Modeling Post-Earthquake Business Recovery Time: An Analytical Framework

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Abstract

This study develops an analytical framework for modeling business recovery times after seismic events. These recovery times are important to understand, as business interruption (BI) is a significant factor in the survival of businesses and communities after disasters, and can cause a large proportion of the losses in such events. To date however, few post-earthquake recovery studies specifically account for business recovery time. The proposed framework considers multiple types of earthquake-induced downtime that may impact business recovery, such as building recovery and disruption to the wider community, as well as tactics employed by businesses to mitigate these times. The framework's potential to provide insight on business recovery is evaluated using observed recovery time data for 22 businesses affected by the 2011 M_w 6.1 Christchurch earthquake in New Zealand. It is found that recovery times calculated according to the framework align significantly better with observed business recovery times compared to calculated downtimes of businesses' pre-earthquake physical locations, which are often used as proxies for business recovery. These findings highlight the importance of accounting for multiple factors when modeling business recovery due to seismic events.

1 Introduction

Earthquake-induced business recovery is a complex process that is affected by many factors, such as physical building damage (Dahlhamer and Tierney, 1998), utility disruption (Whitman et al., 2013), damage to the surrounding neighborhood (Chang and Falit-Baiamonte, 2002; Seville et al., 2014b), supplier interruption (Mayer et al., 2008; Zhang et al., 2009), and mitigation tactics employed by business owners (e.g. conservation of resources or the use of backup technologies) to recover more quickly (Rose and Huyck, 2016). The purpose of this study is to develop an analytical framework for modeling this type of recovery. Understanding and predicting business recovery from an earthquake is important, as business interruption (BI) is a significant factor in the survival of businesses and communities after disasters (Tierney, 1997; Xiao and Van Zandt, 2012), and can represent a notable proportion of the losses in such events (e.g. Swiss Re, 2012; Rose et al., 2011).

To date, business recovery has usually not been explicitly considered in many post-earthquake recovery studies of either individual buildings (e.g. Molina Hutt et al., 2015; Erkus et al., 2018; Terzic and Mahin, 2017), infrastructure (e.g. Chang and Nojima, 2001; Didier et al., 2015), or communities (e.g. Burton et al., 2015; Bruneau et al., 2003; Chang and Shinozuka, 2004; Paul et al., 2018; Mieler, 2018; Kang et al., 2018). Other work simply assumes that business recovery times are equal to the downtime of the building in which the business is located (e.g. Yamin et al., 2017; Mitrani-Reiser, 2007; Terzic et al., 2014, 2016; Baker et al., 2016).

The need to account for factors other than building downtime is beginning to be recognized, however. For example, Cutfield et al. (2016) included for business relocation and building repair time when analyzing earthquake-induced business interruption losses in a conventional and base isolated steel braced frame office building. Almufti et al. (2016) created a data collection framework for tracking the impact of earthquakes on individual businesses over time, which considers building damage as well as information on business activity, such as relocation, customer issues, and methods of financing post-earthquake recovery. Kajitani and Tatano (2014) developed an analytical framework for estimating industrial production capacity loss rate after disasters, which takes into account both facility recovery and lifeline disruption. The framework proposed here builds on the work of these previous studies, by providing a systematic means of modeling post-earthquake business recovery time that accounts for its relationship with multiple types of downtime (both physical and non-physical), and various mitigation tactics.

This paper is structured as follows. The framework is introduced and described in Section 2. In Section 3, we evaluate the ability of the framework to provide insight on business recovery, using observed recovery time data for 22 businesses affected by the 2011 M_w 6.1 Christchurch earthquake in New Zealand. Section 4 highlights the potential for using the framework to predict business recovery in future events.

2 Framework

The framework considers different types of earthquake-induced downtime that have been shown to impact business recovery: (1) Recovery time of the building in which the business is located at the time of the earthquake, (2) Surrounding neighborhood disruption (i.e. the presence of a cordon), which prevents access in and around the business's location, (3) Disruption of utilities that are critical to the operation of the business, (4) Disruption caused by supplier downtime, and (5) Disruption caused by employee inaccessibility. The jth type of downtime (DT_j^*) is calculated as:

$$DT_j^* = f(\underline{X}) \tag{1}$$

where $\underline{X}$ is a set of variables characterizing damage to the built environment.

The framework also accounts for mitigation factors (resilience tactics) that businesses may employ to reduce each downtime (Rose et al., 2009; Wein and Rose, 2011; Rose and Huyck, 2016): (1) 'Relocation'- change in the physical location of the business, (2) 'Management effectiveness' - successful adaptation of management to the changed circumstances, (3) 'Hastening recovery' - ability to reduce the time it takes to recover, (4) 'Location independence' - ability of the business to function independent of its physical location, (5) 'Backup utilities' - use of backup lifelines, (6) 'Utility independence' - ability of the business to function independent of the functionality of a certain utility, (7) 'Conservation' - conservation of scarce inputs, and (8) 'Import substitution' - importation of resources from new regions.

Different mitigation factors are assumed to mitigate different types of downtime. The 'Relocation', 'Management effectiveness', and 'Hastening recovery' factors are assumed to mitigate both building recovery time and employee disruption. We also assume the 'Relocation' factor mitigates neighborhood disruption. The 'Location independence' factor is assumed to mitigate both neighborhood disruption and employee disruption. The 'Backup utilities' and 'Utility independence' factors are assumed to mitigate utility disruption. The 'Conservation' and 'Import substitution' factors are assumed to mitigate supplier disruption.The effect of n applicable mitigation factors on DT_j^* is calculated as follows:

$$DT_j = \prod_{i=1}^{n}(1 - MF_i) \times DT_j^* \tag{2}$$

where DT_j is the mitigated version of DT_j^*. MF_i is the reduction in DT_j^* due to the ith applicable mitigation factor, and may be a function of the size and type of the business. $\prod$ denotes the product operator, implying that the effect of multiple mitigation factors is treated in a multiplicative fashion. Note that for mitigated utility disruption (DT_3), equation 2 is slightly modified to account for the disruption in multiple utilities, i.e.:

$$DT_3 = \max\{\prod_{i=1}^{n_k}(1 - MF_i) \times DT_3^{(k)*}\} \tag{3}$$

where $DT_3^{(k)*}$ is the unmitigated disruption due to the kth utility. This is consistent with the approach adopted in similar calculations for such disruption (Brown et al., 2015, 2019).

Predicted business recovery time ($DT_{business}$) is finally taken as:

$$DT_{business} = \max\{DT_j\} \tag{4}$$

A graphical summary of the framework is presented in Figure 1. Note that the list of downtimes and mitigation factors included is non-exhaustive, but the general structure of the framework is flexible enough to account for additional information if necessary.

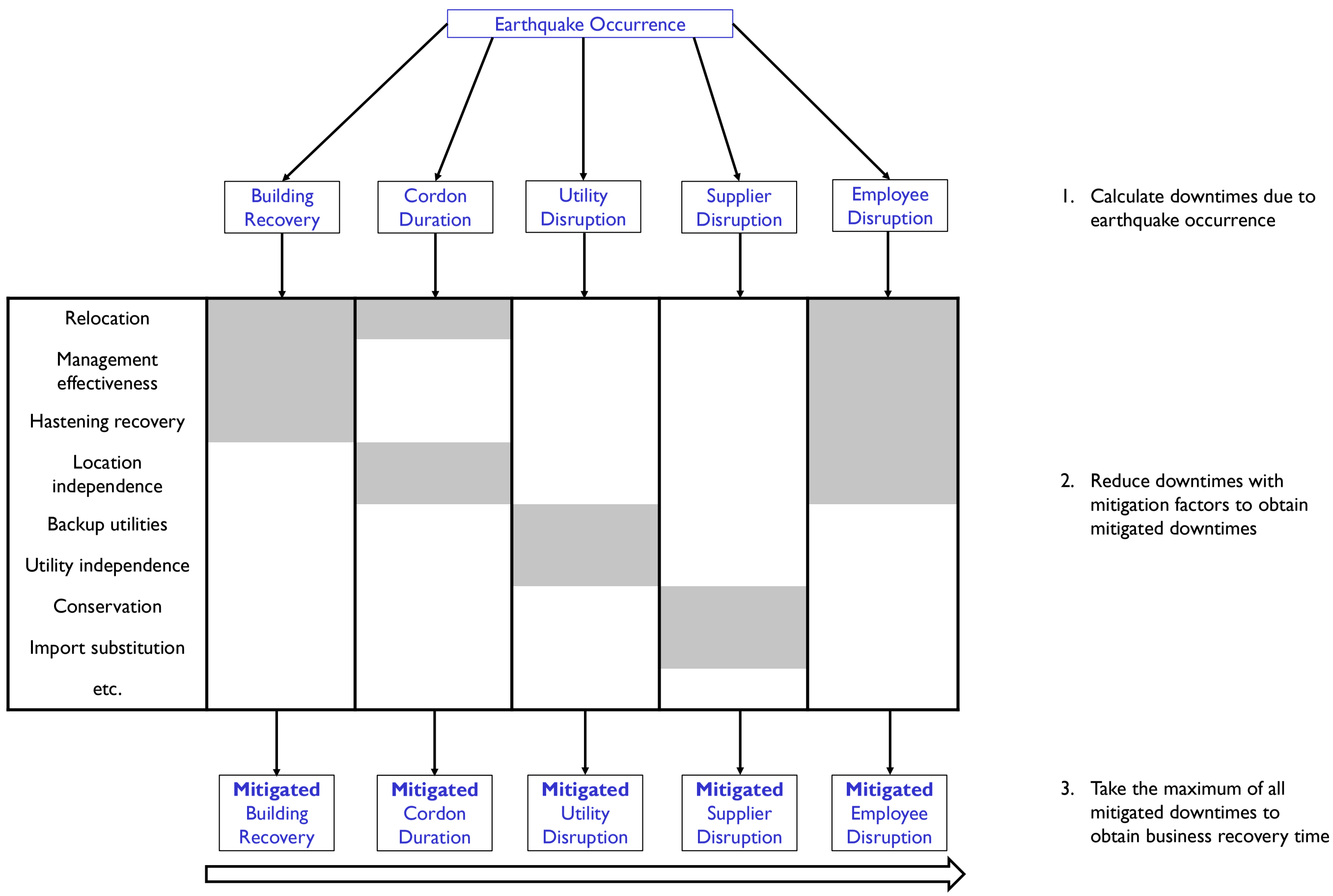

Figure 1: analytical framework for modeling business recovery time after a seismic event. Note that the gray shading indicates the applicable mitigation factors for each type of downtime.

3 Application of Framework

We evaluate the potential of the framework to provide insight on business recovery, using the recovery times of businesses due to the 2011 M_w 6.1 Christchurch earthquake. We specifically try to understand the extent to which non-building related downtimes and mitigation factors can potentially influence business recovery. Different databases collected in the aftermath of the event are used to calculate business recovery times according to the framework and compare them with observed business interruption times. Non-building related downtimes and mitigation factors are directly input to the framework based on information provided in the databases. Specific building recovery times are unavailable and are therefore predicted using an engineering model.

We use the Economics of Resilient Infrastructure (ERI) project survey (Seville et al., 2014a) database, which captured the extent of the disruption, mitigation measures in place, adaptive strategies implemented, and financial information for businesses. affected by the earthquakes. We also make use of two databases - the CEBA database (Lin et al., 2014) and a research database gathered by Kim (2015) - that contain information on building properties and damage recorded during post-earthquake damage assessments and detailed engineering evaluations of buildings. Building addresses are used to link the databases. We examine 22 businesses in total, which had between 1 and 5500 New Zealand employees and covered 13 industry sectors (Seville et al., 2014a): 5 represented Retail Trade, 5 represented Professional, Scientific and Technical Services, 3 represented Financial and Insurance Services, 3 represented Manufacturing, 3 represented Construction, 3 represented Electricity, Gas, Water and Waste Services, 2 represented Accommodation and Food Services, 1 represented Rental, Hiring, and Real Estate Services, 1 represented Arts and Recreation Services, 1 represented Health Care and Social Assistance, 1 represented Other - Automotive Servicing, 1 represented Wholesale Trade, and 1 business represented Public Administration and Safety. These are the only businesses with sufficient information across the databases. Specific details on the type of information used from the databases can be found in the Appendix. Note that employee disruption and the 'Import substitution' mitigation factor are ignored in this example, due to a lack of appropriate data.

3.1 Downtimes

Note that sample data for calculating downtimes are provided in the Appendix.

Building Recovery Time

Building recovery time (DT_1^*) is taken as the mean functional recovery time of a business's pre-earthquake physical location, which is predicted using the REDi rating system (Almufti and Willford, 2013). Functional recovery time combines downtime due to impeding factors, such as post-earthquake inspection and construction financing issues, and the time required to physically repair the building (note that we do not consider the utility disruption component since this is treated separately in our framework). Recovery time is computed in REDi based on structural response predictions using the intensity-based FEMA P-58 simplified analysis procedure. Building properties input to the procedure are lateral system, building design era, building occupancy type, number of stories, fundamental period, and floor footprint area. These are obtained from the CEBA database and the Kim (2015) research database (note that missing fundamental periods are assumed to be 0.1 $\times$ the number of stories). Ground motion parameters input to the procedure are peak ground acceleration and spectral acceleration at the building's fundamental period. These are obtained using nearby strong motion recordings interpolated using an emprical ground motion model and a spatial correlation model (Bradley, 2012, 2013).

The REDi methodology requires information on financing arrangements for repairs (obtained from ERI question 30), to determine delays in funding. The type of financial impediment modeled also depends on whether a business owned, rented, or both owned and rented buildings from which they operated (ERI survey question 15). The insurance impeding curve of the REDi methodology is used for businesses that owned, or both owned and rented their premises, if an insurance claim was made and the settlement was expected to cover at least 50% of property losses (ERI survey question 35). The private loans impeding curve is used for all other financial arrangements, and all businesses that rented their premises. In all cases, it is assumed that no pre-earthquake arrangements had been made with engineers or contractors to expedite the repair process. Note that the relevant ERI survey questions for calculating building recovery time are detailed in Table 2 of the Appendix.

Cordon Duration

A cordon was established around the Central Business District of Christchurch in the aftermath of the earthquake, to prevent access to severely damaged buildings (Chang et al., 2014). It was gradually reduced, and completely removed almost two and a half years later. The duration of the cordon's presence around a business location (DT_2^*) is calculated based on cordon lift dates obtained from the Kim (2015) research database, if available, or geospatial data from the archives of the Canterbury Earthquake Recovery Authority (CERA), accessed at:

http://ceraarchive.dpmc.govt.nz/documents/public-geospatial-data.

Utility Disruption

Utility disruption is calculated using the outages to electricity ($DT_3^{(1)*}$), gas ($DT_3^{(2)*}$), water ($DT_3^{(3)*}$), sewage ($DT_3^{(4)*}$), phone ($DT_3^{(5)*}$), and data ($DT_3^{(6)*}$), reported in question 12e of the ERI survey. These outages are reported in the categories "hours", "days", "weeks", and "months". "Hours" outages are neglected. "Days" outages are assumed to equate to 7 days, which corresponds to the average duration of electricity disruption (approximately 4 days) and cell communication disruption (9 days) after the earthquake (Tang et al., 2014). "Weeks" outages are assumed to equate to 14 days, which corresponds to the duration of gas disruption after the earthquake (Giovinazzi et al., 2011). "Months" outages are assumed to equate to 30 days, which corresponds to the time at which over 95% of occupied units had water restored and 60% of occupied units had sewage services restored (Seville et al., 2014a).

Supplier Disruption

Supplier disruption (DT_4^*) is determined based on how disruptive supplier issues were in the first three months following the earthquake, reported as "not", "slightly", "moderately", or "very" disruptive in question 11 of the ERI survey. A business is assumed to have supplier disruption if supplier issues were "moderately" or "very" disruptive. The disruption is assumed to have lasted 45 days (i.e. the median length of time in three months).

3.2 Mitigation Factors

The value of the 'Relocation' factor applied to building recovery reflects the number of days it took each business to relocate (and therefore its value differs between businesses), since relocation dates are provided in the ERI survey data. No specific data on any other mitigation activities are available, so the 'Management effectiveness' and 'Hastening recovery' factors are taken as the median values of their direct property loss reduction potential from Rose and Huyck (2016), and all other factors are assumed to eliminate their associated downtime. Values used for each factor are summarized in Table 1.

Table 1: Mitigation factors for different types of downtime in the framework. Each row in the table refers to a different mitigation factor, and each column refers to a different type of downtime. Each number in the table indicates the mitigation value applied for the given mitigation factor-downtime combination.

Category	Building Recovery	Cordon Duration	Utility Disruption	Supplier Disruption
Relocation	ERI Survey	1	-	-
Management effectiveness	0.12	-	-	-
Hastening recovery	0.15	-	-	-
Location independence	-	1	-	-
Backup utilities	-	-	1	-
Utility independence	-	-	1	-
Conservation	-	-	-	1

ERI survey answers are used to determine if mitigation factors are applied to a business's downtime. Many of the relevant questions in the survey relate to particular items or conditions, which are recorded as being "not", "slightly", "moderately", or "very" important to a business for mitigation purposes. Note that an item or condition is deemed to be important if it was recorded as being "moderately" or "very" important. Sample data for identifying applicable mitigation factors are provided in Table 3 of the Appendix.

- The 'Relocation' factor is applied if a business relocated due to the earthquake (ERI survey questions 18a and 18b).
- The 'Management effectiveness' factor is applied if the relationships with staff and/or customers were important in mitigating the earthquake's impacts (ERI survey question 12a).
- The 'Hastening recovery' factor is applied if a business continuity, emergency management, or disaster preparedness plan and/or relationships with businesses in the same sector were important for mitigation

of impacts (ERI survey question 12a).

- The 'Location independence' factor is applied if it was not reported in the survey that the business was location-specific, with moving not an option (ERI survey question 19b).

- The 'Backup utilities' factor is applied if backup/alternatives to water, sewage, electricity, and communications were important for mitigation of impacts (ERI survey question 12a).

- The 'Utility independence' factor is applied for a particular utility disruption if the length of time for which the business could cope without the utility (ERI survey question 45) was less than the length of the disruption.

- The 'Conservation' factor is applied if conservation of resources were important in helping recapture lost production/delivery/output due to the earthquake (ERI survey questions 12c) and/or if spare resources were important in mitigating the earthquake's impacts (ERI survey question 12a).

3.3 Error Metrics

The actual (observed) recovery time for each business is obtained from question 13b of the ERI survey, which reports the number of days a business closed temporarily as a result of the earthquake. We use two types of error metric to measure the alignment of recovery times calculated using the framework with those observed. The first is the root mean squared error (RMSE) (e.g. Chai and Draxler, 2014), which is expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{5}$$

where n is the number of businesses analyzed, P_i is the predicted recovery time for the ith business (from equation 4), and O_i is its observed recovery time. This metric is commonly used to measure the quality of models in many disciplines. It assigns more weight to larger absolute errors, making it sensitive to outliers.

We also consider the median absolute error (MdAE) (e.g. Hyndman and Koehler, 2006), i.e.:

$$MdAE = \text{median}(|P_i - O_i|) \tag{6}$$

where $|.|$ denotes the absolute value. P_i and O_i are as defined in equation 5. This metric is not sensitive to outliers, and therefore offers a different perspective on the quality of the predictions to that of the RMSE metric.

3.4 Results

Figures 2 to 6 compare the observed recovery times of the 22 businesses with those calculated using different types of downtime included in the framework. Note that detailed calculations of recovery time using the framework are provided in the Appendix for a sample business. Figure 2 highlights the comparison of observed recovery times with unmitigated building recovery times (DT_1^*), as in Baker et al. (2016). Both the RMSE and MdAE error metric are significant in this case, highlighting the poor alignment between business recovery and building downtimes. It can be seen from the plot that building downtime is significantly larger than business recovery time in most cases.

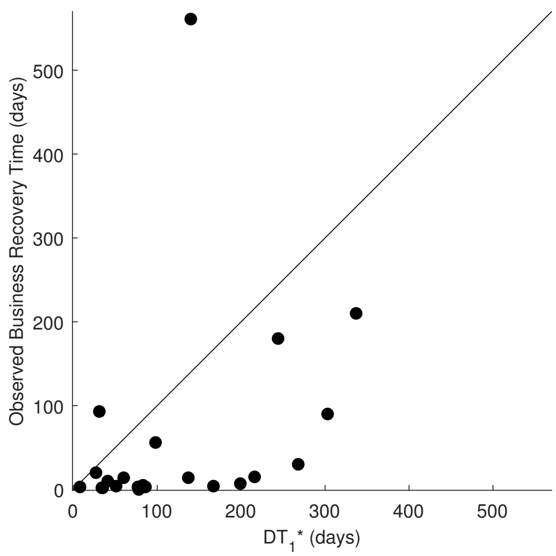

Figure 2: Comparison of observed business recovery times with unmitigated building recovery time, DT_1^*; $RMSE = 144.0$ and $MdAE = 76.0$.

The alignment improves if the relevant mitigation factors are applied to the building recovery times (Figure 3), resulting in a 27% decrease in the RMSE metric and a 77% decrease in the MdAE error metric. The RMSE error metric is still large, however, indicating that there are some significant individual errors in the calculation of business recovery time if only building recovery time is considered.

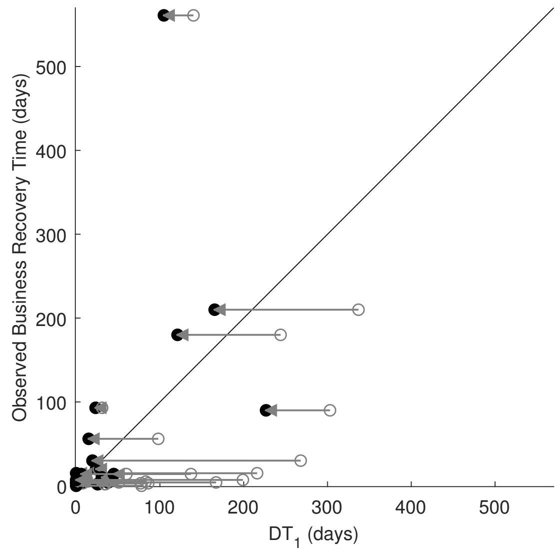

Figure 3: Comparison of observed business recovery times with mitigated building recovery time, DT_1 (black dots); $RMSE = 105.1$ and $MdAE = 17.8$. The gray arrows and open circles highlight the differences between this comparison and the Figure 2 comparison of observed business recovery times with DT_1^*.

There is a 65% decrease in the RMSE error metric and a 48% decrease in the MdAE error metric, if mitigated cordon durations are added to the analysis (Figure 4), implying that considering neighborhood disruption can markedly improve business recovery time predictions for this earthquake.

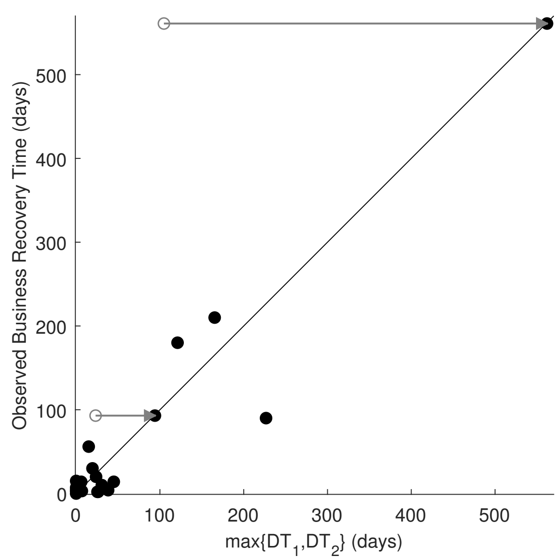

Figure 4: Comparison of observed business recovery times with the maximum of mitigated building recovery time, DT_1, and mitigated cordon duration, DT_2 (black dots); $RMSE = 37.0$ and $MdAE = 9.3$. The gray arrows and open circles highlight the differences between this comparison and the Figure 3 comparison of observed business recovery times with DT_1.

The predictions are further improved if mitigated utility disruptions are also considered in the analysis

(Figure 5), which is highlighted by the 9% decrease in the MdAE error metric. The magnitudes of the error decreases are small however, indicated by the negligible decrease in the RMSE error metric (less than 1%).

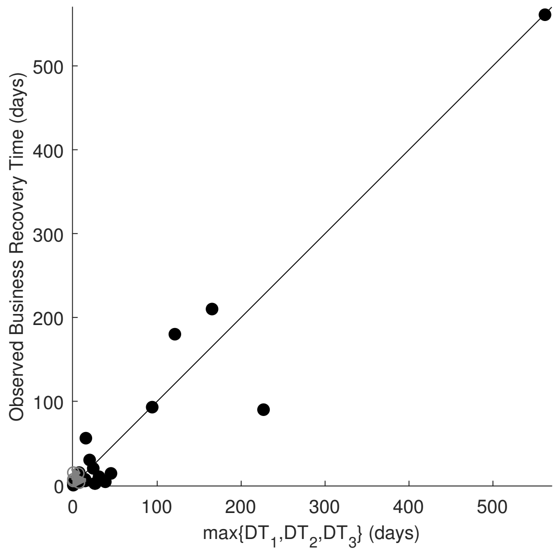

Figure 5: Comparison of observed business recovery times with the maximum of mitigated building recovery time, DT_1, mitigated cordon duration, DT_2, and mitigated utility disruption, DT_3 (black dots); $RMSE =$ 36.9 and $MdAE = 8.5$. The gray arrows and open circles highlight the differences between this comparison and the Figure 4 comparison of observed business recovery times with the maximum of DT_1 and DT_2.

Finally, including supplier disruption in the analysis leads to a slight improvement in the alignment between the observed business recovery times and those calculated using the framework (Figure 6); the RMSE error metric decreases by 3%.

In summary, the RMSE decreases by 75% from the case where only unmitigated building recovery times are accounted for to the case where all downtimes of the framework are considered, while the MdAE decreases by 89% (Figure 7). These findings highlight the notable influence of non-building related downtimes and mitigation factors on business recovery times. It is important to remember that relocation dates and cordon durations were known in this case, and utility and supplier disruption times were estimated directly from after-the-fact observed data; improvements in the errors would not have been as large if these times were predicted using models.

Figure 8 shows the order in which non-zero mitigated downtimes govern across all businesses analyzed with the framework. It can be seen that the interruption of most businesses is controlled by mitigated building downtimes, and then mitigated utility disruptions. Building downtimes are also most frequently

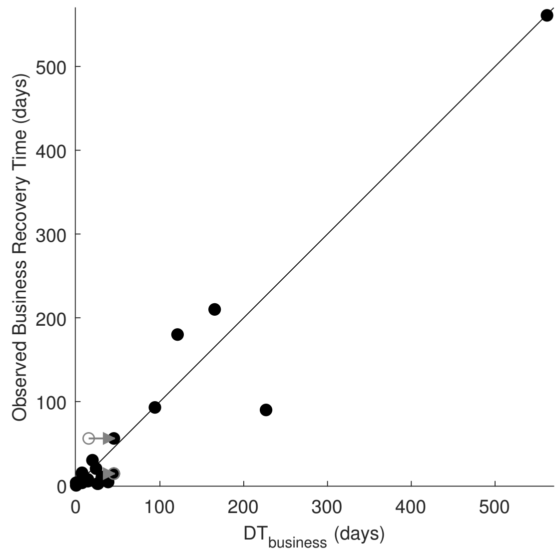

Figure 6: Comparison of observed business recovery times with $DT_{business}$, calculated using equation 4 (black dots); $RMSE = 35.9$ and $MdAE = 8.5$. The gray arrows and open circles highlight the differences between this comparison and the Figure 5 comparison of observed business recovery times with the maximum of DT_1, DT_2, and DT_3.

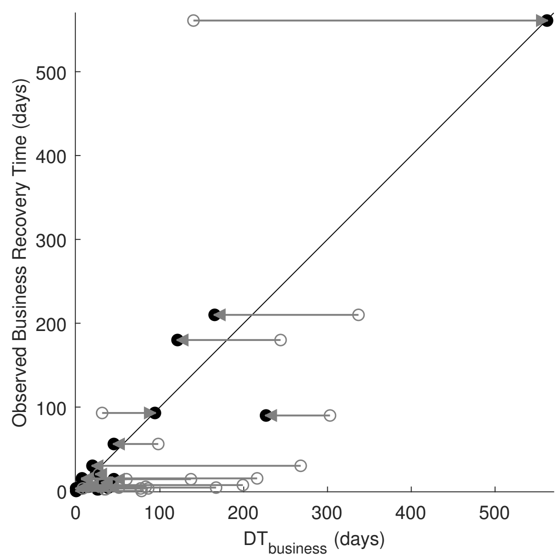

Figure 7: Comparison of observed business recovery times with $DT_{business}$ (black dots). The gray arrows and open circles highlight the differences between this comparison and the Figure 2 comparison of observed business recovery times with DT_1^*.

the second-longest mitigated downtime. While cordon durations significantly reduced both error metrics in Figure 4, they ultimately affected the calculated downtimes of only two businesses and consequently do not appear as impactful in Figure 8. The information in Figure 8 is specific to the 22 businesses considered in this study, but the type of information shown is generally useful when analyzing business interruption with the framework.

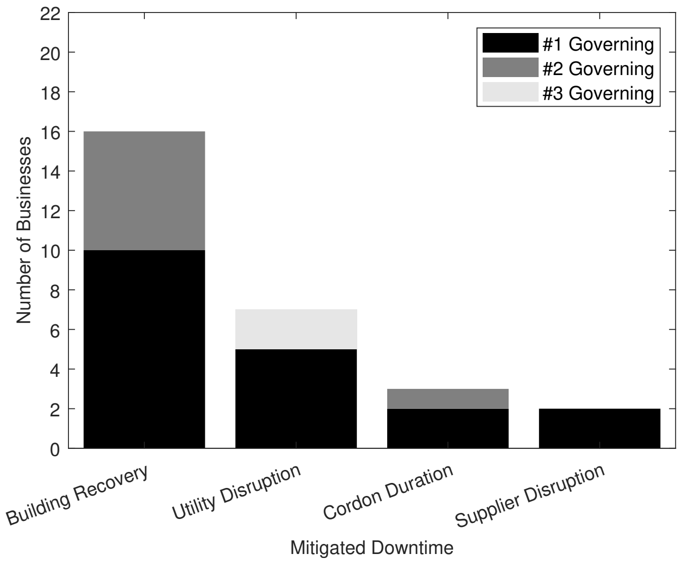

Figure 8: Histogram of non-zero mitigated downtimes and the order in which they govern, for the 22 Christchurch businesses analyzed with the framework. For a given downtime, '#1 Governing' indicates the frequency of its occurrence as the maximum mitigated downtime (i.e. $DT_{business}$), '#2 Governing' indicates the frequency of its occurrence as the second-longest mitigated downtime, etc.

4 Potential for Predictive Modeling

We only considered mean building recovery time predictions, known cordon durations, and after-the-fact observation-based estimates of both utility and supplier disruptions to quantify business recovery for a previous earthquake in Section 3. However, the framework could also accommodate probabilistic downtime models for predicting business recovery in future events. We now highlight the possible availability of some such models for potential application in the framework.

A number of probabilistic models are available for predicting building recovery time, notable examples of which include the REDi methodology (used in Section 3 for calculating mean predictions) and the HAZUS methodology (Kircher et al., 2006). Predictive utility downtime models for electricity, water, and gas are available in the REDi methodology, as well as in Kammouh et al. (2018) (which also includes a model for telecommunications disruption). While cordon durations are not yet modeled explicitly, the framework provided in Hulsey et al. (2018) could be followed to identify buildings in a neighborhood that may trigger its presence. Supplier disruption could be predicted using supply chain risk analysis techniques, such as the

Generalized Semi-Markov Process model (Shedler, 1992) proposed in Deleris et al. (2004). Transportation disruption could potentially be used as a proxy for employee disruption, and predicted using the model proposed in Chang et al. (2012).

5 Discussion and Conclusions

In this study, we developed an analytical framework for modeling business recovery times in the aftermath of seismic events. The framework considers multiple types of earthquake-induced downtime that may impact business recovery, both physical (such as building recovery time) and non-physical (such as supplier disruption), as well as tactics employed by businesses to mitigate these times.

We evaluated the framework's potential to provide insight on business recovery using the recovery times of 22 businesses after the 2011 M_w 6.1 Christchurch earthquake in New Zealand. Specifically, we tried to understand the influence of non-building related downtimes and mitigation factors on business recovery. We used various databases gathered in the aftermath of the earthquake to calculate recovery times using the framework and compare them with observed business interruption times. Two error metrics were used to measure the alignment of the calculated recovery times with those observed. Both types of errors reduced as more factors from the proposed framework were included in the analysis. In particular, business recovery times calculated when all downtimes of the proposed framework were accounted for aligned significantly better with those observed compared to calculated downtimes of businesses' pre-earthquake physical locations, which are often used as proxies for business interruption. The findings highlight the notable influence of non-building related factors on post-earthquake business recovery, and therefore the importance of accounting for them when modeling this type of recovery.

This study is limited in that it treats business recovery as a static, "all or nothing" state, which may not indicate the long-term success of a company (Stevenson et al., 2018), as recovery and resilience are dynamic processes (Cutter et al., 2008) involving a number of steps in time (e.g. Pant et al., 2014; Rose and Krausmann, 2013; Brown et al., 2019). However, the version of business recovery considered in this study is still a useful early indicator of post-disaster progress (Marshall and Schrank, 2014), and can be readily measured using business operation information from various sources, including owners and governments.

It should also be noted that the temporal aspect (i.e. trajectory) of recovery could be captured by the proposed framework if both the downtimes and the mitigation factors were defined as functions of time. For instance, utility disruption over time may be a decreasing step function as each critical utility is restored, and the 'Conservation' mitigation factor may decrease with time as spare resources deplete. Note that building recovery may not be limited to examination of the original business premises in this case; if a business relocated over time for example, the metric should also account for the evolving post-disaster conditions of its new building(s). The dynamic version of the framework could be used to predict the time at which a business would recover to a given level of operation, if the conditions required for that level of operation (e.g. the utilities necessary and the level of supplier disruption that could be tolerated) were known.

The framework proposed in this study advances the state-of-the-art in disaster recovery research by creating an important link between the engineering perspective of recovery that centers on physical structure/infrastructure downtime, and non-engineering perspectives that focus on social/economic disruptions experienced by businesses.

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Appendix: Sample Data and Calculations

We provide data and calculations for the business recovery time of a single sample business examined in Section 3. Table 2 includes data and calculations for the business's unmitigated downtimes, as well as its actual recovery time. Table 3 identifies applicable mitigation factors for the downtimes, based on the answers provided in the ERI survey. These factors are then applied to the relevant unmitigated downtimes to predict the business recovery time in Section A.1.

Table 2: Summary of sample data and calculations for a single business's unmitigated downtimes, as well as its actual recovery time. Data shaded in gray are obtained from the CEBA or research databases. All other data are obtained from the ERI survey, and the corresponding survey question number is noted beside each question.

Data Category	Sample Value
Building Recovery (DT_1^*)	
Lateral system	Concrete Moment Frame
Design era	Post-1994
Occupancy	Hospitality
Stories	10
Floor footprint area (square feet)	82990
15. Does your organisation own or rent the properties from which it is operated? (please tick all that apply)	Own
30. How is your organisation financing its recovery from the earthquakes?	Organisation Cash Flow; Insurance
35. What proportion of property losses do you expect to be covered by your insurance settlement?	50%
$\Longrightarrow$ $\underline{DT_1^* = 140 \text{ days}}$	
Cordon Duration (DT_2^*)	
Time within cordon (days)	562
$\Longrightarrow$ $\underline{DT_2^* = 562 \text{ days}}$	

Utility Disruption (DT_3^*)

12 e. For how long did your organisation experience disruptions to the following infrastructure services?

Electricity ($DT_3^{(1)*}$)	Weeks
Gas ($DT_3^{(2)*}$)	Weeks
Water ($DT_3^{(3)*}$)	Weeks
Sewage ($DT_3^{(4)*}$)	Weeks
Phone ($DT_3^{(5)*}$)	Hours
Data ($DT_3^{(6)*}$)	Weeks

$\Longrightarrow$ $\underline{DT_3^* = 14 \text{ days for Electricity, Gas, Water, Sewage, and Data; 0 days for Phone}}$

Supplier Disruption (DT_4^*)

11. In the first 3 months after the earthquake, how disruptive were supplier issues?	Very disruptive

$\Longrightarrow$ $\underline{DT_4^* = 45 \text{ days}}$

Actual Business Recovery Time (DT_{actual})

13 b. If your organisation closed temporarily, for how long did you close?	561 days

$\Longrightarrow$ $\underline{(DT_{actual}) = 561 \text{ days}}$

Table 3: Identified applicable mitigation factors for the different downtimes, based on answers provided in the ERI survey.

ERI Survey Question	Sample Answer
Relocation	
18 a. Did your organisation relocate your main sites due to the earthquakes?	No
18 b. When and where did you relocate your main sites?	Not applicable
$\Longrightarrow$ Relocation factor DOES NOT apply	
Management effectiveness	
12 a. To what extent has the relationship with staff helped mitigate the impact of the earthquake on your organisation?	Very important
12 a. To what extent has the relationship with customers helped mitigate the impact of the earthquake on your organisation?	Very important
$\Longrightarrow$ Management effectiveness factor DOES apply	
Hastening recovery	
12 a. To what extent has a business continuity, emergency management or disaster preparedness plan helped mitigate the impact of the earthquake on your organisation?	Very important
12 a. To what extent has the relationship with businesses in your sector helped mitigate the impact of the earthquake on your organisation?	Not important
$\Longrightarrow$ Hastening recovery factor DOES apply	
Location independence	
19b. How feasible is it to relocate parts or all of your organisation's operations?	Our business is quite location-specific, moving is not an option

$\Longrightarrow$ Location independence factor DOES NOT apply

Backup utilities

12 a. To what extent have backups/alternatives to water, sewage, electricity, communications helped mitigate the impact of the earthquake on your organisation?	Very important

$\Longrightarrow$ Backup utilities factor DOES apply

Utility independence

45. How long could your organisation continue functioning if normal supply to the following infrastructure services were disrupted?

Water	Could not function
Sewage	Could not function
Gas	Could not function
Electricity	Could not function
Phone	Could not function
Data	Could not function

$\Longrightarrow$ Utility independence factor DOES NOT apply

Conservation

12 c. To what extent has conservation of resources helped recapture lost production/delivery/output?	Moderately important
12 a. To what extent have spare resources (e.g. equipment or extra people) helped mitigate the impact of the earthquake on your organisation?	Very important

$\Longrightarrow$ Conservation factor DOES apply

A.1 Calculation of Predicted Business Recovery Time

1. Calculate Mitigated Building Recovery (DT_1)

DT_1^* from Table 2: 140 days

Applicable mitigation factors from Table 3:

Management effectiveness (0.12)

Hastening recovery (0.15)

Calculate DT_1 using equation 2:

$$\underline{DT_1 = (1 - 0.12) \times (1 - 0.15) \times 140 = 105 \text{ days}} \tag{7}$$

2. Calculate Mitigated Cordon Duration (DT_2)

DT_2^* from Table 2: 562 days

Applicable mitigation factors from Table 3:

None

Calculate DT_2 using equation 2:

$$\underline{DT_2 = (1 - 0) \times 562 = 562 \text{ days}} \tag{8}$$

3. Calculate Mitigated Utility Disruption (DT_3)

DT_3^* from Table 2: 14 days for water, sewage, gas, electricity, and data; 0 days for phone

Applicable mitigation factors from Table 3:

Backup utilities (1)

Calculate DT_3 using equation 3:

$$\underline{DT_3 = \max\{(1-1) \times 14, (1-1) \times 0\} = 0 \text{ days}} \tag{9}$$

4. Calculate Mitigated Supplier Disruption (DT_4)

DT_4^* from Table 2: 45 days

Applicable mitigation factors from Table 3:

Conservation (1)

Calculate DT_4 using equation 2:

$$\underline{DT_4 = (1-1) \times 45 = 0 \text{ days}} \tag{10}$$

5. Calculate Predicted Business Recovery Time ($DT_{business}$)

Calculate $DT_{business}$ using equation 4 and the DT values from equations 7 to 10:

$$\boxed{\mathbf{DT_{business}} = \max\{\mathbf{105, 562, 0, 0}\} = \mathbf{562\ days}} \tag{11}$$

Compare to DT_{actual} from Table 2: 561 days