Modeling the Multisector Business Interruption Ratio in Earthquake-Struck Regions

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Abstract: Business interruption ratio (BIR), the ratio of reduced production or service level of a business to the predisaster level when it reopens in the aftermath of a disaster event, is a significant indicator of the overall disaster-induced economic impacts. This study proposes a new analytical framework for modeling the BIR of businesses in different economic sectors in earthquake-struck regions. The proposed framework assesses and integrates the impacts of (1) the sector-specific dependence of the businesses on different operation factors, (2) the recovery of operation factors during business closure in the aftermath of earthquakes, and (3) the earthquake-induced changes in final demand for the products or services provided by the businesses. A case study in Mianzhu, China, a county greatly impacted by the 2008 Wenchuan Earthquake, was conducted. The results showed that the proposed framework reflected the impacts of the aforementioned factors on BIR and yielded promising BIR estimation accuracies. The findings are expected to advance the existing knowledge about the determinants of BIR and support the development of informed recovery strategies and measures to effectively reduce the business interruption losses in earthquake-struck regions.
DOI: 10.1061/(ASCE)ME.1943-5479.0000964.

Author keywords: Economic loss; Business interruption ratio (BIR); Production capacity; Final demand; Economic sector; Earthquake.

Introduction

Historical cases show that, in addition to direct losses such as damages of buildings and infrastructures, regions impacted by natural hazards also may suffer from enormous and prolonged indirect losses in the form of reductions in economic outputs (ECLAC 2003; Meyer et al. 2013). For example, when struck by Hurricane Katrina in 2005, the city of New Orleans experienced significant business interruption and recession, and it took 5 years for the city's gross domestic product (GDP) to recover to the predisaster level (English 2015). Similarly, when struck by the Great East Japan Earthquake and subsequent tsunami in 2011, many industries such as automobile, electronics, and materials manufacturing stopped or decreased their production due to building collapses or lifeline disruptions (Facts and Details 2013; Kajitani and Tatano 2014). Reducing indirect losses caused by natural hazards is vital to maintaining the regional economic vitality and employment environment (Wallemacq and House 2018). In this respect, it is of significant importance to assess the regional indirect losses following a disaster, to support the development and evaluation of policies and strategies to prevent or reduce possible indirect losses.

Indirect losses of a region caused by natural hazards can be divided into two categories, namely business interruption losses (BILs) and ripple losses (Standardization Administration 2011). BILs are indirect losses that can be attributed to disaster-induced direct losses, whereas ripple losses are those caused by the BILs of upstream and downstream businesses (Meyer et al. 2013). In other words, the concept of BIL focuses on the primary impact of external disruptions on the economic system, whereas the concept of ripple loss focuses on the disruption propagation within the economic system. Therefore, estimating the BIL is the first step to estimating the total indirect economic losses caused by natural hazards.

Earthquakes are among the most destructive natural hazards that can cause great indirect economic losses (Holden et al. 2007; Kajitani and Tatano 2014). Businesses in almost all economic sectors may be forced to close immediately after an earthquake and to stay closed for a certain period, the duration of which is referred to as business closure length (BCL) (Lee 2021). Afterward, the businesses may reopen for operation, usually at a reduced production or service level before gradual recovery to the pre-earthquake level over time (Li et al. 2019; Yang et al. 2016). The BIL is quantified as the integral of the reduced production or service level over the whole disaster event cycle, including the closure and recovery stages (Standardization Administration 2011). Mathematically, the business interruption ratio (BIR), which refers to the ratio of reduced production or service level of a business, compared with the predisaster level, at the time of its postearthquake reopening, is a significant indicator of the BIL (Yang et al. 2016).

Previous studies have attempted to estimate the BIR after natural disasters using different methods, including proportions of total direct losses (Hallegatte 2008, 2014), production function modeling (Koks et al. 2015; Li et al. 2019), functional fragility analyses (Kajitani and Tatano 2014; Yang et al. 2016), and operation process modeling (Cao and Lam 2019; Hofer et al. 2018). However, most of the existing methods bear three limitations: (1) they mostly assume that the BIR is equivalent to the production capacity loss ratio, but rarely pay attention to the impact of final demand, which refers to the amount of final goods and services consumed by end users, on the BIR; (2) they focus on an incomplete list of key business operation factors, and largely ignore a few other important factors, such as infrastructure services and material supplies, that impact the BIR; and (3) they do not recognize the fact that some of the operation factors may have recovered partially or fully when

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Note. This manuscript was submitted on December 30, 2020; approved on June 15, 2021; published online on September 14, 2021. Discussion period open until February 14, 2022; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Management in Engineering***, © ASCE, ISSN 0742-597X.

the businesses reopen, and consequently they tend to underestimate the amount of these operation factors and therefore overestimate the BIR. Due to the aforementioned limitations, the BIR could be misestimated greatly, preventing reliable information that is critical for assessing the overall disaster-induced losses and making disaster risk reduction–related decisions.

To address the aforementioned limitations and provide a more reliable method for estimating the BIR, this study proposes an analytical framework for modeling quantitatively the BIR of individual businesses in multiple economic sectors in earthquake-struck regions. This framework takes into consideration the earthquake-induced changes of both production capacity and final demand. It identifies the impact paths from various direct losses to production capacity and final demand for each sector, and establishes quantitative functions of these impact paths. To implement and test the framework, a case study was conducted. The case study investigated the BIR of manufacturing and retailing businesses in Mianzhu, a county in Sichuan, China, after the 2008 Wenchuan earthquake. The results of the case study showed that the proposed framework can demonstrate the impact of sector-specific dependence of the businesses on different operation factors, integrate the final demand into BIR estimation, and reflect the impact of the recovery of operation factors during the business closure on the BIR estimation. The findings are expected to advance the existing knowledge about the determinants of BIR, and support the development of informed recovery strategies and measures to effectively reduce the BIL in earthquake-struck regions.

Literature Review

Related Work

Previous studies have proposed a few methods to model the BIR after natural disasters. These methods can be divided into four categories, which are based respectively on a share of direct losses, production function modeling, functional fragility analyses, and operation process modeling. All these methods are reviewed in detail.

Methods Based on Share of Direct Losses

Because BIR is caused by direct losses (Meyer et al. 2013), a few studies estimated the BIR as a share of direct losses. For example, when studying the economic impact of Hurricane Katrina in Louisiana, Hallegatte (2008) first assumed that the BIR of each sector was equivalent to the associated direct loss ratio, and then estimated the BIL based on the statistics data of direct losses. Taking into consideration the differences of economic sectors, Hallegatte (2014) extended the aforementioned method in a follow-up study by arguing that the BIR of each sector was linear to its respective direct losses. Similar methods that estimated the BIR based on a share of direct losses were applied to model the BIR after floods (Ranger et al. 2011), storm surges (Hallegatte et al. 2011; Ujeyl and Rose 2015), and earthquakes (Wu et al. 2012; Zhang et al. 2017). The aforementioned studies were supported by empirical findings (Kreibich et al. 2010) which showed that, in principle, the estimation results of those methods were accurate on the order of magnitude.

Methods Based on Production Function Modeling

A few studies attempted to estimate the BIR by considering the specific effects of different operation factors on the production process. Those studies assumed that the relationship between postdisaster business output and the amount of operation factors follows the production function (Li et al. 2019). The Cobb–Douglas production function is the most widely used form of production function to model the BIR caused by capital losses and workforce shortage under earthquakes (Hallegatte et al. 2007) and floods (Koks et al. 2015). The parameters of the Cobb–Douglas production function in those studies were estimated at the sector level, based on historical annual statistic data collected under normal conditions. To improve the granularity of this method, Li et al. (2019) collected firm-level data and reconstructed the Cobb–Douglas production function based on a postdisaster survey, and used the function to estimate the BIR of individual manufacturing firms affected by floods in Shanghai. The different effects of capital losses and workforce shortages on BIR, measured by the aforementioned production function–based methods, can be used to guide the prioritization of postdisaster recovery of different damaged operation factors.

Methods Based on Functional Fragility Analyses

To avoid delays of BIR estimation caused by the absence of data about direct losses in the immediate aftermath of disasters, previous studies have proposed methods to develop quantitative relationship directly between hazard severity and the BIR. For example, Kajitani and Tatano (2014) constructed a fragility curve between the BIR under earthquakes and the peak ground accelerations by conducting a survey among individual firms that suffered from the 2011 Great East Japan Earthquake. The fragility curve categorized the BIR into five levels, and the probability of BIR exceeding each level under a specific peak ground acceleration could be estimated. Motivated by the aforementioned method, similar fragility curves were constructed between the BIR and the water depth of floods (Jiang et al. 2016; Yang et al. 2016). Sultana et al. (2018) applied the random forests method to construct a hazard-loss function that took into account other impact factors such as firm size, economic sector, and emergency plan in the BIR estimation of the 2013 German flood. The results of the aforementioned studies showed that the estimation accuracies generally were satisfactory when the businesses suffered slight damage; however, when the damages were severe, the models tended to underestimate the BIR of the businesses (Sultana et al. 2018; Yang et al. 2016).

Methods Based on Operation Process Modeling

If the operation process of a business can be modeled mathematically, the production or service level in the aftermath of a disaster event can be predicted using simulation (Hofer et al. 2018). One such method was proposed by Zhang and Lam (2015, 2016), who modeled the supply chain flow network between a port and industry firms, and used this model to predict the BIR suffered by different stakeholders due to port disruption. Similarly, Cao and Lam (2019) modeled the loading and unloading container terminal operation, and predicted the BIR caused by a decrease of the amount of loading and unloading due to severe weather conditions. Hofer et al. (2018) constructed a flow network of components of a cheese factory and predicted the BIR caused by component damage based on the production process simulation. Li et al. (2020) proposed a system dynamics modeling–based method for estimating the postearthquake BIR of hospitals by considering the changes of operation factors including buildings, equipment, infrastructure services, supplies, and medical staff.

Knowledge Gap Analysis

Prior studies have made notable progress in estimating the BIR of businesses caused by disasters. However, the existing BIR estimation methods have three major limitations that remain to be addressed, which may lead to the misestimation of the BIR (Table 1). First, the existing methods mostly focus on the production capacity,

Table 1. Summary of existing BIR estimation methods

Category of method	References	Integrates demand	Operation factors considered	Method for differentiating economic sectors	Considers business closure
Share of direct losses	Hallegatte (2008)	No	B, E	Not differentiated	No
	Hallegatte (2014)	No	B, E	Multiply different coefficients	No
	Hallegatte et al. (2011); Ranger et al. (2011); Ujeyl and Rose (2015); Wu et al. (2012); Zhang et al. (2017)	No	B, E	Multiply different coefficients	No
Production function modeling	Hallegatte et al. (2007)	No	B, E, W	Not differentiated	No
	Koks et al. (2015)	No	B, E, W	Consider single sector only	No
	Li et al. (2019)	No	B, E, W	Consider single sector only	No
Functional fragility analyses	Kajitani and Tatano (2014)	No	—	Model different sectors separately	No
	Jiang et al. (2016); Yang et al. (2016)	No	—	Model different sectors separately	No
	Sultana et al. (2018)	No	—	Model different sectors separately	No
Operation process modeling	Hofer et al. (2018)	No	B, E	Consider single sector only	No
	Cao and Lam (2019); Zhang and Lam (2015, 2016)	No	I, S	Consider single sector only	No
	Li et al. (2020)	Yes	B, E, I, S, W	Consider single sector only	No

Note: L = land; B = building; E = equipment; I = infrastructure service; S = supplies; and W = workforce.

and do not consider the impact of final demand. Historical disaster events indicated that the final demand for certain goods or services may change after disasters (Choi et al. 2019; Lee et al. 2020). In turn, associated businesses could have less revenue, even if their production capacity does not change (Corey and Deitch 2011), and in some cases, revenues may even exceed the predisaster level due to temporary surges of final demand (Mianzhu Statistics Bureau 2012). The second limitation of the existing methods is that none of the existing methods fully considers all key operation factors, including land, buildings, equipment, infrastructure services, materials supplies, and workforce. Moreover, they assume that all business sectors are impacted by the same operation factors, and do not recognize the sector-specific dependence of businesses on different operation factors. As a result, their BIR estimations provide limited insight into the influence and criticality of each operation factor, which is crucial for developing measures for BIL mitigation (Yang et al. 2016) and prioritizing them given limited resources during the postdisaster recovery period (Ghannad et al. 2020). Third, all existing methods assume that the impacted businesses continue to operate immediately after the disaster. They ignore the fact that businesses impacted by disasters usually are forced to close for a period, and their operation factors may have recovered partially or fully when they reopen. As a result, the amount of these operation factors may be underestimated, which in turn leads to underestimation of the postdisaster production capacity and overestimation of the BIR.

Proposed Framework

To address the aforementioned knowledge gap and improve the estimation of BIR, this study proposes an analytical framework for modeling the BIR of individual businesses in earthquake-struck regions. Fig. 1 illustrates the proposed framework. According to the business economics theory (Moschandreas 2000), the production or service level of a business is determined by both its production capacity and the demand for its products or services. Accordingly, the proposed framework considers the impacts of both production capacity changes and demand changes on the BIR. Moreover, it identifies all operation factors that are subject to disaster-induced damages, including land, buildings, equipment, infrastructure services, raw materials or goods supplies, and workforce, and models their impacts on the BIR. When quantifying the amounts of these operation factors, the proposed framework considers all possible sources, including undamaged and restored operation factors as well as their substitutions.

Demand for a specific product or service can be divided into final demand and derived demand, which refer to the consumption demand from end users and from downstream sectors, respectively (Mankiw 2003). Only final demand is considered in the proposed framework, because, according to the definition of indirect losses, the derived demand impacts the ripple losses rather than the BIL (Meyer et al. 2013). Thus, the proposed framework assumes that the BIR of a business is determined by the maximum of its production capacity loss ratio and final demand loss ratio after an earthquake

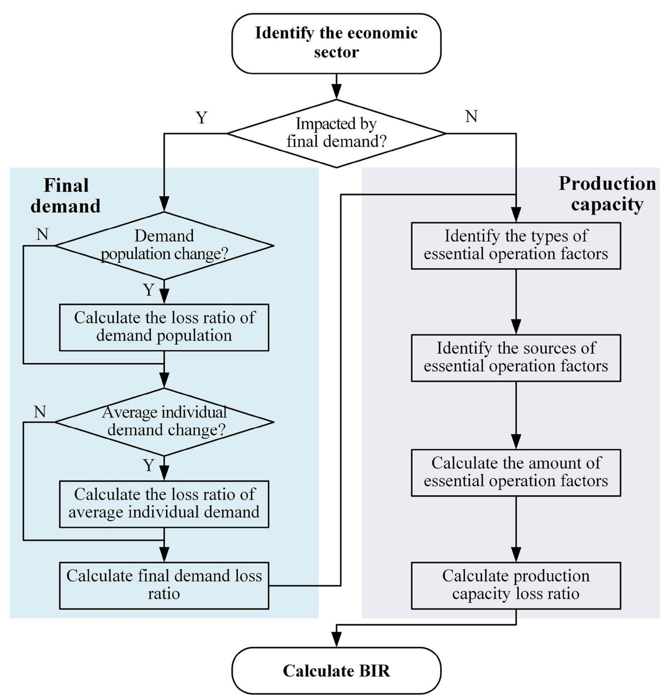

Fig. 1. Proposed framework for estimating BIR of a business after an earthquake.

$$\mathrm{BIR} = \max(LR_{pc}, LR_{fd}) \tag{1}$$

where LR_{pc} and LR_{fd} = loss ratio of production capacity of a business and loss ratio of final demand for its product or service, respectively. Both loss ratios can have negative values, which indicates that the production capacity or final demand increases after the earthquake. The estimation of LR_{pc} and LR_{fd} is explained in detail in the remainder of this section.

Production Capacity

According to the production theory (Mankiw 2003), the production capacity of a business or sector is determined by the quantity of its operation factors, including land, buildings, equipment, infrastructure services, raw material and goods supply, and workforce. All the aforementioned operation factors are subject to disaster-induced damages (Meyer et al. 2013), which may result in production capacity losses (Hallegatte 2014; Li et al. 2019). Because businesses in different economic sectors rely on different sets of operation factors (Mao et al. 2020), the essential operation factors—i.e., those that are essential to the production process—of any business should be identified based on the economic sector to which it belongs. Because production function is used widely to model the effects of various operation factors on production capacity (Dormady et al. 2019; Mankiw 2003), the proposed framework integrates the production function to establish the quantitative relationship between the postdisaster production capacity of a business and the amount of its essential operation factors. Specifically, the production capacity loss ratio when the business reopens can be estimated using

$$LR_{pc} = \frac{PC_0 - PC(\mathrm{EOF}_i)}{PC_0}, \quad \mathrm{EOF}_i \subseteq \{L, B, E, I, S, W\} \tag{2}$$

where EOF_i = group of essential operation factors of sector i; L, B, E, I, S, and W = amount of land, buildings, equipment, infrastructure services, raw material or goods supplies, and workforce of the business when it reopens, respectively; $PC(\mathrm{EOF}_i)$ = production function of EOF_i; and PC_0 = predisaster production capacity of the business.

The proposed framework assumes that the production function of a business should be the same under pre- and postearthquake scenarios, because its technology and management levels, which are regarded as the main determinants of the production function form (Mankiw 2003; Moschandreas 2000), are not changed evidently by disaster events (Li et al. 2019). Thus, the production function of individual businesses can be established by conducting nonlinear regression over specific function forms using data collected under disaster-free scenarios (e.g., during the normal operation of the businesses). Common production function forms include the Leontief production function, Cobb–Douglas production function, and translog production function (Dormady et al. 2019). The most appropriate form of production function can be determined based on a literature review, the goodness-of-fit test or errors of different forms. Then the selected production function form can be used to estimate the production capacity of the business under disaster scenarios. To estimate the production capacity based on Eq. (2), the approaches for quantifying the amount of different operation factors are explained in detail as follows.

Land

Businesses in agriculture, property development, construction, and so on require land for operation. Land may suffer cracking or be buried due to ground motion, landslide, and debris flow during an earthquake and lose its function. Functional land owned by a business comprises land that survives the earthquake and remains functional, and land that is restored from damage during the business closure. Both sources of functional land can be used for postearthquake business operation. Thus, the amount of functional land when the business reopens, which can be measured in land acreage, can be calculated using

$$L = L_r + L_d \tag{3}$$

where L_r = amount of land that survives the earthquake and remains functional; and L_d = amount of land that is damaged initially and has been restored by the time the business reopens.

Buildings and Equipment

Buildings and equipment owned by a business may be damaged and partially or fully lose their functions during an earthquake. Functional buildings and equipment owned by a business comprise those that survive the earthquake and remain functional, those that are damaged initially and are restored during the business closure, and temporarily constructed buildings and newly purchased equipment (Felix et al. 2015). All three sources of functional buildings and equipment can be used for postearthquake business operation. Thus, the number of functional buildings and equipment when the business reopens, which can be measured in floor area and monetary value, respectively, can be calculated based on Eqs. (4) and (5), respectively

$$B = B_r + B_d + B_t \tag{4}$$

$$E = E_r + E_d + E_n \tag{5}$$

where B_r and E_r = number of buildings and amount of equipment, respectively, that survive the earthquake and remain functional; B_d and E_d = number of buildings and amount of equipment, respectively, that are damaged initially and have been restored when the business reopens; B_t = number of temporary buildings that have been constructed in the aftermath of the earthquake when the business reopens; and E_n = amount of new equipment that has been purchased and come into use when the business reopens.

Infrastructure Service

Businesses in different sectors require different essential infrastructure services, including electric power, water, gas, sewerage, transportation, and communication, for operation (Tierney and Nigg 1995). This sector-specific dependence of businesses on the infrastructure services should be identified to implement the proposed framework. Infrastructure services consumed by a business after an earthquake can be provided by public infrastructure service providers (e.g., utility companies) or contingency alternative resources owned by the business (e.g., using electric generators to provide temporary power supplies). Both sources of infrastructure services can be used for postearthquake business operation. Thus, the amount of essential infrastructure services when the business reopens, which can be measured in monetary expenditure (Iimi 2011), can be calculated based on

$$I = \sum_{i=1}^{n} (I_p^i + I_c^i) \tag{6}$$

where I_p^i and I_c^i = amount of ith type of infrastructure service provided by public infrastructure service provider and contingency alternatives, respectively; and n = types of different infrastructure services required by the business.

Raw Materials and Goods Supplies

Raw materials and goods supplies are required for most business activities. For example, manufacturing businesses require raw materials for production, and retailing businesses require supplies of goods for sale. The amounts of raw materials and goods supplies can be quantified based on the monetary expenditure on various types of raw materials and goods

$$S = \sum_{i=1}^{m} S_i \tag{7}$$

where S_i = monetary expenditure on ith type of raw materials or goods; and m = types of raw materials and goods used by the business.

Workforce

Business operation requires workforce to conduct various working tasks. After an earthquake, employees may be prevented from going to work due to casualties, home-related losses, or inability to travel to the workplace (Brown et al. 2015; Sydnor et al. 2017). The business may employ new workers in place of those who are absent from work. Thus, the amount of the workforce when the business reopens, which can be measured in total working hours, can be calculated based on

$$W = W_0 - W_l + W_n \tag{8}$$

where W_0, W_l, and W_n = total working hours before the earthquake, losses of total working hours due to inability of going to work when the business reopens, and the increase of total working hours due to new employees, respectively.

Final Demand

Earthquakes can impact the final demand for products or services in earthquake-struck regions, particularly for businesses in the tertiary industry with outputs consumed directly by end users. Changes in the final demand can, in turn, impact the BIR of those businesses (Chang et al. 2012b). According to the demand theory in economics (Mankiw 2003), for any given product or service, its final demand is the product of demand population and average demand of individual consumers. Thus, the loss ratio of postdisaster final demand can be calculated based on

$$LR_{fd} = 1 - (1 - LR_{id}) \times (1 - LR_{dp}) \tag{9}$$

where LR_{id} = loss ratio of postdisaster average individual demand for a certain product or service; and LR_{dp} = loss ratio of postdisaster demand population. Both loss ratios can have negative values, which indicates that the average individual demand or demand population increases after the earthquake. The concepts of demand population and average individual demand, and how they are calculated in the proposed framework, are explained in the following sections.

Demand Population

The demand population of a specific product or service refers to the number of people who demand it (Mankiw 2003). For a given specific product or service, the first step in determining its demand population is to identify the characteristics of people who demand it based on a literature review or interviews with relevant business owners. Because the demand population can increase or decrease after an earthquake for various reasons, including casualties, emigration, and immigration (Tierney 1997), the second step is to identify the possible causes of demand population changes based on analysis of historical disaster events. The instantaneous increase or decrease of demand population after an earthquake, such as deaths and injuries, can be estimated based on a postdisaster field survey, which usually is conducted by the local government (ECLAC 2003; World Bank 2013). In addition, previous studies (Corey and Deitch 2011; Wasileski et al. 2011) found that the gradual change of demand population, such as that resulting from emigration and immigration, can be related to various factors such as casualties and property losses, and proposed to establish the quantitative relationship between these factors by conducting regression models with data from historical disaster events. Based on the aforementioned data sources, the loss ratio of demand population when the business reopens after an earthquake can be estimated according to

$$LR_{dp} = \frac{DP_l}{DP_0} \tag{10}$$

where DP_0 and DP_l = original demand population before earthquake and loss of demand population, respectively.

Average Individual Demand

In addition to possible changes in the demand population, the individual demand also can change after an earthquake (Felix et al. 2015; Stevenson et al. 2014). It is important to identify the possible impact factors of the individual demand change according to the type of product or service based on a literature review or analysis of historical disaster events. The quantitative relationship between individual demand change (including ratio and time) and its impact factors, as indicated by previous studies or analysis of local historical disaster events, can be applied in the estimation of individual demand change. Because it usually is impossible to survey the demand of all individuals in a region, stratified sampling based on the individuals' residential district and level of income usually is conducted to calculate the average individual demand (Chang et al. 2012b). Thus, at any given time after the earthquake, the loss ratio of average individual demand in the region can be calculated based on the average of the samples of estimated individual demands [Eq. (11)]. Then the loss ratio of average individual demand for a certain product or service provided by a business when it reopens can be calculated based on Eq. (12)

$$D(t) = 1 - \frac{\sum_{i=1}^{n} D_i(t)}{\sum_{i=1}^{n} D_i(0)} \tag{11}$$

$$LR_{id} = D(\mathrm{BCL}) \tag{12}$$

where $D_i(0)$ and $D_i(t)$ = demand of ith individual in samples for a certain product or service provided by a business before the earthquake and at time t after an earthquake, respectively; $D(t)$ = loss ratio of average individual demand in the region at time t; and BCL = business closure length of the business.

Case Study

Basic Information

A case study was conducted in the county of Mianzhu to implement and test the proposed framework. Mianzhu, located at the northwest of Sichuan Basin in China, was among the most-impacted counties during the Wenchuan earthquake, with direct losses exceeding CNY 140 billion (approximately USD 20 billion), which was more than 10 times its GDP of the previous year (The People's Government of Mianzhu County 2009). The annual GDP of Mianzhu decreased by about 30% in 2008, and did not recover to the pre-earthquake level for 3 years (Mianzhu Statistics Bureau 2012). The case study investigated the business interruptions of manufacturing and retailing sectors after the earthquake, which were the largest sectors in the secondary industry and the tertiary industry in Mianzhu, respectively. As of 2007, the manufacturing sector contributed half of the county's GDP, and the retailing sector contributed over 70% of total sales from the wholesale, retailing, catering, and lodging sectors (Mianzhu Statistics Bureau 2008). Both sectors were hit badly by the Wenchuan earthquake.

Data Collection

Two surveys (included in the Supplemental Materials) were developed in the case study, and were used to investigate the impacts of the earthquake on the operation of local businesses and the final demand of households on retailing goods. The business survey included seven parts organized in the following order: (1) questions about business characteristics, including sector, age, monthly production or sales, number of employees, and asset quantity; (2) questions about the number of damaged buildings (measured in square meters), and the time it took to restore the damaged buildings or construct temporary buildings; (3) questions about amount of damaged equipment (measured in monetary depreciated value at the time of the earthquake), and the time it took to restore the damaged equipment or purchase new equipment; (4) questions about the expenditure of each essential infrastructure service (including electric power, water supply, telecommunication, natural gas, and transportation), the downtimes of public services, and related contingency alternatives; (5) questions about expenditures related to raw materials or goods supplies before and after the earthquake; (6) questions about employee changes and average daily individual working hours after the earthquake; and (7) questions about monthly production or sales when the business reopened, compared with the pre-earthquake level. The survey was modified slightly for separate use in the manufacturing and retailing sectors by adjusting a few terms that were sector-specific, such as production and factory in the manufacturing survey, versus sales and store in the retailing survey. Respondents were asked to refer to their detailed records, if available, to answer the questions.

The household survey included five parts organized in the following order: (1) questions about household characteristics, including respondent working sector, respondent age, family member, and housing area; (2) questions about house damage and the time taken to restore or rebuild the damaged house; (3) questions about the number of other property losses (measured in monetary value); (4) questions about disruption of transportation for goods purchase; and (5) questions on about pre-earthquake monthly total consumer spending and its breakdown in terms of different types of goods.

Both surveys went through several rounds of revision, during which input and feedback from local official statisticians were collected and incorporated. Then a pilot test of the business and household surveys was conducted to improve the design of the surveys. To cover respondents with diverse characteristics, and based on the suggestions of local official statisticians, two manufacturing businesses and four retailing businesses from different subsectors and five households with main members who worked in different sectors were selected for the pilot surveys. The full-scale business survey of the manufacturing sector was conducted between October 31, 2019 and January 8, 2020. Through the Bureau of Economy and Information Technology of Mianzhu, an electronic version of the survey was sent to all manufacturing businesses in Mianzhu that were above a designated size (annual revenue over CNY 5 million, or approximately USD 684,000) as of 2007 and had experienced the Wenchuan earthquake. Smaller businesses were not investigated, because they accounted for less than 10% of the total production value of the manufacturing sector in Mianzhu, and most of them had closed or changed ownership since 2008. The business survey of the retailing sector and the household survey were conducted between October 24 and November 6, 2019, and were filled in by official statisticians of the Commerce Bureau of Mianzhu during face-to-face interviews with owners of retailing businesses and households that experienced the Wenchuan earthquake. To improve the reliability of the responses, only businesses with ownership that had not changed since 2008 and with representatives who responded to the survey were owners or senior managers in 2008 were surveyed in the case study.

The survey included all businesses above the designated size in several subsectors. For these subsectors, the production or sales reported by the businesses were compared with the production or sales recorded in local official statistics records to ensure there was no significant discrepancy. By the end of the surveys, a total of 33 responses were collected from manufacturing businesses, among which 3 responses were found to be invalid. These respondents were sampled from a total of 67 manufacturing businesses above the designated size in Mianzhu that survived Wenchuan earthquake and were still operating at the time of the survey. A total of 194 valid responses were collected from retailing businesses, which covered all 21 administrative towns in Mianzhu. A total of 359 valid responses were collected from households, which covered all 21 administrative towns.

Error Metrics

The actual BIR of each business when it reopened was calculated based on the respondents' answers to three questions in the survey, including "How much was the average monthly production/sales before the earthquake?", "How much was the monthly production/sales when the business reopened?", and "What was the percentage of the monthly production/sales compared with the pre-earthquake level?". The third question was a redundant question, which was designed to allow the authors to verify whether the answers to the three questions by the same respondent were inherently consistent. Two commonly used error metrics were used to measure the alignment of the BIR estimated by the proposed framework with the BIR that the businesses actually experienced: the root mean square error (RMSE) (Chai and Draxler 2014) and the median absolute error (MdAE) (Hyndman and Koehler 2006)

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (E_i - O_i)^2}{n}} \tag{13}$$

$$\mathrm{MdAE} = \mathrm{median}(|E_i - O_i|) \tag{14}$$

where E_i and O_i = estimated and actual BIR of ith business respondent, respectively; and n = total number of business respondents. RMSE assigns more weight to larger absolute errors, making it more sensitive to outliers. Therefore, both metrics can indicate the overall estimation accuracy, and comparison of the two metrics can indicate whether the estimation accuracy is affected by outliers.

Additional sensitivity analysis was conducted in this study to test the impact of possible noise involved in the collected survey data regarding the amounts of operation factors and final demand. By increasing and decreasing the amounts of all operation factors and final demand by 5% and 10% respectively, the estimation errors, measured by RMSE and MdAE, were calculated.

Results

Overview of Survey Responses

The business survey respondents covered 12 manufacturing subsectors and 8 retailing subsectors, out of 19 manufacturing subsectors and 9 retailing subsectors that existed in Mianzhu (Table 2). The subsectors were classified according to the Chinese Standard Industrial Classification GB/T 4754-2017 (Standardization Adiministration 2017). Two manufacturing subsectors with the most respondents were beverage and chemical feedstock manufacturing, because Mianzhu is famous in the country for its liquor and phosphorite production. Among the 194 retailing business respondents, 135 sold necessities, mainly food, beverages, and tobacco; 66 sold nonnecessities; and 7 sold both.

Basic business characteristics of all business survey respondents are summarized in Table 3. Respondents from the manufacturing and retailing sectors had a similar distribution of business age. Manufacturing businesses generally had more employees, larger building areas, and higher outputs than retailing businesses. Most retailing businesses were owned and operated by one or two individuals.

Table 2. Statistics of respondents

Sector	Subsector	Number of respondents
Manufacturing	Beverage manufacturing	9
	Chemical feedstock and chemical manufacturing	5
	General-purpose equipment manufacturing	3
	Manufacturing of agricultural and nonstaple foodstuffs	2
	Foodstuffs manufacturing	2
	Nonmetallic mineral products	2
	Electric machinery and equipment manufacturing	2
	Chemical fiber manufacturing	1
	Automotive manufacturing	1
	Manufacturing of textile costumes, shoes, and caps	1
	Wood processing and manufacturing	1
	Printing and reproduction of record media	1
Retailing	Food, beverages, and tobacco	89
	Textiles, clothing, and household goods	31
	Products of agriculture, forestry, animal husbandry, and fishery	15
	Hardware and building materials	29
	Household appliances and furniture	17
	Medicine and medical equipment	7
	Stationery, sporting goods, and electronic products	7
	Automobiles, motorcycles, and bicycles	6

Implementation of Proposed Framework

Manufacturing Sector

According to the definitions of derived demand and final demand (Mankiw 2003), manufacturing businesses have derived demand from downstream sectors and are not subject to the impact of final demand. Therefore, to estimate their postearthquake BIR, only their production capacity was considered.

Based on a review of relevant literature (Koks et al. 2015; Li et al. 2019; Mankiw 2003), the production capacity of manufacturing businesses is determined mainly by the amount of buildings, equipment and workforce. Therefore, in the case study, the BIR of a manufacturing business at the time of its postearthquake reopening was estimated based on the number s of functional buildings and amounts of functional equipment, and the total working hours, as shown in Eq. (15), which is a transformation of Eqs. (1) and (2)

$$\mathrm{BIR} = \frac{PC_0 - PC(B, E, W)}{PC_0} \tag{15}$$

With respect to the production capacity, different production function forms were tested for implementing Eq. (15), including the Leontief production function, the Cobb–Douglas production function, and the translog production function. The errors of the BIR estimation, measured with RMSE and MdAE, were calculated (Table 4).

The results indicated that the error metrics, measured by RMSE and MdAE, of the Cobb–Douglas production function were notably smaller than those of the other two production function forms. This indicated that the Cobb–Douglas production function was the most applicable form of production function in the case study

$$PC = 0.048 \times B^{0.410} \times E^{0.473} \times L^{0.117} \tag{16}$$

where PC = production capacity of manufacturing business when it reopens.

Fig. 2 shows the estimated BIR of all manufacturing businesses and their actual BIR found in the survey.

Retailing Sector

Because everyone consumes retail goods in one way or another in daily life, the demand population of retailing businesses was considered to comprise the entire population in Mianzhu in the case study. Changes in the demand population of retailing businesses

Table 4. BIR estimation errors based on different production functions

Error metric	Production function: Leontief	Cobb–Douglas	Translog
RMSE	0.229	0.149	0.216
MdAE	0.135	0.105	0.158

Table 3. Business characteristics of respondents (mean)

Economic sector	Business age (years)	Employees[a]	Building area (m^2)	Monthly production/sales (thousand CNY)[b]
Manufacturing	21.39 (7.47)[c]	72.16 (82.05)	5,936 (6,258)	2,396 (2,837)
Retailing	19.32 (6.27)	1.95 (0.74)	136.95 (123.06)	3.87 (7.17)

[a]All operating staff including owners are included in number of employees.
[b]Exchange rate was approximately 6.94 CNY/USD in 2008.
[c]Numbers within parentheses are standard deviations.

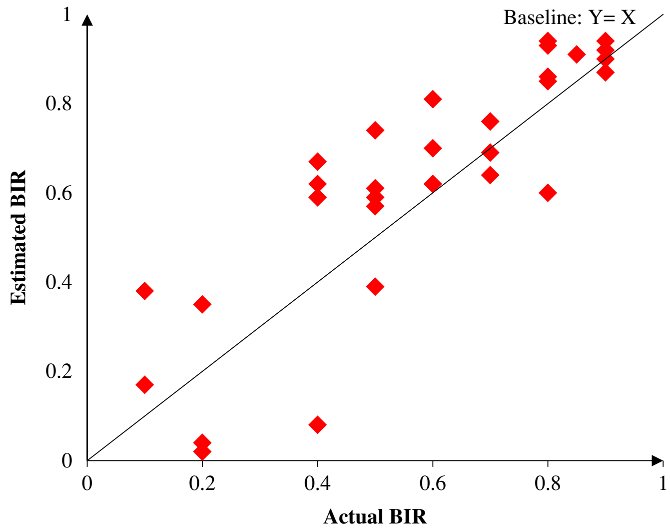

Fig. 2. Comparison of the actual BIR and estimated BIR of all manufacturing businesses.

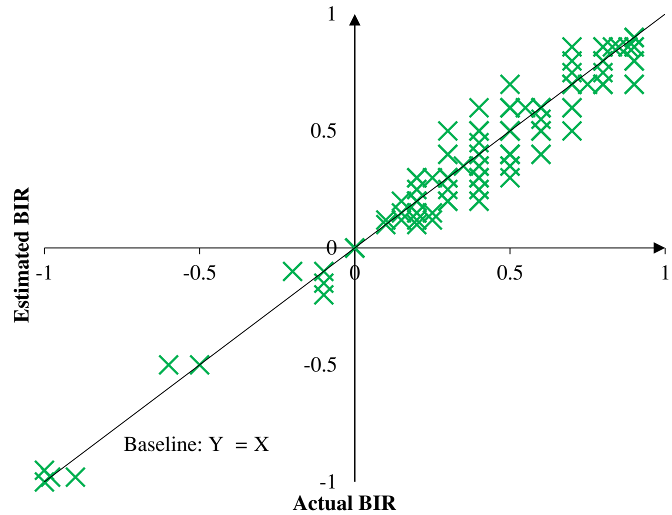

Fig. 3. Comparison of the actual BIR and estimated BIR of all retailing businesses.

could be caused by deaths, emigration, and immigration. Based on the records from local authorities (The People's Government of Mianzhu County 2009), deaths caused by the earthquake accounted for nearly 2% of the entire population, and there was little emigration when businesses reopened in the case region. Immigration included emergency response teams, volunteers, and construction workers of aid projects. Based on the records from local authorities (The People's Government of Mianzhu County 2009), emergency response teams and volunteers deployed to the county accounted for less than 1% of the entire local population. In addition, most aid projects had not started, and few construction workers had been dispatched from outside the county by the time the local retailing businesses reopened. Based on the aforementioned analysis, it could be concluded that there was little change in the demand population. On the other hand, based on the survey responses of local households, the loss ratio of individual demand in the case study was calculated based on Eqs. (11) and (12). It was found that the individual demand for necessities after the earthquake only temporarily increased due to losses of necessity inventory for a short time in the immediate aftermath of the earthquake, after which the demand quickly returned to its normal level, whereas the individual demand for nonnecessities varied significantly after the earthquake.

According to prior studies (Lee 2019; Sydnor et al. 2017), the production capacity of retailing businesses after the earthquake was determined mainly by the amount of goods supplies. The BIR of a retailing business can be estimated based on the amount of goods supplies and loss ratio of average individual demand, as shown in Eq. (17), which is a transformation of Eqs. (1), (2), (7), (9), and (12)

$$\mathrm{BIR} = \max\left(1 - \frac{PC(S)}{PC_0}, D(\mathrm{BCL})\right) \tag{17}$$

There were two steps to implementing Eq. (17). In the first step, based on the data of actual BIR and individual demand collected in the surveys, respondents with actual BIRs larger than the loss ratio of average individual demand were selected. The BIRs of the selected respondents were equal to the loss ratio of production capacity caused by the amount change of goods supplies [Eq. (17)]. In the second step, different production function forms were tested to implement the production function $PC(S)$ based on the actual BIR and the amount of goods supplies of the selected respondents. The regression result indicated that the Cobb–Douglas production function was the most applicable form, and that the production capacities of retailing businesses were approximately equal to 1.2 times the amount of goods supplies.

Fig. 3 shows the estimated BIRs of all retailing businesses and their actual BIRs. Negative values indicate that the postearthquake production or service level was higher than pre-earthquake level. The errors of the BIR estimation, measured with RMSE and MdAE, were 0.087 and 0.050, respectively.

Sensitivity Analysis

Table 5 lists the estimation errors when the amounts of operation factors and final demand were increased or decreased by 5% or 10%. For manufacturing businesses, the RMSE varied within 0.023 (4.0%) when the amounts varied. The MdAE varied within 0.045 (7.8%). For retailing businesses, the RMSE increased by as much as 0.021 (3.5%), whereas the MdAE increased by as much as 0.02 (3.3%).

Discussions and Conclusions

This study proposes an analytical framework to model the postearthquake BIR of businesses in multiple sectors in earthquake-struck regions. The proposed framework integrates the impacts of both the production capacity and final demand. It identifies the impact paths of various direct losses on production capacity and final demand for each sector and establishes quantitative functions of these impact paths. A case study was conducted in Mianzhu, a Chinese county that was struck by the 2008 Wenchuan earthquake, to test the proposed framework. This section discusses the performance of the proposed framework, its practical implications, the limitations of this study, and recommended directions for future research.

Performance of Proposed Framework

The case study results showed that the proposed framework can estimate the BIR estimation of businesses with promising accuracy. As a comparison, this study also estimated the BIR of manufacturing businesses using the methods proposed by Zhang et al. (2017) and Li et al. (2019). These two methods reflect the latest progress in

Table 5. BIR estimation errors under variations of operation factors and final demand

Economic sector	Error metric	Variation				
		−10%	−5%	0	5%	10%
Manufacturing	RMSE	0.132 (23.0%)	0.137 (23.8%)	0.149 (26.0%)	0.168 (29.2%)	0.191 (33.2%)
	MdAE	0.085 (14.7%)	0.082 (14.2%)	0.105 (18.3%)	0.127 (22.2%)	0.150 (26.1%)
Retailing	RMSE	0.106 (17.8%)	0.093 (15.6%)	0.085 (14.3%)	0.085 (14.3%)	0.093 (15.6%)
	MdAE	0.070 (11.7%)	0.063 (10.5%)	0.050 (8.4%)	0.055 (9.2%)	0.060 (10.0%)

Note: numbers in parentheses are percentages of average actual BIR.

BIR estimation based on a share of direct losses and production function modeling, respectively. Methods based on functional fragility analyses and operation process modeling were not compared because those methods either required extra data that were not available or were applicable only to certain sectors that were beyond the scope of the case study. The results showed that the estimation errors using the aforementioned two methods, measured by RMSE, were 63% and 39% larger, respectively, than those achieved using the proposed framework. The associated MdAE values were 57% and 28% larger, respectively. The relatively higher accuracy achieved in this study was attributed mainly to the proper consideration of the recovery of operation factors during business closure, which is ignored in all existing BIR estimation methods and leads to underestimation of the amount of operation factors and the consequent overestimation of the BIR. For the retailing businesses, the estimation error measured with RMSE was within 15% of the average actual BIR, and the associated MdAE value was within 10% of the average actual BIR. This indicated that the estimated BIR values for the retailing businesses were reasonably accurate (Chai and Draxler 2014; Hyndman and Koehler 2006). Moreover, the results of sensitivity analysis showed that the BIR estimation results were not significantly sensitive to noise in values of the input variables, suggesting that the performance of the proposed framework would not be impacted notably, even if the amounts of operation factors and final demand were not quantified highly accurately.

The results of the case study also indicated that the framework can reflect the significant role of the economic sector, a major factor considered in the proposed framework, in determining the BIR of the businesses. The impact of the economic sector revealed in this study is twofold. First, the BIRs of businesses in the service industry are impacted directly by changes of local final demand, whereas businesses in upstream sectors such as the manufacturing sector are not. This distinction between different sectors was observed not only in the case study but also in various historical disaster events (Corey and Deitch 2011; Sultana et al. 2018). Secondly, the sets of essential operation factors needed for business operations and their impacts on the BIR vary significantly between different sectors. The case study results showed that the production capacity of retailing businesses was impacted mainly by goods supplies, which was not recognized in previous studies (Ranger et al. 2011; Xie et al. 2014), whereas the reduction of production capacity of manufacturing businesses was caused mainly by losses of buildings, equipment, and workforce.

Moreover, the results of the case study demonstrated the significance of final demand in the BIR estimation. In the case study, driven by the reconstruction activities of damaged dwellings, office buildings, and infrastructure, final demand for hardware and building materials and for household appliances and furniture increased notably over a period after the earthquake, which significantly impacted the sales of related retailing businesses. As a result, the sales of more than 22% of these businesses exceeded the pre-earthquake level when they reopened. This finding corresponded to the official statistics of retailing sales in the case region (Mianzhu Statistics Bureau 2012). Driven by the increase in the final demand, these retailing businesses increased the frequency of goods supplies, which improved their production capacities despite the fact that the amount of other operation factors remained the same. This addressed the limitation of previous studies, which all assumed that the production capacity of all businesses always decreases after a disaster.

Practical Implications of Findings

The findings of this study imply several practical strategies and measures that could help mitigate the BIR in earthquake-struck regions. First, the recovery of certain operation factors should be prioritized. For example, recovery of transportation should be given high priority, because transportation is significant for goods supplies in retailing (Ghannad et al. 2021). For manufacturing, access to functional buildings, through either restoration of damaged buildings or construction of temporary buildings, should be prioritized to avoid a typical bottleneck in recovering the production level. The proposed framework also suggests that repair of slightly damaged buildings and equipment and construction of temporary buildings should be prioritized, because these properties can be used immediately to support the production.

The findings also have several implications for manufacturing production capacity modeling. First, the case study results indicated that the Cobb–Douglas function outperformed other production function forms for modeling the production capacity of manufacturing businesses. This finding corresponded to those of previous studies that also indicated that the Cobb–Douglas function is advantageous in modeling the production capacity of businesses, especially in the manufacturing sector (Koks et al. 2015; Li et al. 2019). Moreover, the production function of businesses in the manufacturing sector was computed using the Cobb–Douglas function, and the pre- and postearthquake production functions were compared. The results showed that there was no significant difference between these two production functions. This verified the assumption that the earthquake did not fundamentally change the production function of businesses, and implies that data collected during the normal operation of businesses can be used to estimate their production capacities under disaster impacts.

Limitations and Future Work

This study has four important limitations. First, specific quantitative equations derived in the case study [e.g., Eq. (16)] may not be applicable directly to other cases, and local and case-specific data may be required to establish or calibrate these equations. Future research could compare these equations across different cases to assess and improve the generalizability of these equations. Second, the proposed framework was been tested only in the manufacturing and retailing sectors, and more economic sectors, such as agriculture and catering, and small businesses under a designated size could be studied to further demonstrate the efficacy of the proposed framework. Third, the application of the proposed framework relies on data about available operation factors at the time of business reopening. However, such data are not always accessible before or immediately after an earthquake, which makes predicting the BIR ahead of time a challenge. However, the prediction of the sources of different operation factors is possible using methods that are well established in the literature. For example, a number of probabilistic models are available for predicting the restoration time of buildings and equipment after disasters, of which the FEMA P-58 methodology is a notable example (FEMA 2018). Prediction of these sources of operation factors and the subsequent prediction of BIR were beyond the scope of this study, and will be examined in future work. Fourth, there is a potential collinearity issue in the amounts of operation factors. For example, the postdisaster workforce losses could result from employees' home damages (Stevenson et al. 2014) or disruptions to their commuting conditions (Sydnor et al. 2017), and the raw materials and goods supplies could be impacted by disaster-induced changes in transportation flow (Chang et al. 2012a). Although such collinearity issue would not affect the results reported in this study, it could affect the predictability of the amounts of operation factors and the associated BIRs before an earthquake happens. The collinearity could be identified and quantified by analyzing historical records, which will be examined in future work.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This material is based upon work supported by National Key R&D Program of China under Grant No. 2017YFC0803300, the National Natural Science Foundation of China (NSFC) under Grant No. U1709212, and the Beijing Natural Science Foundation (BJNSF) under Grant No. 8202027. The authors are grateful for the support of the Ministry of Science and Technology of China (MOST), the NSFC, and the BJNSF. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agencies. The authors also thank the Statistics Bureau, Bureau of Economy and Information Technology, and Commerce Bureau of Mianzhu for their generous assistance with survey design and data collection in the case study.

Notation

The following symbols are used in this paper:

B = number of buildings when business reopens;
B_d = number of buildings damaged initially and that have been restored when business reopens;
B_r = number of buildings that survive earthquake and remain functional;
B_t = number of temporary buildings constructed in aftermath of earthquake when business reopens;
$D(t)$ = loss ratio of average individual demand in region at time t after earthquake;
$D_i(t)$ = demand of ith individual for certain product or service at time t after earthquake;
DP_l = loss of demand population;
DP_0 = original demand population before earthquake;
E = amount of equipment when business reopens;
E_d = amount of equipment damaged initially and restored when business reopens;
E_n = amount of new equipment purchased and put into use when business reopens;
EOF_i = group of essential operation factors of sector i;
I = amount of infrastructure services when business reopens;
I_c^i = amount of ith type of infrastructure service provided by contingency alternatives;
I_p^i = amount of ith type of infrastructure service provided by public infrastructure service provider;
L = amount of land when business reopens;
L_d = amount of land damaged initially and restored when business reopens;
L_r = amount of land that survives earthquake and remains functional;
LR_{dp} = loss ratio of postdisaster demand population;
LR_{fd} = loss ratio of final demand;
LR_{id} = loss ratio of postdisaster average individual demand;
LR_{pc} = loss ratio of production capacity;
PC_0 = predisaster production capacity;
S = amount of raw materials and goods supplies when business reopens;
S_i = monetary expenditure on ith type of raw materials or goods;
W = amount of workforce;
W_l = losses of total working hours due to inability to go to work when business reopens; and
W_0 = total working hours before earthquake.

Supplemental Data

Surveys S1 and S2 are available online in the ASCE Library (www.ascelibrary.org).

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