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Analysis of Economic Resiliency of Communities Affected By Natural Disasters: The Bay Area Case Study

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Abstract

The paper focuses on the economic impact of natural disasters on different economic sectors in a given community considering their interdependencies. In the last twenty years, several catastrophe models have been developed for measuring economic losses. Nevertheless, due to the lack of data and the complexity of the problem, significant levels of uncertainties are still present. In fact, the factors that drive the economic recovery process before, during, and after natural disasters needs to be determined to select the optimal resources allocation and preparedness measures right after an extreme event. In most of the previous catastrophe models interdependencies between physical and nonphysical infrastructures are mostly neglected. This paper is proposing a model that describes the economic effects and characteristics that should be taken into account to predict the monetary impact of natural disasters, focusing in particular on the economic interdependencies of industries and lifelines. Different types of losses are considered using real economic data provided by surveys on natural disasters such as Northridge earthquake, Des Moines flood, etc. The data associated with the physical damages are obtained from HAZUS database. The Economic Resilience Index provided in the PEOPLES framework is adopted and applied to the specific case study of the San Francisco Bay Area. Sensitivity analysis is performed for each economic sector considered in the analysis.

Keywords: economic resilience, systems interdependencies, natural disaster cost.

1. Introduction

Modern communities are evolving towards interdependent systems. While interdependencies are positively considered in normal operating conditions as they promote a greater economic growth, they have serious drawbacks in the aftermath of natural or man-made disasters. After a catastrophic event such as an earthquake, the region is affected by different types of losses which depend on the level of interdependency among different economic sectors, their business downtime and restoration. In the last decade, several studies have addressed the behavior of communities in the aftermath of a disaster event from a global perspective. Renschler et al. [1] have defined seven dimensions of community resilience based on which they derived an index that can characterize the behavior of a region. Among these dimensions, the economic is certainly the most important. The study demonstrated that the possibility to measure the economic changes at the regional level triggered by a disaster is a crucial step towards disaster risk reduction. Recent discussions within the Engineering and Economics communities are focused on defining the economic structure of local and regional communities and the connections between productive sectors and consumers that will maximize the economic benefits. The economic structure needs to be defined by identifying the weak points of the economic system that are to be "protected" to enhance the economic resiliency for natural

and man-made disasters. In this perspective, Tierney et al. [2] analyzed business characteristics that influence the long-term recovery after a catastrophic event. Rose et al. [3] focused on the estimation of indirect economic losses within a region stemming from a disruption of the water service. Wasileski et al. [4] examined how physical damage to the infrastructure, lifeline disruption and business characteristics, among others, impact business closure and relocation following major disasters. Pant et al. [5] developed a specific approach for the evaluation of interdependencies among multiple infrastructures able to support decision-making and resource allocation. Although the studies mentioned above deal with the economic effects of extreme events in the communities, they all focus on specific aspects of the problem. In this paper, a methodology is proposed for estimating regional economic resilience that encompasses all types of losses that should be taken into account to predict the effects of natural disaster on a regional economy. The methodology uses economic framework that is an extension of HAZUS [6] framework. The proposed framework divides losses in two main categories: direct and indirect. The direct losses include economic losses caused by physical damage to buildings and utilities. Economic losses generated by physical damage of buildings are based on Terzic et al. [7] model. Within the proposed methodology, a further step is made to develop a correlation between physical damage to utilities, their downtime and losses. To account for the indirect losses that stem from the interdependence between different economic sectors, the structural growth model introduced by Wu Li [8] is utilized. The proposed methodology is demonstrated on a case study for the San Francisco Bay Area, a region with strong initiative in reducing earthquake risk by identifying performance goals that are to be achieved through design to improve resiliency of the region (Poland et al. [9]). For this case study, the economic resiliency of the region is based on combination of the existing and simulated data. Simulated data were only used if the real data were not available. To take into account the uncertainty of the data used in the analysis, sensitivity analysis is performed to identify the preventive measures that could be facilitated to improve economic resiliency. Finally, an economic performance index, named economic resilience index R_{EC}, is used as a measure of the economic ability of a region to withstand catastrophic events.

2. Description of the methodology

Natural disasters may generate significant economic losses at both, local (regional) and global level. Generally, regional losses are significantly higher than the global losses, and therefore will be a focus of this study. To estimate the total economic losses of a region struck by a natural disaster the losses are disaggregated into direct and indirect. The direct economic losses are associated with the business-interruption cost due to physical damage of structures (buildings and lifelines) and indirect losses are associated with the inter-industry transactions.
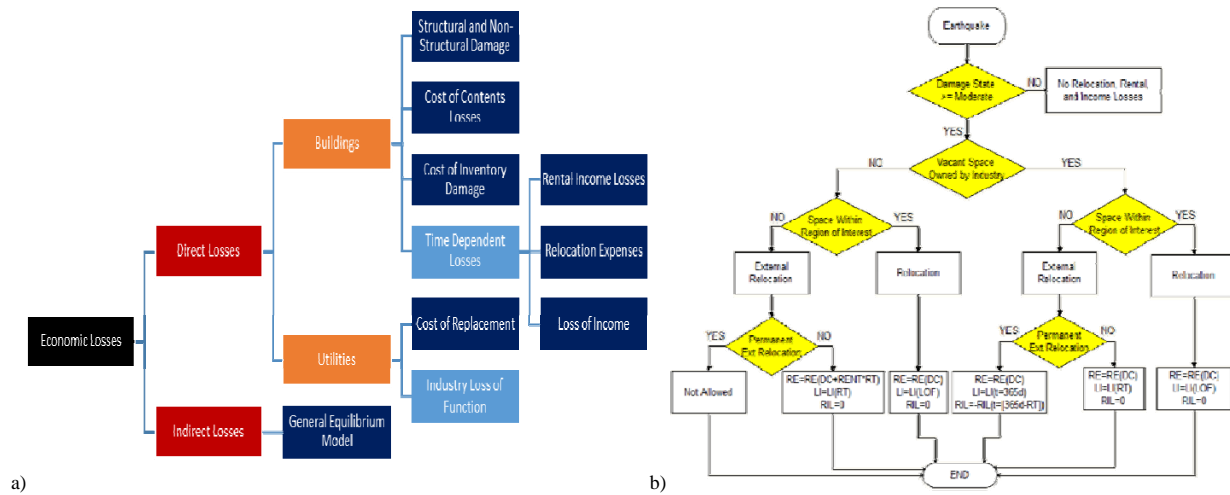

a)   b)

Fig. 1. (a) Economic Loss Framework; (b) Time Dependent Losses Algorithm for owner-occupied businesses.

2.1. Economic Loss Framework

The proposed framework for calculating economic losses due to hazard events, schematically presented in Fig. 1a, is an extension of HAZUS framework [6]. HAZUS is a software developed by FEMA to estimate different types of losses generated by a natural hazard. The framework divides the losses in direct and indirect. The direct losses stem from building but also from utility damage (while this kind of interdependency is disregarded by HAZUS) and are associated to the cost of

reconstruction and business interruption. The indirect losses in the methodology are estimated as general equilibrium effects of a disrupted inter-industry economy instead of being computed through the traditional Input-Output model of HAZUS. Three main modifications of the framework shown in Fig. 1a are applied to capture all the types of possible losses. The first is represented by the analysis of the *industry loss of function* due to the disruption of utilities. The second is given by a new method which is able to find the probabilistic distribution of the time-dependent direct losses that affect a specific region of interest. Finally, the *structural growth model (SGM)* is applied instead of the usual *Input-Output model* to quantify the indirect effects that arise as a cascade effect due to the business interdependencies.

2.2. Direct time-dependent losses

The proposed methodology refines the analysis of the *time-dependent direct losses* related to the building physical damage. The basic model, inspired by HAZUS, assumes that *relocation* occurs if the damage state of the building is greater or equal to *moderate* and in that case the losses are given by *relocation expenses* (RE), *rental income losses* (RIL), and *loss of income* (LI). Otherwise, the *time-dependent direct losses* are given only by the LI due to the loss of functionality that could arise even with slight damage of the building. Besides, since the goal of the paper is to quantify the global economic effects of a disaster on a specific region of interest, it should be taken in account that relocation can occur in different ways that influence the losses. To accomplish this goal Eq. (1), Eq. (2), and Eq. (3) have been implemented. The difference respect to the HAZUS approach stems from two observations. Since the goal is to model the losses of a specific region, it is important to distinguish between inside and outside relocation. Moreover HAZUS does not take in account the possibility that the industries which are forced to relocate own extra space in which move the activity, and that this space may be again inside or outside the region of interest. The implemented algorithm take into account these different possibilities by choosing different time windows used to compute LI and RIL (while in HAZUS are always computed using the loss of function and the recovery time respectively, which take into account for mobilization time) and considering or not new rental costs or rental losses depending on if the property is business-owned. The flowchart of the method that refers to businesses that are owner occupied is represented in Fig. 1b.

$$RE_i = \left[\left(1 - \%OO_i\right) \bullet \sum_{DS=3}^{5} \left(POSTR_{DS,i} \bullet DC_i \right) + \%OO_i \bullet \sum_{DS=3}^{5} \left(POSTR_{DS,i} \bullet \left(DC_i (+RENT_i \bullet RT_{DS}) \right) \right) \right] \tag{1}$$

$$LI_i = (1 - RF_i) \bullet FA_i \bullet INC_i \bullet (\sum_{DS=1}^{5} POSTR_{DS,i} \bullet t_{DS}) \tag{2}$$

$$RIL_i = \left(1 - \%OO_i\right) \bullet FA_i \bullet RENT_i \bullet \left(\sum_{DS=3}^{5} POSTR_{DS,i} \bullet t_{DS} \right) \tag{3}$$

Where:
- *%OO$_i$* = percent owner occupied for occupancy *i*;
- *POSTR$_{DS,i}$* = probability of occupancy *i* being in structural damage state *DS*;
- *DC$_i$* = disruption costs for occupancy *i*;
- *RENT$_i$* = rental cost for occupancy *i*;
- *RT$_{DS}$* = recovery time for the damage state *DS*;
- *RF$_i$* = recapture factor for occupancy *i*;
- *INC$_i$* = income per day per square foot for occupancy *i*;
- *t$_{DS}$* = period of time which depend on *DS*, business property and place of relocation (see Fig.1b).

The yellow blocks in the flowcharts (Fig. 1b) are the decision blocks. Due to the scarcity of data, it is very difficult to obtain exact data for these blocks. For this reason it has been adopted a probabilistic approach to take into account for the uncertainty of the decisional variables. However, if more data regarding the decision blocks are available, they could easily be substituted in the method to obtain outcomes that are more reliable. The methodology implemented in the paper is based on three assumptions. The first is that the greater is the business size, the higher is the possibility that the businesses own vacant space to relocate the activity. The second is that the probability that the vacant space is located within the region of interest is equal to the percentage of vacant buildings in the region (this value is approximated using HAZUS database). Finally, it is assumed that the longer the recovery time, the higher is the probability that the external relocation will be permanent. It should be also noted that the *income losses* considered in the paper refer to *the output losses* suffered by the industries, which eventually represent the loss of functionality of each sector. A more detailed description of the methodology is provided in Martinelli et al. [10]. The *cost of business interruption* due to the physical damage of buildings is represented through a graph which shows the normalized output losses as a step function, where the different steps shown

in Fig. 2a for the Educational sector represents the number of damage states that contribute to the loss of business functionality. After computing the building damage losses, the business losses due to lifelines disruptions are also taken into account in the proposed methodology. However, due to the scarcity of data a hybrid approach has been adopted where both simulated and real data have been used. The lifeline functionality after the event is obtained by using the simulated data given by HAZUS. The real data are represented by the *probability of business closure due to lifeline disruption*. They have been derived using a procedure similar to the one explained by Chang et al. [11] using data collected with surveys conducted on two natural disasters (Northridge earthquake and Des Moines flood) described in the works of Tierney [12] and the simulated results given by Rose [13]. In particular, a new function called *autonomy curve* which corresponds to the *probability of business closure* for a given lifeline is derived using Eq. (4) and Eq. (5). These *autonomy curves* represent the ability of each economic sector to withstand a utility outage of different entity without losing functionality.

$$AF_i = 1 - P_{BI,i} \tag{4}$$

$$P_{BI,i} = P_{BC,j} \bullet P_{UOi,j} \bullet \alpha_i \tag{5}$$

Where:
- $P_{BI,i}$ = probability of business interruption due to utility i outage;
- $P_{BC,j}$ = probability of business closure for occupancy j;
- $P_{UO,ij}$ = percentage of business with utility i outage for occupancy j;
- α_i = average percentage of businesses that closed due to utility i outage.

The autonomy factor curves have been calibrated using the known temporal lifeline outage in the case study considered, while different type of curves have been selected depending on the type of utility considered. For example, when analyzing the *Retail and Wholesale sector,* for the electricity, water, and phone network a four parameters logistic function has been chosen, while for the waste and gas system a multi-linear curve has been selected as shown in Fig. 2b. All the figures shown in the paper refer to the San Francisco Bay Area case study.
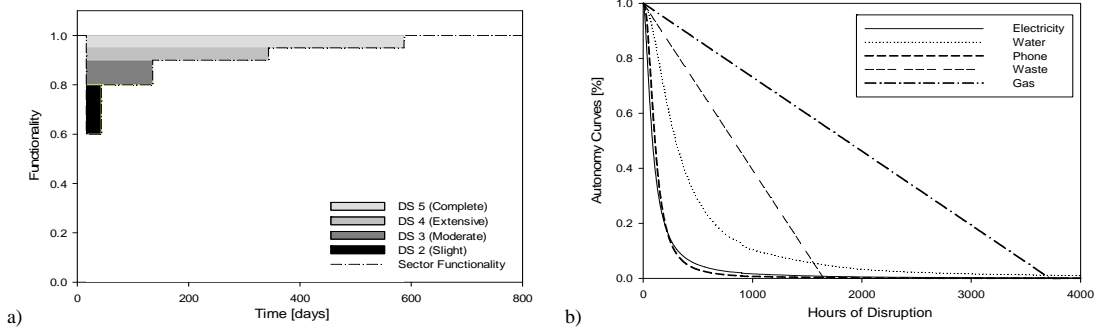

Fig. 2. (a) Loss of functionality for the Educational sector and (b) autonomy factor curves of different lifelines for the Retail and Wholesale sector.

The influence of each utility disruption on the economic sector functionalities is modeled applying the *autonomy curves (AF)*, determining the new sector functionalities using the following equation:

$$f_{sector}(t) = f_{utility}(t) + \left[1 - f_{utility}(t)\right] \bullet AF_{utility}(t) \tag{6}$$

Where f_{sector}=functionality of the economic sector; $f_{utility}$=functionality of the utility; AF=autonomy curves. The limitation of Eq. (6) is that the normal operating condition after lifeline disruption is reached at the same time for both the lifeline and the economic sector, as shown in Fig. 3 which considers the example of the water service. In reality, a lag exists between economic sector and lifeline recovery. So Eq. (6) can be used until the economic sector begins to recover. Then a lag factor θ is introduced to take into account the delay of a functionality with respect to the other. The mathematical formulation for the lag factor is given by:

$$\begin{cases} \theta = 0 & t < t_r \\ \theta = \dfrac{t - t_r}{X_{gg}} & t_r < t < t_{fr} \end{cases} \tag{7}$$

$$f_{sector}(t + \theta \bullet t_r) = f_{utility}(t) + \left[1 - f_{utility}(t)\right] \bullet AF_{utility}(t) \tag{8}$$

Where:

- t_r = time instant when the recovery of the economic sector starts when using Eq. (6);
- t_{fr} = time instant when the recovery of the economic sector ends using Eq. (6);
- X_{gg} = lag time of the economic sector with respect to the utility;
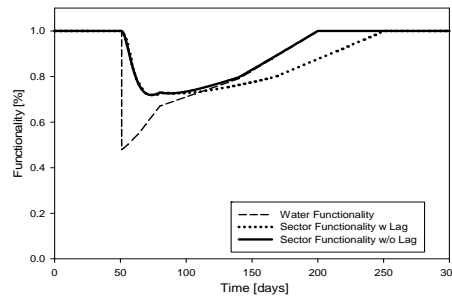- $AF_{utility}$ = autonomy curves of the economic sector with respect to the utility.

Fig. 3. Sector functionality influenced by the water service restoration

The lag time needs to be calibrated, however as a first approximation, the lag time θ for the economic sector is assumed as a fraction of the utility restoration time. Once all the *autonomy curves* which describe the interdependencies between the economic sector and the different lifelines are determined, they are combined with the economic sector functionality for determining the effect of all the different utilities. The new updated functionality curves are then combined to determine a single functionality curve for each economic sector which captures the interdependencies between each lifeline. It is important to mention that the methodology overestimates the losses due to utility disruption since it has been assumed that the businesses were affected separately by the utilities which affect the most the sector functionality. Moreover, interdependencies are considered separately one by one, and it is not taken into account the possibility that businesses that are forced to close due to utility disruption can reduce their losses by interacting with other utilities, or by making up production at different times. To reduce this overestimation, the recapture factors provided by HAZUS have been used to decrease the losses. Finally, the losses due to utilities disruption for each economic sector have been summed with the output losses due to building damage and a loss range is determined. The lower bound of this loss range is represented by the envelope of the two functionality curves affected separately by physical damage and the utilities disruption. The upper bound is represented by the sum of the two functionality losses. Then, depending on the conditional probability for a business to be affected simultaneously by building physical damage and utility disruption, it has been found a probable value within this range. Eq. (9) is adopted to compute the global functionality:

$$F_{tot,sec} = \min(F_{sec,utilities}; F_{sec,building}) - P(BD \cap UO) \bullet \left(1 - \max\left(F_{sec,utilities}; F_{sec,building}\right)\right) \tag{9}$$

Where:

- $F_{sec,utilities}$ = functionality of the sector influenced by the utilities;
- $F_{sec,building}$ = functionality of the sector influenced by the building damage;
- $P(BD \cap UO)$ = probability that business is simultaneously affected by building damage(BD) and utility outage (UO).

2.3. Indirect Losses

After estimating the direct effect of the disaster event on each economic sector, the methodology applies the structural growth model to the scenario of interest, as described in Cimellaro et al. [14], to estimate the indirect effects that stems from the interdependence between the sectors. In other words, the model applies to the business functionalities an initial perturbation that corresponds to the direct damages experienced by the sectors and then evaluates the recovery process which is controlled by the *price adjustment velocity* and by the *depreciation factors* of the goods. At the end of the analysis, it is possible to obtain a graph, shown in Fig. 4b which depict the general equilibrium effects and from which the monetary losses due to the business interdependences can be derived.

2.4. Economic Resilience Index (R_{EC})

Finally, the methodology evaluates the economic behavior of the analyzed region using a comprehensive resilience index R_{EC} determined according to the PEOPLES framework [1]. R_{EC} is the area under the function which is the sum of the direct and indirect losses normalized with respect to the value of the business functionality over the same control period.

3. The San Francisco Bay Area case study

The SF Bay Area (Fig. 4a) is considered as case study to show the implementation issues of the methodology. Since the predictions of the USGS estimated the maximum probability of 30% for a M>6.7 in the Hayward Fault, the baseline scenario chosen is a M6.9 earthquake in the Hayward fault in Oakland. The structural and non-structural losses and the utilities functionalities have been derived from HAZUS after having loaded the soil map and the liquefaction susceptibility map of the region.
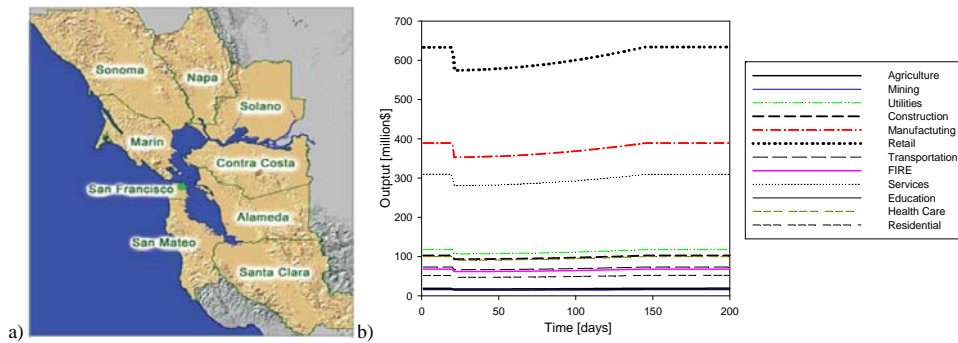

Fig. 4. (a) region considered in the SF Bay Area case study; (b) Indirect general equilibrium effects for the different sectors.

Then the methodology described is implemented to estimate the direct time-dependent losses. To do that, the values of INC_i in Eq. (2) have been updated coherently with the output data of each sector published by the Economic Census.
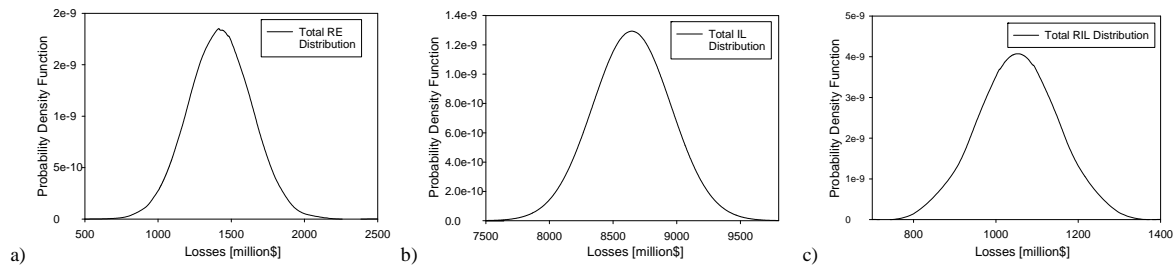

Fig. 5. Relocation expenses RE (a), loss of output IL (b), rental income losses RIL (c).
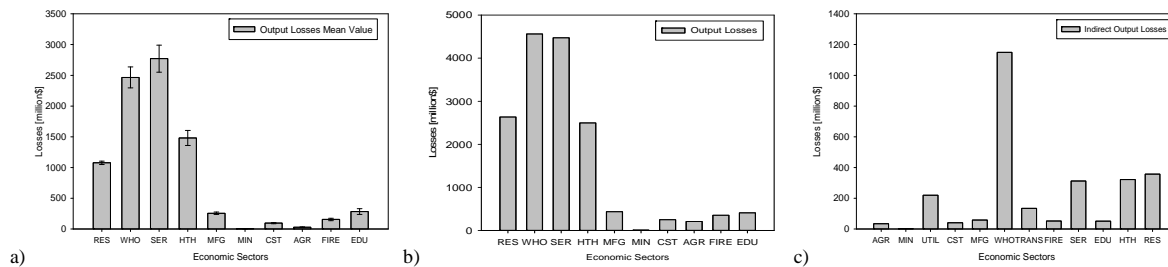

Fig. 6. Mean value and dispersion of the output direct losses due to (a) building and (b) building + utility damage; (c) Indirect losses.

The *loss distributions* for the economy in the region obtained by the methodology are shown in Fig 5. The estimated *relocation expenses* are 1.5 and 2.1 billion $ with the proposed methodology and with HAZUS respectively, while the estimated *rental income losses* are 1.06 and 1.21 billion $ respectively. In Fig. 6a are represented the mean and the dispersion of the direct output losses for each sector due to building damage while in Fig. 6b are shown the losses taking into account also the utility disruption. The contribution of utility disruption to business loss of function has been computed

assuming that the mean number of utilities which lost their businesses is 2.5 and that a business has about 50% of probability of being both affected by building damage and utility disruption. The results show that for the Bay Area the sectors which have greatest losses are the Retail&Wholesale, the Residential and the Services&Government while the Mining and Agriculture experienced smaller losses. While for the Retail&Wholesale and the Services&Government sectors the great part of the loss stem from the interdependencies which affect the business interruption, for the Residential sector a significant contribute is given by the relocation expenses. The small losses of the Mining and Agriculture sectors are mainly due to the relatively small volume of business. To estimate the indirect losses, the structural growth model has been applied [8]. The proposed method starts computing the Input-Output matrix of the region of interest using the procedure explained by Chamberlain [15] from the *Make* and *Use* matrices provided by the BLS (Bureau of Labor Statistics) [16]. Since public data are available only at the national level, the San Francisco Bay Area Input-Output matrix has been derived assuming a scaling factor based on the GDP value which has been applied to the US Input-Output matrix. The final indirect losses are represented in Fig. 6c. Similar to what has been done to estimate the output losses due to building damage and utility disruption, the indirect losses have been reduced using the recapture factors provided by HAZUS to take into account for the ability of business to make up production at different times. It should be noted that the direct output losses has not been represented for the Utilities and the Transportation sector due to the unavailability of the data necessary to apply the described methodology but have been taken into account in the total loss analysis considering the data provided in HAZUS. Finally, in the specific case study, the indirect losses represent approximately 15% of the direct losses.

3.1. Sensitivity Analysis

Performing sensitivity analysis is useful to show how the total losses are influenced by the different parameters. In table 1 are reported the different analysis performed for the total direct-time dependent losses, each one distinguished by a specific assumption listed sideways.
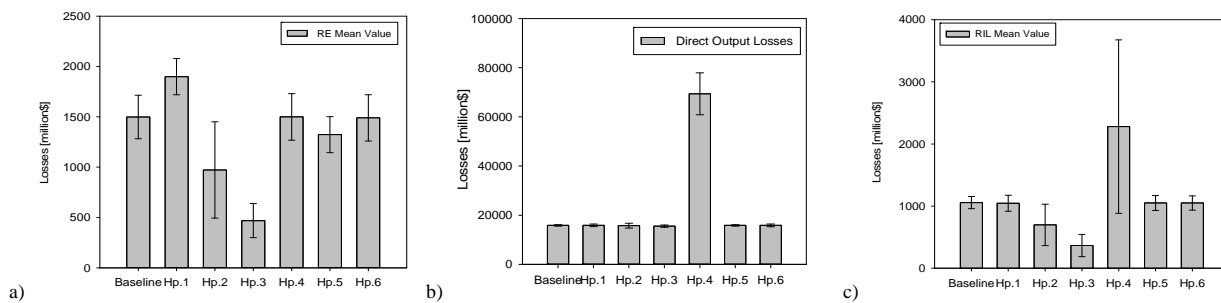

Fig. 7. Time-dependent relocation expenses (a), direct output losses (b), and rental income losses (c) for the different scenarios.
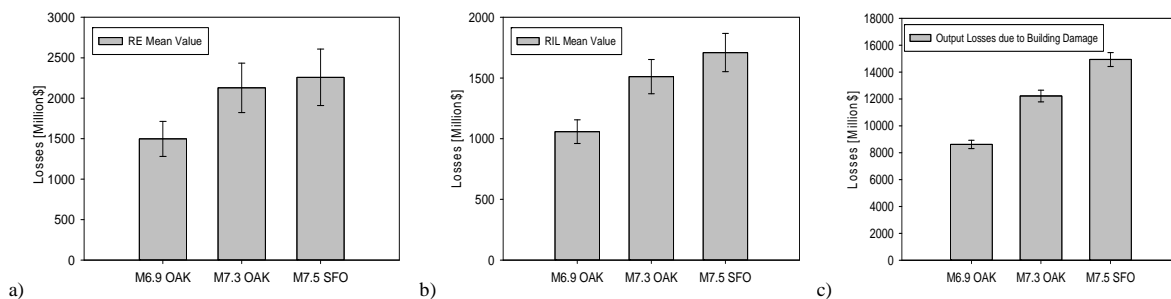

Fig. 8. Variation of the total direct time-dependent economic losses for the different assumed earthquake magnitudes.

Fig. 7b shows that the most important thing to avoid is the permanent external relocation of businesses that quadruples the loss of productivity of the sectors in the region; moreover, it does not allow the economy of the region to bounce back the pre-event levels of productivity since part of the functionality is lost forever. Indeed, the smaller losses are found assuming a high probability of vacant space within the region. Though it is difficult to reach this condition in reality, the observation can be taken as a guideline for the preventive measures implementation of the individual sectors. To show the uncertainty stemming from the unknown magnitude of the earthquake, Fig. 8 shows the differences for the case of three different earthquakes. Finally, Table 1 summarizes the outcomes of the case study in term of R_{EC} index.

Table 1. Summary of total economic losses and resilience indices for the case study.

	M6.9	M7.3	M7.5
Total Relocation Expenses (million$)	1498	2129	2258
Total Rental Income Losses (million$)	1057	1511	1709
Total Direct Output Losses (million$)	18407	29094	25267
Total Indirect Output Losses (million$)	2555	4198	2359
Total Structural/Non-Structural Losses (million$)	29388	42804	49108
R_{EC}	0.96	0.938	0.955

4. Concluding remarks

The paper proposes a new methodology to evaluate the economic losses following a natural disaster. A new probabilistic framework to estimate economic losses has been presented, where the indirect losses have been estimated using the structural growth model (SGM), while interdependencies between the different economic sectors and lifelines during disruption are modeled using *autonomy curves* defined by the authors. The sensitivity of the uncertainties in different parameters have been analyzed and a final global economic resilience index R_{EC} has been obtained which can be used in a general community resilience frameworks (e.g. PEOPLES), to estimate the effects of the economic dimension. The *autonomy curves* have been derived using the probabilities of business closure collected from business surveys and simulation conducted mainly in California so they are only representative of the case study analyzed. However, these *autonomy curves* represent the main finding of the study. In fact, as shown by the sensitivity analysis which simulates different earthquake magnitudes, the M7.5 earthquake causes less direct and indirect output losses compared to M7.3 earthquake in Oakland even if it has a higher magnitude. The justification can be found in the fact that the M7.5 earthquake in San Francisco considering the HAZUS approximation, will cause less utility losses and so the costs due to business interruption will be smaller. Further research will focus on removing the limitation of the current methodology.

Acknowledgements

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