing Travel Time for Commuting in Los Angeles

To deploy the economic facet of the framework that the authors focus on in this study, results from a sister paper by Koc et al. [58] on coupled assessment of mobility-infrastructure network resilience were used. In their work, Koc et al. carried out the hazard analysis and the network analysis encapsulated in the framework for a case study investigating the commuting in Los Angeles and the potential impacts of the governing seismic hazard in Downtown Los Angeles Area. Using state-of-the-art earthquake hazard analysis, Koc et al. found the disturbances in the physical transportation network (bridges only) along with the downtimes of the damaged components. Consequently, using the Census Transportation Planning Products (CTPP) data [59], they quantified the increasing travel times and distances that commuters (the dominant driving mode only in Los Angeles) would have to bear at the Traffic Analysis Zone (TAZ) level of detail. During the restoration and recovery of the network, the improving travel times and distances were also quantified to achieve an understanding of resilience. Adopting these results at an aggregated level for the 5 counties in the Greater Los Angeles Area commuting zone, the authors carried out preliminary economic analysis to deploy the economic facet of the framework. Within the scope here, economic impacts are quantified only from an increased travel time standpoint where the authors use the average tradeoff value of time values published by California Department of Transportation [60]. Local input-output data are obtained from IMPLAN Group [61]. The industry breakdown scheme is aggregated by the authors to transform the 536 industries in IMPLAN data into 7 industries to match the industry aggregation in the CTPP dataset. There are 5 counties in the Greater Los Angeles Area, including Los Angeles, Orange, Riverside, San Bernardino and Ventura counties. For each county, direct-input coefficients matrix (A matrix) and direct-output coefficients matrix (B matrix) are generated. Model year is set to be 2017.

4.1 Data Processing and Preliminary Results from Economic Analysis

With the gathered data, economic analysis was carried out as follows. First, treating 5 counties as origins and destinations, total travel times per economic sector between all origins and destinations were calculated by simply multiplying the number of commuters with average travel times before and after the earthquake. This is done at 5 discrete time intervals, between day 0 (before the hazard) and day 1, from day 1 to 7, from day 7 to 30, from day 30 to 90, and from day 90 to 1 year, respectively. This way, changes in total travel times during restoration are obtained at a reasonable resolution in terms of timeline. Take the interval from day 1 to day 7 as an example, the increase in total travel time for all commuters from region i to region j in sector k can be calculated as:

$$\Delta TT_{ij}^{k,\,day\,1\,to\,day\,7} = (7-1) * \left(TT_{ij}^{k,\,day\,7} - TT_{ij}^{k,\,day\,1} \right) \tag{10}$$

Then, the total cost of increasing travel time, ΔTTC_{ij}^{k}, can be calculated based on Eq. (2). The average tradeoff value of time for automobiles are taken from Vehicle Operation Cost Parameters[5] table to represent the average tradeoff value of time.

These costs are then aggregated by sectors. The decreasing consumer expenditure for each sector is calculated based on a supply-side IO model as shown in Eq. (5), and is allocated to each county using average household income levels obtained from IMPLAN.

Lastly, a supply-side IO model is used to estimate the total output losses based on Eq. (7). Accounting for the tradeoff value of time only, the annual total output loss in the Greater Los Angeles Area is estimated to be over 270 million USD. Table 1 shows the total output losses for five counties, and Table 2 shows the direct and indirect losses for seven industries in the study region. Direct losses refer to the total tradeoff value of increasing travel times. Total losses are estimated economic impacts across the whole economy, in which the impacts of economic transactions are taken into consideration. The indirect economic loss caused by increased commuting times is about 117 million dollars, accounting for 42.36% of total economic losses. According to Tables 1 and 2,

[5] The Vehicle Operation Cost Parameters are statewide representative average values recommended by California Department of Transportation [60] to be used in the economic analysis of highway and other projects.

sectors of information, finance, real estate, and technology services etc. suffer the most, and these losses are exacerbated during the process of economic activities.

Table 1. Estimated total output losses in five counties (million USD).

	Los Angeles	Orange	Riverside	San Bernardino	Ventura
1. Agriculture, forestry, fish & hunting, mining, construction	4.26	4.60	3.19	3.09	4.37
2. Manufacturing	7.81	7.78	4.82	5.01	7.08
3. Transportation & warehousing, utilities, wholesale trade, retail trade	12.52	12.84	8.39	8.34	12.02
4. Finance & insurance, real estate & rental, scientific & technology services, information, management of companies, administrative & waste services	22.85	24.72	13.88	13.14	22.36
5. Education services, health & social services	8.09	8.63	5.49	5.69	8.09
6. Arts, entertainment & recreation, accommodation & food services	4.11	4.32	2.77	2.81	4.05
7. Other services	4.64	4.82	3.24	3.31	4.64
Total	64.27	67.73	41.79	41.40	62.62

Table 2. Direct and indirect output losses in the Greater Los Angeles Area (million USD).

	Direct losses	Indirect losses	Total losses
1. Agriculture, forestry, fish & hunting, mining, construction	11.26	8.25	19.51
2. Manufacturing	19.65	12.85	32.50
3. Transportation & warehousing, utilities, wholesale trade, retail trade	32.89	21.22	54.11
4. Finance & insurance, real estate & rental, scientific & technology services, information, management of companies, administrative & waste services	35.4	61.56	96.96
5. Education services, health & social services	32.35	3.65	36.00
6. Arts, entertainment & recreation, accommodation & food services	13.8	4.26	18.06
7. Other services	14.78	5.88	20.66
Total	160.14	117.66	277.80

5 Limitations of the Framework

One major limitation of this study is that it only captures the economic impacts of increasing transportation costs. Other direct economic losses such as costs of physical damages to infrastructure and increasing freight shipping costs are not included. Therefore, there might be some underestimation of economic losses in the current version of the framework.

Second, some assumptions and simplifications have to be made in order to obtain the direct losses. The assumption that people will maintain their commuting trips as usual after earthquakes ignores the possibility that some commuters choose to work from home or change their transport mode considering changes in travel costs and travel time. In addition, the value of travel time is intangible. It is hard to capture the effects of spending more time on commuting trips holistically with the averaged tradeoff value of time. Also, the accuracy of the indicators to estimate the increasing transportation costs are crucial, such as mileage reimbursement rates. These indicators vary by regions as well as industries and may not be readily available.

Lastly, the inherent shortcomings of the IO models cannot be ignored, such as linearity and the assumption of no substitution effects. In this paper, supply-side and demand-side IO models are chosen because of modest data demand compared to alternatives such as CGE models. As a result, some realism may be sacrificed. More advanced modeling can achieve a more realistic analysis.

6 Conclusion and Future Work

The relationship of hazards and transportation systems will be a focus of increasing attention in the coming decades, mostly because hazardous events are becoming more frequent and more severe, threatening the civil infrastructure at increasing rates with unprecedented risks. With this paper, we pressed on the need of advancing the multidisciplinary research in this domain without losing the individual contributions of participating disciplines for the sake of simplicity. The gaps in the area were identified through a literature review and results were presented based on a categorization designed according to the objective of the paper. We find that more than often, networked transportation systems are abstracted from economic analyses. Moreover, despite the advances in hazards science, realistic simulations of locally relevant hazards are not fully integrated into economic studies. These will limit our ability to comprehensively quantify the economic impacts of infrastructure disruptions caused by disasters. Building on this foundation, we presented an exemplary impact analysis framework that is designed to study the adverse economic impacts of earthquakes on commuting in metropolitan areas. This paper did not include a full case study, however, we are currently deploying the framework in Los Angeles, where commuting to work is a daily undertaking for most working Angelenos. This initial effort will help us refine the framework. Other items in our future work agenda include incorporation of comprehensive direct losses (e.g., dollar value of physical damage to infrastructure), and multimodal mobility analysis into the framework. The latter will enable us to study mode-choice behavior in disaster settings. Overall, we will improve upon the current version of the framework presented here towards more accurate economic impact analysis.

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