THE ROLE OF INSURANCE IN BUSINESS RECOVERY AFTER A NATURAL DISASTER: THE CASE OF THE 2011 CHRISTCHURCH EARTHQUAKE

BY

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Abstract

We aim to investigate the role of insurance in business recovery following the devastating Christchurch earthquake in February, 22nd, 2011. We analyze data from two business surveys conducted after the earthquake to examine how insurance affected business operation in the aftermath of the earthquake both in the *short-term* and *longer-term*. For the short-term analysis, we use a combination of propensity score matching (PSM) and linear probability model (LPM) to analyze the data. We first estimate the propensity scores for insurance take-up of each firm conditional on the firm's individual characteristics. Stratification based on the estimated propensity scores is used to match the treated (insured) and the control (uninsured) firms. We then estimate the probability of firms' continuing operations with a set of control variables to account for the level of damage and disruption caused by the quake in each stratum. We find little evidence of any beneficial effect of insurance coverage on business continuity in the short-run. For the longer-term analysis, we analyze the available survey data using logistic regression. The result suggests that business interruption insurance significantly promotes increased level of long-term productivity for surviving firms following the earthquake.

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Chapter 1

Background of the Study

The role of insurance in supporting recovery in the aftermath of a natural disaster is under-investigated. There are scant literature on how effective is insurance in aiding recovery of individuals, businesses, as well as the affected economy as a whole. Understanding how insurance aids or fails to aid recovery in the aftermath of a natural disaster is of clear interest and globally relevant as the frequency and the magnitude of disasters are both increasing. Consequently, our finding should contribute to a more informed and consequently better designed insurance policy as a tool to mitigate risks associated with natural catastrophes. The objective of this thesis is to investigate the role of insurance in business recovery in the aftermath of a natural disaster. We use the Christchurch earthquake in 2011 as a case study.

1.1 The 2011 New Zealand Earthquake

The Christchurch earthquake on Feb. 22, 2011 was the worst natural disaster in New Zealand's history, with an estimated loss of US$35 billion (Simpson, 2013). The quake hit the Canterbury region at 12:51pm, with a magnitude of 6.3 with several big aftershocks in the following months.[1] It caused 185 fatalities and damaged over 100,000 buildings (McSaveney, 2014). The earthquake was actually an aftershock from the September 2010 earthquake. Table 1.1 presents the top-five worst (in term of magnitude) Christchurch. The first major quake was in 2010 with the magnitude of 7.1. The second and the third major quakes hit the city of Christchurch on Feb. 22, 2011 and caused the most destructive loss in New Zealand's history.

After the earthquake in February, about 1,600 commercial buildings in the Central Business District (CBD) were marked to be demolished, which is approximately 60% of all the buildings in the CBD area (Stevenson et al., 2012a). As the earthquake was followed by over 3,000 aftershocks, the whole CBD was cordoned off for a prolonged period of time, with the

[1] See Christchurch Earthquake Response (2011) for the scientific information regarding the earthquake.

last cordoned area made accessible almost two and a half years after the earthquake. This restricted access of the CBD caused a sudden negative shock to businesses including businesses that did not experience direct damage to their premises or property from the earthquake event (Stevenson et al., 2012b).

Table 1.1 Top 5 worst Christchurch earthquakes

Date&Time	Magnitude[2]	Intensity[3]	Location
04 Sep 2010 4:35am	7.1	X	840 meters from Ansons Rd, Charing Cross 7571, New Zealand
22 Feb 2011 12:51pm	6.34	VIII	340 meters from Rapaki Rd, Hillsborough, Christchurch 8022, New Zealand
22 Feb 2011 2:50pm	5.91	VI	490 meters from 32 Pentre Terrace, Cashmere, Christchurch 8022, New Zealand
13 Jun 2011 2:20pm	6.41	VIII	690 meters from Barnett Park Track, Redcliffs, Christchurch 8081, New Zealand
23 Dec 2011 3:18pm	6	VII	250 meters from 466-468 Marine Parade, South New Brighton, Christchurch 8062, New Zealand

Source: GeoNet (n.d.)

1.2 Impact of the Earthquake on Insurance Industry

The February quake has an estimated insured loss of US$16.5 billion (MunichRe, 2015). As such, it is ranked the sixth most expensive insured event to the insurance industry globally since 1980 (MunichRe, 2015). The proportion of insured loss is also exceptional for this event, with up to 70% of damages being insured (figures vary, but all estimates suggest this is the most comprehensively insured earthquake in history).[4]

[2] GNS Science (n.d.) defines *Magnitude* as "Earthquake size is a quantitative measure of the size of the earthquake at its source. The Richter Magnitude Scale measures the amount of seismic energy released by an earthquake."
[3] GNS Science (n.d.) defines *Intensity* as "The severity of earthquake shaking is assessed using a descriptive scale – the Modified Mercalli Intensity Scale."
[4] Comparatively, the Tohoku tsunami in 2011 has an estimated insured loss of only 19% (MunichRe, 2015). See more detailed comparison of the Christchurch earthquake with other catastrophes in Parker and Steenkamp (2012).

As the quake originated from an unknown fault line, there was comparatively little preparedness for business recovery in the aftermath; and low commercial insurance claims ratio for earthquake risk prior to the event (ICNZ, 2014a).[5] Consequently, insurance firms had no experience in dealing with such a large volume of claims in the immediate aftermath of the earthquake. Since then, there have been continuing delays in claim settlement (Muir-Wood, 2012). Three years after the earthquake, between 10-40% of claims have still not been settled of which the majority of unsettled claims are commercial claims (ICNZ, 2014b, and 2015)[6]; in contrast with the 2011 earthquake in Japan and the 2010 one in Chile where practically all claims have been completely settled in about 2 years (Marsh, 2014).

1.3 Objective of the Thesis

The objective of this thesis is to investigate the role of insurance in business recovery by using the 2011 Christchurch earthquake as a case study. We aim to examine the role of insurance in both *short-term* and *longer-term* contexts.

For short-term context, we aim to find out how insurance affect business recovery in the immediate aftermath. As there were almost no insurance payouts during this period, the purpose is to observe if insurance increases the likelihood of business continuity in the aftermath as the insured entities are aware of their insurance cover, and can expect to be able to fund their recovery through insurance payouts. For longer-term context, we aim to investigate the role of insurance in supporting business recovery in terms of organizational profitability and productivity. The insurance role here is more direct as in most cases at least some of the insurance claim has already been paid.

The earthquake in Christchurch is useful as a case study for several reasons: (1) Insurance cover was widely available and commonly purchased in New Zealand, making it

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[5] The loss ratio (total loss divided by gross premium) for earthquake risk of private insurers in New Zealand was 5.49% in 2009 as opposed to 31163% in 2011 (ICNZ, 2014a).

[6] For instance, Deloitte (2015) reported the outstanding insurance claims of Vero Insurance, one of the larger general insurers in New Zealand, that *"To date, Vero had made $3.8 billion in damage and business continuity claims payments, which represents about 80.0% of its total estimated costs. Of this, around 25.0% of claims payments have been made to residential policyholders, and the remaining 75.0% to Vero's commercial clients."*

easier to obtain substantial samples of affected and unaffected insureds. (2) The proportion of insured damage to total loss of the 2011 earthquake is substantial. This allows us to gather sufficient observations of the insureds and uninsureds for the study. (3) Given the existence of a public residential insurance scheme (EQC) and a public accident insurance scheme (ACC), insurance in New Zealand is very affordable. As such, budget and credit constraints are less likely to have been inhibiting factors preventing firms from purchasing insurance. These constraints are therefore less likely to constitute a material difference between the insured and uninsured, leading to selection bias. (4) The surveys we use in the empirical analysis are detailed post-disaster surveys that include both questions about the nature of insurance coverage, the impact of the earthquake, and the nature and extent of continued post-disaster operations. It is this information that enables us to conduct the empirical study described herein. To our knowledge, this is the first research that examines empirically the role of insurance in business recovery following a natural disaster.

1.4 Business Survey Data

In this study, we utilize the data of two business surveys prepared and collected by *Resilient Organizations*, a research organization based in Christchurch. The survey was designed to be a longitudinal study of organizational resilience following the earthquake in 2010 (when no one predicted there would be a series of even more destructive aftershocks). The questionnaire was sent to both for-profit and not-for-profit organizations located in Christchurch Central Business District and the affected areas around the Christchurch city.

The survey questionnaire was primarily designed to measure the impact of the earthquakes on infrastructure and assets. It asks firms about the level of damage and the disruption experiences following the series of earthquake in Canterbury. There is a section devoted to capturing insurance data; and it is this section that enables us to undertake this empirical study on the role of insurance in the aftermath of a natural disaster.

The data collection method of both surveys is similar. Participants were initially contacted by phone in order to establish contact with the heads of the organizations. The questionnaire was then sent to their nominated person via physical or electronic address. The firms were given options to respond via phone call, online, or mail. Figure 1.1 displays the survey timeline along with the date of the earthquakes. Table 1.2 summarizes a brief description of each survey.

Figure 1.1 Survey timeline

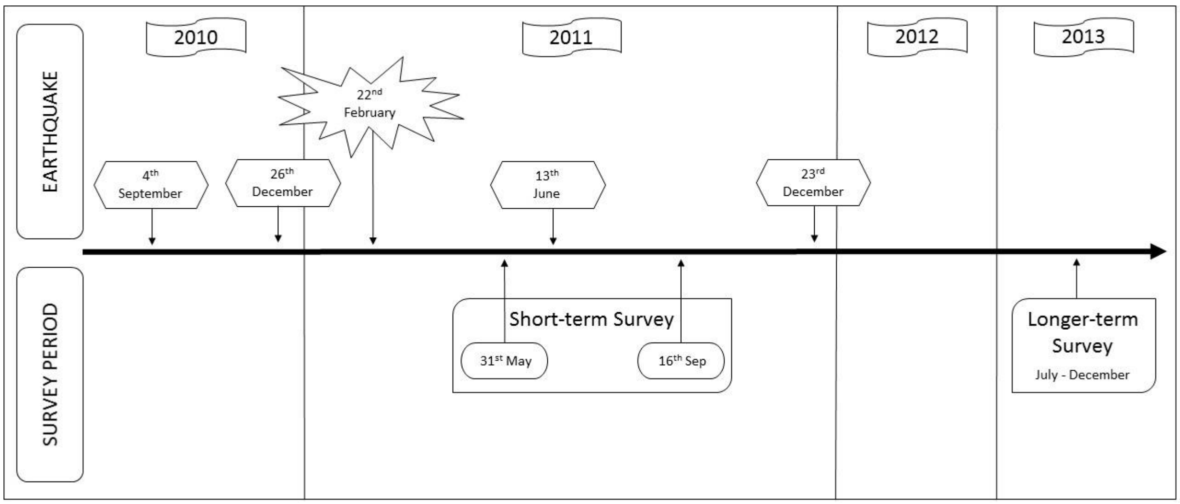


Table 1.2 Survey description

Description	[1]Short-term	[2]Longer-term
Start Date	31-May-2011	Jul-2013
Completion Date	18-Sep-2011	Dec-2013
Participated Firms	309	2176
Returned Response	176	541
Response Rate	57%	25%
Valid Response[3]	140	461

Source: [1]Kachali (2013), [2]Brown et al. (2014), and [3]Author's calculation

The short-term survey was conducted three to six months after the 2011 earthquake. It was initially intended for following-up on the recovery process of the 2010 earthquake but was then revised to also capture the short-term impact of the 2011 earthquake. For our study, the short-term survey is used to capture the role of insurance in supporting immediate post-quake recovery. The longer-term survey was completed in 2013. It was designed to follow-up on the progress of recovery several years afterwards. We use the longer-term survey to investigate the role of insurance in supporting reconstruction and recovery of business operations.

The questions in the questionnaire mostly require Yes-No answers or Likert (scaled). Unfortunately, this includes most of the insurance related questions. We would have preferred data on the actual values of premiums and claims classified into property damage and business interruption insurance. Nevertheless, given that the published research on the role of disaster insurance is scarce, we believe that even the available data provides useful and interesting insights.

1.5 Outline of the Thesis

This thesis is organized as follows: the next chapter discussed related literature. In particular, we discuss the existing studies of the role of insurance in the aftermath of a disaster. Due to the use of two surveys with different content, we use two different methods of analyzing data. Therefore, the thesis is divided into two parts in chapters 3-8. Part I relates to the short-term survey while part II relates to the longer-term one. Chapters 3-5 include a description of the methodological framework, data analysis, and the empirical results, respectively, for the short-term analysis. Chapters 6-8 are devoted to the study of the longer-term and also include the methodological framework, the data analysis, and the empirical results, respectively. The final chapter provides conclusions and discussions, and elucidates some caveats to this study.

Chapter 2

Literature Review

Insurance is widely recognized as one of the vital mitigation tools against loss and damage from natural disasters (UNISDR, 2015). It allows individuals and businesses to transfer all or part of their risk exposure to insurance companies in exchange for a certain amount of premium; with the purpose of being indemnified should there be any unexpected adverse circumstances. It is important as a mitigation tool especially in the case of catastrophic loss when the magnitude of loss is large and the affected entities require external financial resources to support their recovery.[7]

From an insurance perspective, disaster exposure is considered an unknown risk. Kunreuther and Pauly (2006) describe it as risk without sufficient statistical data available to estimate probabilities of future occurrence accurately. Disaster risk is unknowable for insurance business because the accurate prediction of future occurrence is generally impractical. Due to the nature of natural disaster risk, the damage caused by disasters could be unexpectedly devastating and significantly impact massive number of individuals and businesses as well as the economy as a whole. With the potential magnitude of loss that could be destroyed by natural disasters, insurance thus could play a critical role in providing funds to support recovery in the aftermath of natural disasters. However, the literature on such a role for insurance is very limited. What is the extent to which insurance assists or can assist individuals and businesses in recovery?

In reviewing the literature on natural disaster insurance, we focus on the role of insurance as a mitigation tool against natural disasters. We begin with the discussion of the cost of natural disasters. We further discuss disaster insurance coverage and the role of insurance against natural disasters.

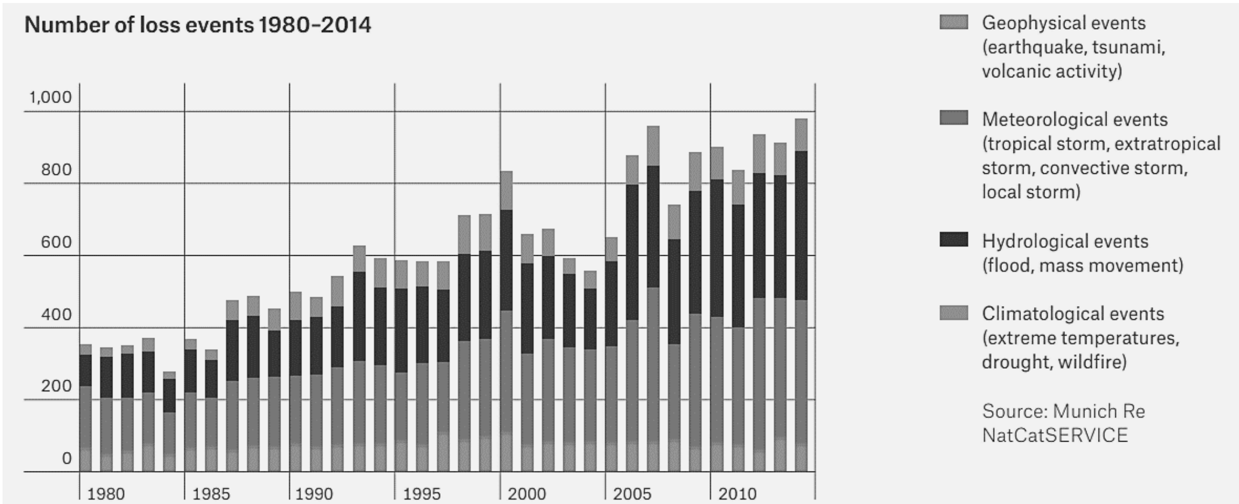
[7] The importance of insurance in dealing with natural disasters is documented in the *Economic Report of the President* of the U.S. for the first time in 2007 (Kunreuther & Michel-Kerjan, 2010).

2.1 Cost of Natural Disasters

As shown in Figure 2.1, the number of reported natural disasters is increasing with the majority of events caused by meteorological (e.g. storm) and hydrological (e.g. flood) disasters. The cost of natural disasters is increasing even faster, and, unfortunately, at a higher rate than that of the insured losses, see Figure 2.2. A study of 42 countries by Cebr (2012) found that 17 countries are under-insured; while most of them are developing countries, two of them are developed countries. In analyzing underinsurance for specific events, Cebr (2012) found significant under-insurance in all major disasters. In most cases, the uninsured portion of losses exceeds the insured one. For instance, the Japanese earthquake in 2011 has the proportion of underinsurance of 83%. Even in New Zealand, there is also evidence of underinsurance following the disastrous event in 2011 (Muir-Wood, 2012; Brown et al., 2013). The underinsurance gap is more obvious in the case of commercial insurance (Muir-Wood, 2012; Schanz & Wang, 2014; Deloitte, 2015). Moreover, an analysis by Schanz and Wang (2014), found that the average insurance gap has broadened during the past 40 years, from 0.02 percent to 0.13 percent of global GDP.

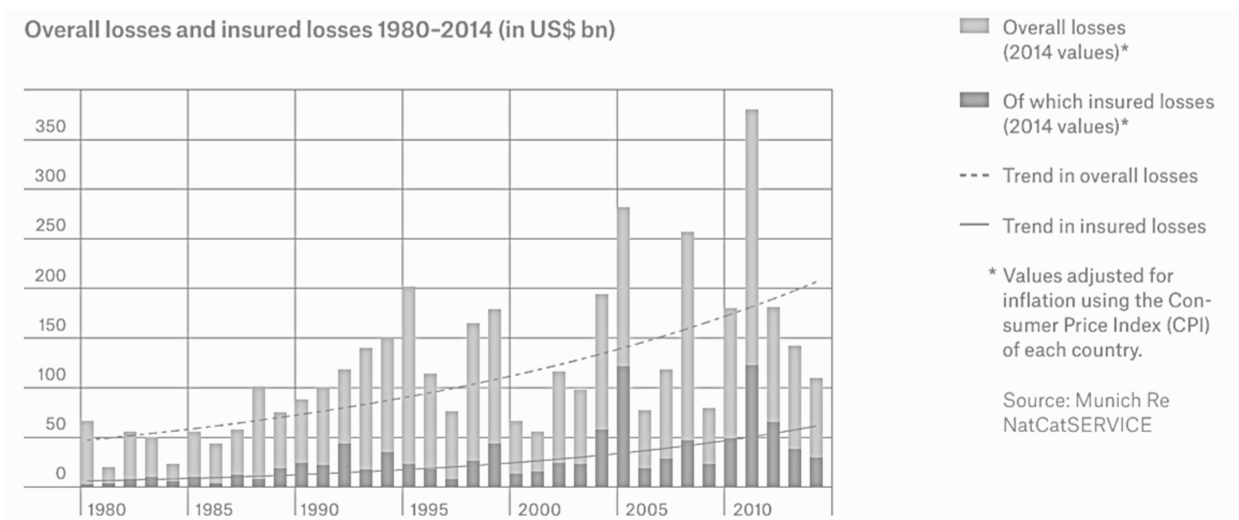
Von Peter et al. (2012) find that the uninsured part of disaster loss adversely impacts the entire economy. In developed countries, they found that the insured portion of disaster losses has no significant impact on the economy following a disaster whereas the uninsured part of disaster losses has an adverse impact; the negative impact of the uninsured losses is strong even 2-3 years after the disasters.

Figure 2.1 Number of natural disasters, 1980-2014



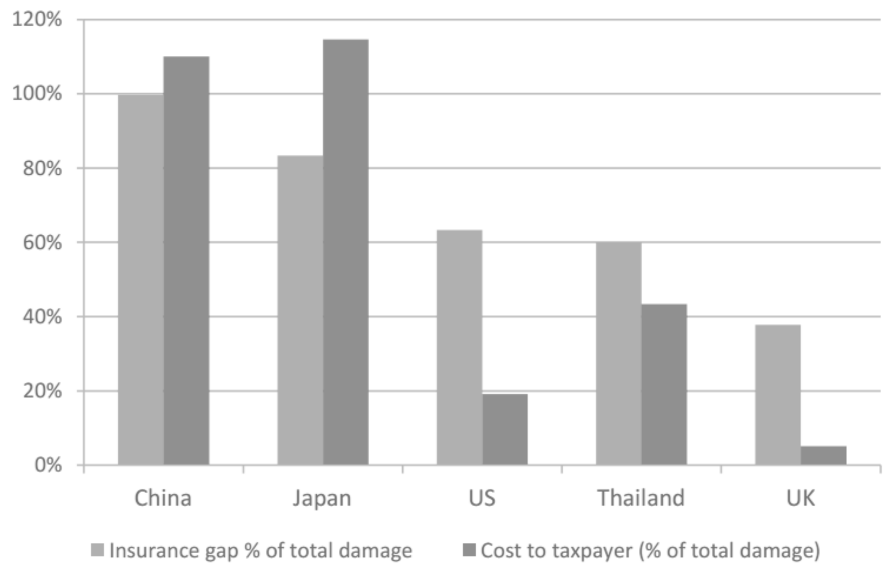
Source: MunichRe (2015)

Figure 2.2 A comparison of overall losses and insured losses, 1980-2014 (in billions US$)



Source: MunichRe (2015)

Figure 2.3 The insurance gap and the cost to taxpayer



Source: Cebr (2012).

Cebr (2012) analyzes case studies of natural disasters in five countries: Hurricanes Katrina, Rita and Wilma in the United States in 2005; the widespread flooding in the UK in 2007; the earthquake in China in 2008; flooding across Thailand in 2011; and the Great Japan earthquake and Tsunami in 2011. Figure 2.3 compares the insurance gap and the cost to taxpayers as a percentage of total loss of these five disasters. Except the U.K., other disasters had insurance gaps of over 50%. Depending on each specific case, some disasters could be burdensome to taxpayers. For instance, China and Japan have a cost to taxpayers of over 100% of total loss; the extra cost includes the cost for reduction measures and fiscal stimulus measures. Lashof and Stevenson (2013) estimated the cost of disasters in 2012 in the U.S.; it shows that only 25% of total disaster loss is insured which, they argue, leaves the remaining cost of US$96 billion to the federal governments. This high cost includes the costs of disaster recovery, the costs of implementing preventive measures such as wildfire fighting, and the costs of public insurance program (flood insurance and crop insurance).

2.2 Disaster Insurance: Coverage and Availability

Disaster insurance is generally available through homeowner insurance for individuals and commercial insurance for businesses. However, extreme catastrophic risk could be left uninsurable by private insurers (Kleindorfer & Kunreuther, 1999). For instance, flood insurance in the U.S. is not available from commercial insurers but is only offered by the government (Michel-Kerjan, E. & C. Kousky, 2010); flood insurance in Netherland is also unavailable through private insurance (Botzen & Van Den Bergh, 2008).

Insurers are not willing to provide coverage for natural disasters for several reasons (e.g. Kunreuther, 1996; Jaffee & Russell, 1997; Kunreuther & Michel-Kerjan, 2009a; Kousky, 2010; Linnerooth-Bayer et al., 2011). One of the reason is that catastrophic risk is an unknowable risk making it difficult to estimate future occurrences, thus, actuarially fair-pricing is often impractical (Kunreuther & Pauly, 2006). Consequently, the insurers would charge higher premium to compensate for the unknown risk of disaster (Kunreuther & Michel-Kerjan, 2009b).

A survey of actuaries and underwriters by the Wharton Risk Center reported that they would charge 25% higher premium to compensate for unknown risks although there is no information whether the additional premium assuredly offset the unknown portion of the risk (Kunreuther & Michel-Kerjan, 2009b). As a result, the higher premium rate discourages individuals and businesses from buying insurance protection and hence demand for disaster insurance is lower. The high cost of protecting future uncertainty may be unattractive as compared to the needs of day-to-day expenditures; this is especially true for budget-constrained individuals (Kunreuther & Michel-Kerjan, 2009c; Linnerooth-Bayer et al., 2011; OECD, 2013).

In addition, insurers are reluctant to insure catastrophic risk because it requires them to accumulate high loss reserve due to the potential severity of disaster risk (Jaffee & Rusell, 1997; Kunreuther & Michel-Kerjan, 2009b). Jaffee and Russel (1997) pointed that there are additional costs associated with carrying capital as loss reserve such as tax and accounting expenses, these additional costs further discourage insurers from supplying disaster insurance.

Kunreuther and Michel-Kerjan (2010) propose four guiding principles for designing a better insurance policy to deal with loss or damage against natural disasters. These four principles work together to enable private and public sectors as well as insurance sector to confront catastrophic risks more effectively.

The first principle reflects how insurance premium should be determined. Insurance premium must reflect the risk that is insured (Kunreuther & Michel-Kerjan, 2010). Risk-based pricing allows insurance companies to collect sufficient capital to deal with the risk that is transferred to them. In addition, risk-based premium signals individuals and businesses about the severity of the perils that they are facing. It further contributes fair pricing so that those high-risk individuals (e.g. live in hazard-prone area) would have to compensate for their risk by paying higher premium.

The second principle examines the affordability of insurance to high-risk individuals. As pointed out in Kunreuther and Michel-Kerjan (2010), if insurers fully apply the first guiding principle, the risk-based premium for high-risk individuals could be very expensive. This extreme cost of protection against natural disasters might become prohibitively expensive or unaffordable.

The third principle is regarding the demand for disaster insurance. Risk-based pricing is applicable only if there is sufficient demand for disaster insurance (Kunreuther & Michel-Kerjan, 2010). It is essential to have adequate number of risk pooling in order for disaster insurance to be available. High demand for disaster insurance also has the benefit of minimizing the financial burden to the government in aiding recovery of both the insured and uninsured.

The fourth important principle is maintaining the solvency of insurers and reinsurers. This principle is a basis that administers financial strengths of (re-)insurers so that they are able to handle disaster risk as well as enable them to be capable of meeting their contractual obligation, i.e. indemnifying policyholders (Kunreuther & Michel-Kerjan, 2010).

In practice, however, if the actual disaster cost is excessive to the insurers, they would adapt by increasing premium rates resulting in lower loss ratios and lower negative impact to the insurance companies (Born & Viscusi, 2006). Besides, in surveying homeowners in California, Palm (1995) reveals that there was a significant increase in the purchase of earthquake insurance after the 1989 Loma Prieta earthquake. Therefore, the increasing premium rate should not prevent insurers from raising more capital to fund disaster loss.

2.3 Role of Insurance against Natural Disasters

The most notable paper examining the role of insurance in recovery from disasters is the paper by Kunreuther (1996), he pointed out that insurance has two main roles in facing natural disasters. The first role is that it fundamentally provides indemnification for any loss or damage from natural disasters and hence, it relieves the cost to recover physical loss and/or financial loss for the affected policyholders. The second role of insurance is to encourage implementation of loss prevention program (Kunreuther, 1996). Insurers have a role in promoting the application of loss preventive measures by offering incentives such as premium reduction to encourage the insured to apply preventive measures (Kunreuther, 1996). In addition, insurance also provides price signals regarding the degree of expected risk in different locations and by different asset types (Kunreuther, 1996). For instance, UK insurers charge flood risk based on risk zones (Field, 2012). However, as in some cases, disaster insurance is subsidized through public insurance program, this lower premium might misrepresent the actual degree of risk and lower the effort of implementing mitigation tool (Cummins & Mahul, 2009).

As pointed by Kunreuther (1996), one way to use insurance to enforce the implementation of loss reduction measures is through mortgage condition. The normal practice is that insurers co-operate with banks to require mortgagee to purchase insurance to be eligible to apply for a loan. This approach ultimately raises the demand for property insurance. After that, insurers may provide additional requirements or recommendations for policyholders to implement loss reduction mechanisms in exchange for premium discount. For instance, the insurer under the Caribbean Disaster Mitigation Project (CDMP) offered its policyholders premium discount if they applied loss reduction measures against hurricane risk (Warner et al., 2009). Moreover, a study of homeowner survey by Botzen and Van Den Bergh (2009) in the Netherland also found that over 60% of homeowners are willing to implement preventive measures in exchange for premium discount.

In practice, insurance companies do not generally offer lower premium discount than the amount required to invest for effective prevention (Doherty et al., 2008). The public sector could potentially play a role in supporting insurance industry to enforce these preventive measures ex ante, by either providing incentives and subsidies, or assisting with monitoring. For instance, a state of Connecticut in the U.S. launched *Shore Up CT* program to offer low-interest-rate loan program for property owners in coastal zones to finance property modification for flood protection and wind-proof structures (Kunreuther, 2015).[8] What is not addressed in this literature is that how well insurance is performing as a mitigation tool in the aftermath of a natural disaster. How does insurance support disaster recovery? In which area or sector is it more efficient? To what extent? To our knowledge, these questions have not been answered. Analyzing these questions would shed lights on the precise benefits of adopting insurance as a means to support reconstruction and/or recovery in the aftermath of a natural disaster, and will enable a more comprehensive cost-benefit analysis of disaster insurance.

[8] See http://shoreupct.org/ for more information.

PART I SHORT-TERM SURVEY

Chapter 3

Methodological Framework

The main objective of the next three chapters is to investigate the role of insurance on business recovery following the Christchurch earthquake in 2011 in the short-term. This is the period of three to six months after the earthquake. In this period, very few insurance claims have been paid (Marsh, 2014); it is most likely that the affected firms relied on other sources of funding to finance their recovery, e.g. their organization's cash flow or the government's assistance. Therefore, the purpose for short-term analysis is to ask whether insured firms are more likely to continue their business operations than uninsured firms as they know that damages incurred are (potentially) insured and therefore costs would be reimbursed.

In analyzing the difference between insured and uninsured in surviving natural disasters, we use a combination of Propensity Score Matching (PSM) and Linear Probability Model (LPM) to investigate the effect of insurance on recovery. A detailed discussion of each method is included in the following sections.

3.1 Propensity Scores Matching (PSM)

Our aim here is to investigate the role of insurance in business recovery immediately after the Christchurch earthquake in 2011. Potentially, the set of firms that have purchased insurance might be different than the set of firms that have not. This case is a textbook case of 'selection bias' when the selection for treatment (to use the terminology common in micro-econometrics) is not random and the different characteristics of treatment and non-treatment firms leads to misleading statistics when identifying treatment effects. If the selection bias, however, is observable (i.e. the different characteristics of treatment and non-treatment firms are observable) then there are several ways to overcome this bias. In an ideal case, and with enough observations, one could potentially find firms that have exactly the same observable characteristics but differed in their decision whether to purchase insurance. The best analogy for this is the twins' studies that are common in, for example, psychological research on the nature/nurture dichotomy. This approach is impossible in this case as it would be extremely unusual to have enough observations to allow for this perfect matching.

A 'matching' algorithm was proposed by Rosenbaum and Rubin (1983). When the set of pre-treatment observable variables is large, exact matching on the covariates (a 'twins' method) is impractical. Rosenbaum and Rubin (1983) introduced matching for the pre-treatment observations using estimated propensity scores. The propensity score is an index (a measure of probability) which describes the probability of receiving treatment. The propensity scores for each observed unit are calculated from an estimated limited dependent variable model (a probit or logit model) (Caliendo & Kopeinig, 2008).

The procedure for selecting a set of pre-treatment variables to include in these propensity score estimations is important as adding irrelevant variables into the regression could potentially increase the selection bias (Caliendo & Kopeinig, 2008). Omitting relevant variables would also lead to increase bias (Dehejia & Wahba, 1999). Therefore, only the variables that theoretically affect the outcome and the treatment variables should be included in the estimation.

Once every unit has an associated 'propensity of treatment' measure, the balancing between the treatment and control groups is done in two steps. First, the sample is reduced by removing all these observations whose associated propensity scores fall outside the *common support* for the treated and control groups. (those observations that have very high likelihood of being treated, and those that have very low likelihood of being treated).

In the second stage, the literature describes several potential matching algorithms, including stratification matching, one-to-one nearest neighbor matching, and radius matching. We start our discussion of the evidence with stratification matching, the most common algorithm for limited samples. Rosenbaum and Rubin (1984) demonstrate that stratification based on estimated propensity scores will balance X covariates if the *unconfoundedness* and the *common support/overlap* assumptions hold.[9] The notations are introduced below:

[9] See Rosenbaum and Rubin (1983) and Imbens (2004) for detailed explanations of the identifying assumptions of propensity score estimation.

Assumption 1 *Unconfoundedness*: if $(Y_1, Y_0) \Pi \; T_i \mid X_i$ then $(Y_1, Y_0) \Pi \; T_i \mid P(X_i)$

Assumption 2 *Overlap*: $0 < P(T_i \; = 1|X) < 1$

The *unconfoundedness* assumption states that if the outcomes (Y_1, Y_0) are independent (Π denotes independence) of the treatment (T_i) given a set of Xcovariates, then the outcomes (Y_1, Y_0) are independent of the treatment (T_i) given propensity scores, $P(X_i)$. If the *unconfoundedness* assumption holds, it also implies that the treatment variable is exogenous (Rosenbaum & Rubin, 1983).

The *common support/overlap* assumption states that the estimated propensity scores of the treated and control units must overlap. This assumption ensures that, at the same estimated propensity score, there are sufficient observations in the treatment and control group that have identical probability of receiving treatment. If the two assumptions hold, Rosenbaum and Rubin (1983) refer to this circumstance as 'strong ignorability', i.e. "when treatment assignment is strongly ignorable given the observed covariates X". When conditional on the estimated propensity scores, we remove the correlation between treatment assignment and X covariates, i.e. $X_i \perp \; T_i \mid P(X_i)$.

Here, we aim to account for the different characteristics of insured and uninsured firms in pre-quake Christchurch. We apply the propensity score estimation as a means to control for selection bias. Thus, the propensity score in this study is the probability of insurance adoption prior to the earthquake. We firstly estimate the propensity scores model as follows:

$$\Pr(INS_i = 1|X_i) \; = \; F(X_i'\beta)$$

Where INS_i is a dummy variable that denotes 1 if the firm had insurance at the time of the earthquake and 0 otherwise. X_i is a set of pre-treatment variables listed in Table 5.1. β is a vector of the estimated coefficients of X_i. F is the cumulative distribution function of logistic distribution.

Any limited dependent variable model can be used to estimate propensity scores (Caliendo & Kopeinig, 2008). In this paper, logistic regression is used. Once propensity scores are estimated, we identify the *common support* area which is the region at which the propensity scores of the treatment and control groups overlap. After estimating propensity scores, a matching procedure is applied to match the control units and the treated units in the *common support* based on the estimated scores. We match the observations by stratifying the sample into quartiles using the propensity scores associated with each observation. Stratification based on the estimated propensity scores is preferable for this study because we have a relatively small number of observations. Implementing other types of matching would reduce the sample further. Besides, it allows us to add other control variables to capture the post-quake damage and disruption that are not included in the propensity scores estimation.

3.2 Linear Probability Model (LPM)

Imbens (2004) proposed that a combination of propensity score matching and regression estimation would provide more efficient estimators than propensity score matching alone because the propensity score method does not account for the correlation between the outcome variables and other control variables.[10]

A combination of propensity score matching and regression-based estimation allows us to include additional covariates to estimate the average causal effect of insurance adoption on the outcome variable. We add a set of control variables that accounts for the damage the firms experienced as a result of the 2010 and 2011 earthquakes. The hypothesis here is that these damages have effects on the outcome of interest (i.e. continuation of operation). The model to estimate the effect of insurance on short-term business recovery is as follows:

$$\Pr(Y_i = 1 | INS_i, Z_i) = \alpha + \tau\, INS_i + \gamma\, Z_i + u_i$$

Where Y_i is the outcome variable denoting 1 if the firm continue its operation after the earthquake (not permanently closed) and 0 otherwise. Z_i is a vector of control variables as listed in Table 5.2. τ is the estimated average treatment effect of insurance on the outcome variable. γ is a vector of the estimated coefficients of Z_i. u_i is the error term. After we stratify the sample by the observation's estimated propensity scores, we then estimate the model for

[10] The paper by Robins and Ritov (1997) also shows an explicit advantage of combining the two methods.

each stratum separately. White's standard errors are used to correct for heteroscedasticity which presents in the model (Angrist & Pischke, 2009).

As the predicted estimates are interpreted as conditional probabilities, they must essentially lie between 0 and 1. One of the issue of estimating limited dependent model with Linear Probability Model (LPM) is that the predicted values could lie outside the boundary of 0 and 1; there is no priori way to ensure that the estimated values would be strictly within the logical boundary (Gujarati, 2003). This is also true as in the case of our study here. While, under general circumstances, the logit/probit model would be a solution to guarantee that the estimations would be within the boundary; the application of these non-linear models, however, requires that there must be variations of samples of the binary choices otherwise the prediction would be unsuccessful.[11] After stratifying the data based on the estimated propensity scores, the observations in each block are assumed to be indifferent in all ways except the treatment effect. In other words, the characteristics of firms in each block are (almost) identical except the condition whether they had adopted insurance which means that there are not sufficient variations of the covariates. Therefore, logit/probit models are not applicable because the estimation procedure will not be successful. This led us to use LPM as the estimation model. We are aware that the estimated marginal effects for LPM specifications could be biased and inconsistent but the sign of the coefficients will be reliable (Angrist & Pischke, 2009).[12]

The basic premise we would like to examine is that insured firms are overall better able to continue operating in the aftermath of a sudden disastrous event. We set out to find the evidence that supports this hypothesis; or rather we set out to reject the null hypothesis of no observable difference between insured and uninsured firms in the aftermath recovery.

[11] See STATA (n.d.a; n.d.b) for more explanations.

[12] See Horrace and Oaxaca (2006) for more explanation on the results of the bias and inconsistency of the linear probability model.

Chapter 4

Data Description

The short-term survey was conducted three to six months after the most destructive earthquake in February 2011. The questionnaire was originally planned to observe the continuing recovery of organizations after the 2010 earthquake. It was then redesigned to also capture the impact of the 2011 earthquake. The questionnaire also includes a section on insurance coverage. Specifically, the firms were asked about the type of insurance they had contracted for at the time of the earthquake. It was sent to 309 organizations.[13] The organizations that were surveyed were generally located in the Central Business District (CBD) of Christchurch and the Lyttleton Town Centre (the site of the main Canterbury region's deep-sea port).

From the information in Table 1.2, there are 176 returned responses but after eliminating non-valid responses, we were left with 140 usable responses. Non-valid responses were considered as duplicates responses, surveys with missing information for some of the key questions, and responses from central and local government entities. State-owned enterprises (SOE) are still included in the study as they operate as for-profit organizations according to the State-Owned Enterprises Act in 1986 (Laking, 2012).

According to nationwide statistics shown in Table 4.1, 90% of the firms in New Zealand have fewer than five employees. Comparatively, our sample contains a smaller percentage of small firms – 55%. Moreover, the overall share of zero-employee businesses in New Zealand is 69% while the proportion of our samples is only 20%. The aggregate figures for New Zealand, however, may be somewhat misleading, as in many cases these very small firms (especially the ones with no employees) are inactive or their operations are very small. So, while our sample is

[13] A large share of participants in this short-term survey is the organizations that were in the pre-survey and agreed to participate in the ongoing studies of this survey series. The pre-survey was conducted in November 2010, about a month after the earthquake in September 2010. It was primarily constructed to observe the impact of the earthquake on organizations around Christchurch area. The participants were selected based on their industry sector. In the pre-survey, approximately 100 firms from 9 unique business sectors, categorized by the Canterbury Regional Economic Development Strategy (CREDS) 2005-2015, were sampled. A total of 879 firms were called to participate in this survey. The response rate was 43% with a returned response of 379 organizations.

not representative in the strictest sense, it most likely reflects better the size distribution of economically active firms.

Table 4.1 Comparison of number of employees between nationwide and the short-term survey

Number of employees	[1]Nationwide			[2]Short-term Survey		
	No. of Enterprise	%	Cum.%	No. of Enterprise	%	Cum.%
0	323,935	68.90%	69%	28	20%	20%
1-5	97,888	20.80%	90%	49	35%	55%
6-9	19,571	4.20%	94%	12	9%	64%
10-19	15,980	3.40%	97%	12	9%	72%
20-49	8,420	1.80%	99%	13	9%	81%
50-99	2,489	0.50%	100%	10	7%	89%
100-499	1,739	0.40%	100%	12	9%	97%
500+	324	0.10%	100%	4	3%	100%
Total	470,346	100%		140	100%	

Source: [1]Ministry of Economic Development of New Zealand (2011), [2]Author's calculation

Our core variable in this study is property damage insurance because of the nature of the damage (structural and non-structural damage due to the earthquake) and the availability of the insurance at the time of the earthquake. Property damage insurance refers to insurance coverage for any loss or damage arising to the insured properties caused by the insured perils. It includes coverage for property, furniture, fixture, fittings, organization's contents, assets, equipment, and machinery. Adopting the terminology from the labor literature which developed the methods to overcome selection bias, acquiring property damage insurance is, therefore, the treatment. The firms that had property damage insurance are thus in the treatment group and the firms that did not are in the control group.[14] We use the words 'treatment' and 'treated' to refer to the firms that had property damage insurance.

[14] Organizations that indicated that they adopted property insurance coverage may have insured themselves with a commercial insurance policy, or, if they are sole traders or operate their business from home, they may be insured under a residential insurance policy. Prior to the quake, there was a significant difference between the residential insurance and the commercial insurance coverage in New Zealand. While properties insured under commercial insurance were covered on a *sum-insured basis*, properties insured under the residential insurance contract were covered on a *replacement basis* (which, in principle, means that there was no limit on the amount insured). This difference *ex post* became important as the replacement-basis arrangements led to significant and on-going delays in claim settlement following the earthquakes. This distinction, however,

The second type of insurance in this study is business interruption insurance (BI). It refers to insurance coverage for loss of revenue and/or increased cost of working as a result of damage to the insured properties. Note that business interruption insurance is normally purchased with property damage insurance (ICNZ, 2013). Moreover, it will trigger only if the insured properties covered under the property damage insurance is damaged by the insured perils. If the insured property is not damaged due to the insured perils, the BI policy will not cover (ICNZ, 2013). Hence, all firms that had adopted business interruption coverage also had adopted property damage insurance.[15]

Another type of insurance is motor insurance. In this study, we are particularly interested in motor insurance for commercial uses such as transportation business. There are three types of motor insurance available in New Zealand: (1) Comprehensive cover, (2) Third party, fire, and theft, and (3) Third party only (ICNZ, 2013). Only the comprehensive cover provides coverage for earthquake. However, we do not have any information of which type of motor insurance was purchased by the firms. This makes it difficult to assess the impact of having motor insurance coverage on business recovery.

Table 4.2 Number of observations classified by types of insurance

Type of Insurance	**Obs.**	**% of Total**
Property Damage (PD)	106	75.70%
Business Interruption (BI)	68	48.60%
Motor	73	52.10%

Table 4.2 shows the number of firms that had insurance coverage for property damage (PD), business interruption (BI), and motor (MOTOR). Of the total 140 observations, 106 firms had property damage insurance at the time of the quake – 76% of the sample. More than half of the

appears not had been perceived as important before or immediately after the earthquake—i.e. before these delays started to be noticed—so we do not think they mar our estimation strategy.

[15] In some cases, policyholders could have purchased an extension under business interruption insurance to cover any loss or damage to their suppliers and/or customers. In this case, the insured could make a claim to their BI policy even if the firm's insured properties were not damaged. This type of insurance is called "*Contingent Business Interruption*". We have no information of whether the surveyed firms had this extension covered in their policy. However, a private conversation with the Insurance Council of New Zealand on the 1st of April 2014 suggested that the availability of contingent BI coverage in New Zealand is limited.

firms that had property damage insurance also had business interruption insurance, and 50 firms had all three types of coverage.

The number of firms that had insurance is shown in Table 4.3, classified into three groups based on the number of employees. About 69% of the firms with five or fewer employees (small-sized) in our dataset had adopted insurance. The firms that employ between 6 and 49 people (medium-sized) have the highest proportion of insurance adoption which is around 90%. About 76 of the firms with greater than 50 employees were insured. Small firms might not purchase insurance because they have a self-insurance policy (although micro firms might neglect to manage their risk exposure and do not buy insurance). Large firms might have their own captive insurance or are self-insured.[16] We find only small differences of the average number of employees between the treated and the control groups. The firms with (without) insurance had an average number of employees of 56 (60) with the standard deviations of 154 (178). In both cases, the standard deviations are quite large.[17]

Table 4.3 Number of observations with insurance classified by number of employees

Number of Employees	Total Obs.	Insured		Uninsured	
		Obs.	%	Obs.	%
0 - 5	77	53	68.8%	24	31.2%
6 - 49	38	34	89.5%	4	10.5%
50 or more	25	19	76.0%	6	24.0%

The number of firms classified by firm characteristics is shown in Table 4.4. We have about 30 firms from each ownership structure, i.e. sole proprietorship, partnership, and limited liability organizations. When examining the firms by their ownership structure, we find that roughly the same proportion of each structure had insurance. With regard to the distribution of the location of businesses in this survey, the majority of the firms were located in the Lyttleton Town Centre, which is where the earthquake was centered – 82% of these firms had insurance.

[16] Captive insurance company is established to provide insurance coverage for its owner (the parent companies) and its subsidiaries. Large (and multinational) organizations tend to have their own captive insurance companies as one of their subsidiaries. The majority of Fortune 500 companies in the U.S. own captive companies (NAIC, 2014).
[17] See Table 1 in Appendices for the descriptive statistics of total number of employees.

Fifteen firms were located in the Central Business District (CBD) area – 67% of them had insurance.

Table 4.4 Number of insured vs uninsured observations by firm characteristics

Definition	**Had insurance**		**No insurance**	
	Obs.	**%**	**Obs.**	**%**
Organisational ownership structure				
Sole proprietorship	34	77.3%	10	22.7%
Partnership/JV partner	30	85.7%	5	14.3%
Limited Liability	30	69.8%	13	30.2%
Location before the earthquake				
CBD	10	66.7%	5	33.3%
Lyttleton	29	82.9%	6	17.1%
Kaiapoi	8	72.7%	3	27.3%
Business Sector				
Retail trade	27	75.0%	9	25.0%
Wholesale trade	6	100.0%	0	0.0%
Manufacturing	9	75.0%	3	25.0%
Construction	3	75.0%	1	25.0%
Transportation and Warehousing	3	50.0%	3	50.0%
Fast-moving consumer goods (FMCG)	17	85.0%	3	15.0%
Lifeline utilities	13	81.3%	3	18.8%
Ownership of Properties				
Own	33	86.8%	5	13.2%
Rent	73	71.6%	29	28.4%
For-profit organizations				
For-profit	96	78.7%	26	21.3%
Not-for-profit	10	55.6%	8	44.4%
Positive Return on Investment (ROI) in the past five years				
Positive ROI	43	86.0%	7	14.0%
Risk Management Practice				
Risk management officers	83	76.9%	25	23.1%
Written BCM	30	71.4%	12	28.6%
Had practiced emergency response	33	73.3%	12	26.7%

The highest number of firms was in retail trade sector – 75% of these firms were insured. There are 20 firms in Fast-Moving Consumer Goods (FMCG) sector – 85% of them had insurance. The firms in FMCG sector are from retail, wholesale, and manufacturing sector. FMCG and retail trade are positively correlated. Another sector of interest is lifeline utilities. These businesses are required, by law, to prepare for emergencies, according to the Civil Defense Emergency Act 2002. These include, but are not limited to, fuel distribution, the electricity provider, and transportation businesses. There are 16 firms in lifeline utilities – 81% of them had insurance. The number of firms in other sectors are quite small.

There are more firms that rent their domiciles than own them in our dataset. About 73% of the firms rent their properties – 71% of these firms had insurance. We also have data on risk management practices of the firms, i.e. the employment of a risk management officer, having a written Business Continuity Management (BCM) plan available, and whether the firms had practiced emergency response prior to the quake. The majority of firms had employed risk management officers; surprisingly only 77% of these firms had additionally purchased insurance. Roughly the same amount of observations had a written BCM available and had practiced emergency response prior to the quake, about half of them (26 firms) had both – about 70% of them had insurance. Hence, these two variables are positively correlated.

Table 4.5 shows the impact of the earthquake in various areas. A total of 15 organizations have permanently closed after the earthquake. From our data, 13 firms were still closed at the time that this survey was conducted; though these firms might re-open again once they have positive business outlook (Hatton et al., 2014). This on-going closing could be due to physical damage or cordons (Stevenson et al., 2012b). This variable is our main focus here. From the data, 73% of the firms that had permanently closed also had insurance. The reason for business closure could be due to other unobserved factors. Or else, the business closure could be due to underinsurance (Muir-Wood, 2012; Brown et al., 2013).

In addition, 77 firms reported a decrease in revenue – 78% of these firms had insurance. Unfortunately, we do not have the actual revenue of the firms. We would have preferred to have the actual revenue of the firms before and after the earthquake to examine the impact of the earthquake on the change in revenue. Nevertheless, 76 firms had reported their estimated percentage change in revenue as shown in Table 4.6. The revenue was reduced by 25% on average for those who had insurance and 47% for those who had no insurance. By analyzing the data at face value, it seems that the insured firms experienced less negative impact than the uninsured ones.

Table 4.5 Number of insured vs uninsured observations by the impact of the earthquake

Definition	Had insurance		No insurance	
	Obs.	**%**	**Obs.**	**%**
<u>Business Closure</u>				
Permanently closed	11	73.3%	4	26.7%
Temporarily closed	56	75.7%	18	24.3%
Ongoing closing	13	81.3%	3	18.8%
<u>The change in revenue after the earthquake</u>				
Decreased	52	77.6%	15	22.4%
Increased	31	91.2%	3	8.8%
Unchanged	22	68.8%	10	31.3%
<u>Structural and non-structural damage</u>				
Structural damage	81	78.6%	22	21.4%
Non-structural damage	77	81.1%	18	18.9%
Disrupted by structural damage	56	78.9%	15	21.1%
Disrupted by non-structural damage	56	82.4%	12	17.6%
<u>Affected by the 2010 earthquake</u>				
Affected by the 2010 earthquake	91	76.5%	28	23.5%
Revenue decreased	43	79.6%	11	20.4%
<u>Financial Recovery Plan</u>				
Plan to recover through insurance	45	100%	N/A	
Plan to recover through organization's cash flow	76	78.4%	21	21.6%
Expected to receive wage subsidy	35	85.4%	6	14.6%

Table 4.6 Average percentage change in revenue after the 2010 and 2011 earthquake

Description	Insured			Uninsured		
	Obs. %	**Mean (SD)**	**Min, Max**	**Obs. %**	**Mean (SD)**	**Min, Max**
Percentage change in revenue	76	-25.13	-100%,	13	-47.62	-100%,
	85.4%	(45.84)	100%	14.6%	(38.33)	5%
Percentage change in revenue after the first EQ	61	-12.84	-100%,	11	-24.28	-60%,
	84.7%	(25.77)	25%	15.3%	(23.24)	20%

With regard to the structural and non-structural damage, almost all firms reported that they experienced structural damage following the earthquake. Of all these firms, 71 firms reported that their businesses were disrupted by structural damage – 79% of them had insurance. Similar numbers of firms had experienced non-structural damage which includes the damage to furniture, fixtures, fittings, equipment, machinery, inventory, and motor vehicles – 82% of them had insurance.

In addition to the damage from the 2011 earthquake, we also have data regarding the 2010 earthquake. Almost all the firms reported that they were affected by the earthquake in 2010 and 54 firms also reported that their revenue had decreased after the 2010 quake. Although the 2010 earthquake had a more minor impact on businesses than the 2011 one, the firms that might have survived had they experienced only one earthquake might not be able to survive after the latter series of earthquake. On average, nonetheless, the firms that had insurance seem to experience less negative impact on their revenue after both earthquakes.

Three survey questions focus on the firms' recovery plans; i.e. whether they plan to recover through insurance, to recover using the organization's cash flow, or plan to use the wage subsidy available from the National Government. The majority of the firms reported that they plan to recover through their organization's cash flow. Interestingly, only 45 firms reported that they plan to recover through insurance even though more than twice as many firms reported that they had insurance. The survey was implemented fairly soon after the earthquake, so it might be the case that respondents were focusing on the more-immediate source of funding available (though at that point in time it was not yet apparent that it will take several years for most claims to be processed). About 40 firms expect to also receive a wage subsidy from the government – 85% of them had insurance.

Chapter 5

Empirical Results

The first section lists the variables for propensity score estimation (PSM) and linear probability model (LPM). The second section presents the empirical results of PSM and LPM separately.

5.1 Variables

We categorize the variables into two groups: variables for propensity scores estimation and variables for the regression analysis. In each group of variables, there are both outcome variables and explanatory variables. We adapt the list of explanatory variables that potentially influence business recovery from the paper by Webb et al. (2002). The details of each group of variables are discussed separately below.

5.1.1 Variables for Propensity Score Estimation

In estimating propensity scores, the outcome variable is insurance adoption. The variable equals 1 if the firm purchased property damage insurance (which is the main insurance coverage for natural disasters) and 0 otherwise. The explanatory variable is a set of pre-treatment variables. In this research, we use the characteristics of the organizations as pre-treatment variables because these variables are time constant and potentially determine the treatment choice. These firm-characteristics are employed to estimate the propensity scores which are the probability of adopting insurance prior to the earthquake of each firm. The pre-treatment variables including the means and standard deviations are listed in Table 5.1. There are 16 pre-treatment variables in total. The categories of the pre-treatment variables include firm size, ownership structure, location prior to the earthquake, business sector, and risk management practice of firms.

We create two dummy variables to represent the firm size. One variable represents small firms that employ five people or less; one variable represents larger firms that employ 50 employees or more. We have two dummy variables to capture the ownership structure, that is sole proprietorship companies and limit liability companies. We use these two ownership structure to represent the firms that are potentially small (sole proprietorship) and the firms that are potentially large (limited liability companies).

Table 5.1 List of the pre-treatment variables, their means and standard deviations

Variable		Insured		Uninsured	
		M	SD	M	SD
Firm Size					
ESMALL5	1 = employ full-time employees less than 5	0.5	0.51	0.71	0.47
ELARGE50	1 = employ full-time employees greater than 50	0.18	0.39	0.18	0.39
Organisational Ownership Structure					
OSOLE	1 = sole proprietorship company	0.33	0.47	0.3	0.47
OLTD	1 = limited liability company	0.29	0.46	0.39	0.5
Location Before the Earthquake					
LCBD	1 = located in Central Business District (CBD)	0.1	0.3	0.15	0.36
LLYT	1 = located in Lyttleton Town Centre	0.28	0.45	0.18	0.39
Business Sector					
BRT	1 = retail trade	0.26	0.44	0.27	0.45
BFMCG	1 = FMCG (Fast-Moving Consumer Goods)	0.17	0.37	0.09	0.29
BUTIL	1 = lifeline utilities	0.13	0.33	0.09	0.29
Risk Management Practice					
RDPT	1 = have risk management department/staff	0.79	0.42	0.74	0.45
RBCM	1 = have business continuity plan (BCM)	0.29	0.46	0.36	0.49
REMG	1 = had practiced emergency response	0.32	0.47	0.36	0.49
ROI	1 = positive average annual return on investment (ROI) in the past 5 years	0.41	0.5	0.21	0.42
OWN	1 = own the business premise	0.32	0.47	0.15	0.36
PROF	1 = for-profit organization	0.91	0.3	0.77	0.44
NSITE	number of sites (nationwide)	54.56	485.89	16.21	53.34

We create two dummy variables to represent the physical location of firms before the earthquake. The first variable represents the firms that were located in the Central Business District (CBD) area which is where the government had restricted access for over two years after the quake. The second dummy variable represents the firms that were located in the Lyttleton Town Centre which is where the organizations were most affected by the first earthquake. We have three variables representing business sectors which are retail trade, fast-moving consumer goods (FMCG), and lifeline utilities. Three dummy variables are used to capture the risk management practice of each organization which are having risk management department/staff, had practiced emergency response, and had business continuity plan in place. These variables are included in our study because we assume that firms with better risk management practice might have higher insurance take-up.

We have three more dummy variables to capture the return on investment, the ownership of business premises, and whether the firm is a for-profit organization. The return on investment is used to capture the financial situation of firms prior to the earthquake and is expected to increase the probability of insurance adoption. For the ownership of the business premises, we assume that taking ownership of its business premises would increase the probability of adopting insurance owing to the fact that the insured would have direct insurable interest over the owned properties. In addition, we have one continuous variable which is the total number of business sites in New Zealand. We assume that the higher number of business locations, the more likely they are to acquire insurance coverage.

5.1.2 Variables for Linear Probability Model

In this group of variables, the main outcome of interest is whether the firm survives in the aftermath of the earthquake. Most firms have temporarily closed after the earthquake, therefore, we define survival as firms that are not permanently closed three to six months after the incident. As with the objective of this paper, we aim to investigate whether having insurance increases the probability of business survival immediately after the earthquake.

The explanatory variables are a set of independent variables that capture the level of damage and disruption following the earthquake. The variables include the change in revenue, the disruption of structural and non-structural damage, the impact of the 2010 earthquake, and the financial recovery plan of the firms. The mean and standard deviations of each variable are shown in Table 5.2.

Table 5.2 List of the variables for regression, their means and standard deviations

Variable	Definition	Insured		Uninsured	
		M	SD	M	SD
Outcome Variable					
SURV	1 = still operating (not permanently closed)	0.9	0.31	0.89	0.33
Insurance					
INS	1 = had property damage insurance	0.76	0.43	N/A	
BI	1 = had business interruption insurance	0.64	0.48	N/A	
The Change in Revenue After the Earthquake					
REVDE	1 = the firm's revenue had decreased	0.5	0.51	0.45	0.51
REVCH	percentage of the change in revenue	-18.02	40.38	-18.21	32.96
Structural and Non-Structural Damage					
DSTRUC	1 = moderately or highly disrupted by structural damage	0.53	0.51	0.45	0.51
DNONSTR	1 = moderately or highly disrupted by non-structural damage	0.53	0.51	0.36	0.49
Affected by the 2010 Earthquake					
BREVDE	1 = the firm's revenue had decreased	0.41	0.5	0.33	0.48
Financial Recovery					
RINS	1 = plan to recover through insurance	0.43	0.5	N/A	
RCF	1 = finance recovery with organizational cash flow	0.72	0.46	0.62	0.5
RWAGE	1 = entitled to earthquake wage subsidy	0.34	0.48	0.18	0.39
CDAY	number of closing days	8.27	24.53	10.22	28.05

Two insurance variables, property damage insurance (INS) and business interruption insurance (BI) are included in the model to see the effect of insurance on the outcome variables. To capture the physical damage of the earthquake, two dummy variables indicating whether the firm's operation was disrupted (stopped) by structural and non-structural damage are used in the estimations. There are some organizations that experience structural and/or non-structural damage but their business operation are not affected. Therefore, we use dummy variables to capture the disruption (rather than the damage) of structural and/or non-structural damage instead.

To capture the change in revenue, we use two dummy variables to indicate whether the firm's revenue had decreased after the earthquake and the percentage change in revenue. We have one more variable to represent the impact of the 2010 earthquake on revenue. This is a dummy variable that indicate whether the firm's revenue had decreased after the 2010 earthquake. In addition, we have three variables that represent how each firm planned to finance its recovery. According to our data, three major methods of funding recovery are through insurance, organizational cash flow, and government's wage subsidy.

5.2 Empirical Results

The empirical results of propensity scores matching and linear probability model are presented in detail in the following section.

5.2.1 Propensity Scores Estimation

We are looking for a model that could estimate the propensity scores such that there will be no significant difference between the treated and untreated firms. Table 5.3 shows the estimated coefficients of logit regression. The mean and the standard deviation of the estimated propensity scores are 0.757 and 0.184 respectively as shown in Table 5.4. The range of the estimated propensity score is 0.261 and 0.993. Although some of the estimated coefficients are not significantly different from zero, we include them in the model. As noted by Schafer and Kang (2008), the fit statistics of the overall model is more important in propensity scores estimation.

In the next step, we discard the observations that lie outside of *common support* region in order to eliminate the observations whose estimated probability of acquiring insurance is too high (they would have always purchased insurance) or too low (they would have never acquired insurance under any observable circumstances). The *common support* ensures that there are observations, in both treatment and control groups, that have (almost) identical probability of assigning to the treatment.

Table 5.3 Estimated coefficients of propensity scores

Variable	Coefficient		Robust S.E.
ESMALL5	-1.33	**	0.62
ELARGE50	-1.27	*	0.84
OSOLE	-0.32		0.59
OLTD	-0.92		0.74
LCBD	-0.30		0.68
LLYT	0.60		0.67
BRT	-0.29		0.54
BFMCG	1.34	*	0.78
BUTIL	0.86		0.93
RDPT	0.51		0.52
RBCM	-1.00	*	0.63
REMG	-0.43		0.59
ROI	0.72		0.56
OWN	0.00		0.00
PROF	0.92	*	0.61
NSITE	1.08		0.65
_cons	1.05		0.80
Log-likelihood	-64.6207		
Wald χ2	26.9		
P-value	0.0426	**	
Pseudo R2	0.1674		

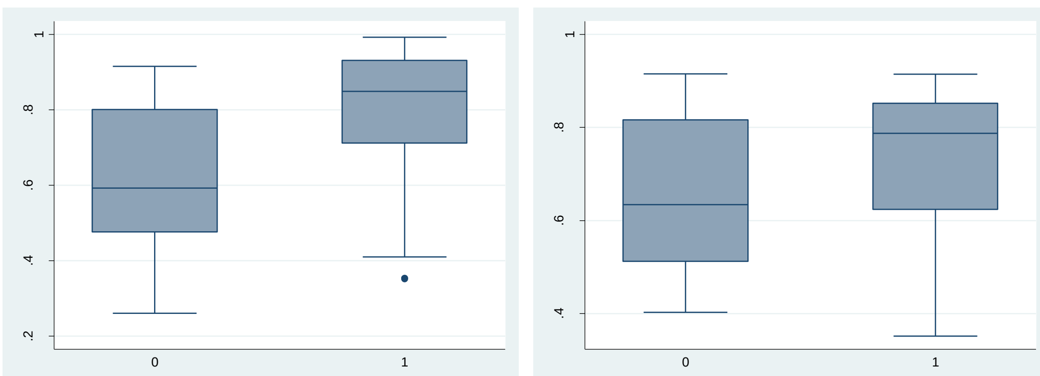
Significance level 0.01***, 0.05**, 0.1*

Table 5.4 Means and standard deviations of the estimated propensity scores

Estimated Propensity score		Treatment (Insured)	Control (Uninsured)
Mean	0.757	0.801	0.619
Std.Dev.	0.184	0.156	0.197
Min	0.261	0.351	0.261
Max	0.993	0.993	0.915
Obs.	140	106	34

The classic way of choosing a *common support* region is by reviewing a visual distribution of the estimated propensity scores (for example, a histogram[18]) and choosing the overlap scores of the treated and the control group. However, this method might not be feasible in many cases when the visual distribution does not explicitly show an overlap area of the treated and the control group. In this study, we select the observations in the *common support* region using *Minima and Maxima* criterion as introduced by Caliendo and Kopeinig (2008). The basic principle of *Minima and Maxima* criterion is to eliminate all observations whose associated propensity scores are below the minimum and over the maximum of the opposite group.

Figure 5.1 Boxplot of estimated propensity scores before (left) and after (right) matched



The *Minima and Maxima* criterion from the estimated propensity scores in our study is [0.351, 0.915] as shown in Table 5.4. We have 4 observations from the control units (the firms that do not have insurance) below the *minima criterion*, i.e. $\mathrm{P}(\mathrm{INS}_{i0} = 1|\,\mathrm{X}) < 0.351$, and 31 observations from the treated units (the firms that had insurance) over the *maxima criterion*, i.e. $\mathrm{P}(\mathrm{INS}_{i1} = 1|\,\mathrm{X}) > 0.915$. Consequently, we remove 35 outliers from the estimation. Figure 5.1 shows the boxplot before and after eliminating the outliers. After removing the outliers, the estimated propensity scores of the treated and control units are better matched.

After that, we stratify the data into four sub-groups based on the estimated propensity scores, henceforth refer to as *Blocks*. Rosenbaum and Rubin (1984) conclude that stratifying the

[18] See Figure 1 in Appendices for the visual distribution of the estimated propensity scores.

data based on the estimated propensity scores into five stratums can reduce approximately 90% of the observed selection bias. We stratified the estimated scores into four groups due to limited number of observations. We initially tested the difference-in-mean of the X covariates in both five and four blocks using the standard t-test as suggested by Dehejia and Wahba (2002). The covariates between the treatment and the control groups in each block are more similar when stratifying into four sub-groups.

The number of observations of adopting insurance in each block as well as the t-score of difference-in-mean are shown in Table 5.5. It is clearly shown that the mean probability of buying insurance between the treated and control units are significantly different using total observations. However, after stratifying the data into blocks, we found that there is no significant difference-in-mean of propensity scores between the treated and the control units in each block. We further test the difference-in-mean of all X covariates in each block. We found some significant differences in the mean of some X covariates in some blocks. Minor covariates' imbalance is allowed because we do not implement exact one-to-one matching.

Table 5.5 Number of observations and the mean propensity scores in each block

Block	**Number of Observations**			**Mean (SD)**	**Min (Max)**	**t-score**	
	Total	**Treatment**	**Control**				
All	105	75	30	0.72 (0.16)	0.35 (0.92)	-5.5454	***
Block 1	25	12	13	0.49 (0.07)	0.35 (0.59)	0. 8264	
Block 2	27	20	7	0.68 (0.06)	0.6 (0.76)	0. 2456	
Block 3	26	22	4	0.81 (0.02)	0.77 (0.85)	-0. 0689	
Block 4	27	21	6	0.88 (0.02)	0.85 (0.92)	1. 5297	

Significance level 0.01***, 0.05**, 0.1*

Table 5.5 shows the number of observations and the mean propensity scores in each block. Each block has different number of observations in the treatment and the control groups. However, we have relatively sufficient number of observations in each block that allows us to further estimate the causal effect of insurance on the outcome variable. The observations in *Block 1* are the firms that have the least likelihood to acquire insurance with an average score of 49%. The firms in *Block 4* are the firms with the highest likelihood to acquire insurance with an average score of 88%. The average probability of insurance adoption of *Block 3* and *Block 4* are quite similar with small standard deviations. In term of number of treated and control units in each stratum, *Block 1* is the only block which has more units in the control group than in the treatment group.

At this stage, the observations in each block are assumed to be indifferent in all ways except the treatment conditions (Angrist & Pischke, 2009). Hence, the samples in each block are assumed to be randomized (Rosenbaum & Rubin, 1983, and 1984). As discussed previously, a combination of propensity score and regression increase the efficiency of the estimates (Imbens, 2004). We are thus able to include additional control variables that do not determine the treatment choice (purchase insurance) but may have an impact on the outcome of interest (firm's post-quake survival). In this case, we are able to control for the different level of damage wrought by the earthquake to each firm in each block.

5.2.2 Linear Probability Model

After stratifying the data based on the estimated propensity scores, we run the standard Linear Probability Model (LPM) regression on each block separately, estimated with White's standard errors. The estimated coefficients are reported in Table 5.6.

Initially, we run a separate regression without control variables using *INS* as the independent variable. The coefficient in *Block 4*, which is the firms that have the highest likelihood of acquiring insurance, shows positive coefficient whereas the other blocks show negative signs. As such, the firms with high likelihood of having insurance appear to have positive effect of insurance on business recovery – 28 percentage point more likely to continue operating in the aftermath. Comparatively, the firms with less likelihood to have insurance, *Block 1*, show 1.3 percentage point less likely to continue its operation.

However, these results do not remain once we add the control variables —those that control for the damage of the earthquake— the signs have changed in the different direction. The overall fit of the models of *Block 1* and *Block 2* are significant at 0.05 significance level with adjusted r^2 of 28.2% and 25.4% respectively while the models of *Block 3* and *Block 4* are not significant. Note that the insurance variable, *INS*, is not significant in any cases.

Table 5.6 Estimated coefficients of Limited Probability Model (LPM)

Variables	All		Block 1		Block 2		Block 3		Block 4	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
No control variables										
INS	0.014	0.063	-0.013	0.153	-0.15	0.083	-0.091	0.064	0.286	0.206
_cons	0.882	0.056	0.846	0.104	1	N/A	1	N/A	0.667	0.2
With control variables										
INS	0.062	0.065	0.096	0.187	0.077	0.133	0.065	0.133	0.131	0.373
BI	-0.029	0.057	-0.238	0.274	-0.237	0.166	0.018	0.169	0.192	0.191
CDAY	0.003	0.001	0.001	0.001	0.005	0.003	0.003	0.002	0.088	0.07
REVDE	-0.064	0.08	-0.341	0.171	0.352	0.208	-0.036	0.165	0.059	0.216
REVCH	0.001	0.001	-0.002	0.003	0.009	0.003	0.004	0.002	0.002	0.003
DSTRUC	-0.123	0.056	0.014	0.225	-0.114	0.115	0.127	0.187	-0.311	0.18
DNONSTR	-0.085	0.05	-0.375	0.315	0.132	0.135	-0.229	0.171	0.029	0.088
BREVDE	0.068	0.059	0.052	0.309	0.049	0.12	0.203	0.138	0.057	0.135
RINS	0.022	0.063	-0.048	0.317	0.124	0.129	0.077	0.183	-0.057	0.116
RCF	-0.112	0.069	-0.305	0.207	-0.231	0.123	-0.354	0.224	0.285	0.219
RWAGE	0.102	0.059	0.26	0.142	0.169	0.121	0.125	0.135	-0.029	0.21
_cons	0.92	0.055	1.025	0.14	0.81	0.125	0.884	0.114	0.668	0.209
Obs.		140		25		27		26		27
P-value		0.043	**	0.047	**	0.046	**	0.962		0.326
Adjusted R^2		0.151		0.282		0.254		0.029		0.294

Significance level 0.01***, 0.05**, 0.1*

The insurance variable in all blocks shows positive signs. The firms in *Block 4*, which is the firms with the highest likelihood of acquiring insurance, seems to have the highest effect of insurance on business survival – 13.1 percentage point more likely to survive the earthquake. Comparatively, the firm in *Block* 1, the ones with the least likelihood of acquiring insurance has the second highest likelihood of survival – 9.6 percentage point more likely.

Interestingly, the firms in *Block 1* and *Block 2,* which are the firms that have less likelihood to adopt insurance, have approximately 23 percentage point less likely to continue its operation if they have business interruption insurance. Contrastingly, the firm in *Block 4* have 19 percentage point higher likelihood to continue its business operation if they have BI. Assuming a firm had adopted both property damage and business interruption insurance, holding other things equal, the impact of both insurance on *Block 1* and *Block 2* would be negative. Comparatively, the impact of both insurance on *Block 3* and *Block 4* would be positive but they are not statistically significant. Nonetheless, we find little evidence to support the hypothesis that insurance supports immediate business recovery in the aftermath of a disaster.

PART II LONGER-TERM SURVEY

Chapter 6

Methodological Framework

In this part, we aim to investigate the role of insurance on longer-term business recovery during reconstruction phase (two to three years after the earthquake). In this period, reconstructions are on-going. All insured firms have notified their claims to the insurance companies. In this instance, the role of insurance is more apparent as in most cases at least some insurance claims were disbursed. Therefore, the research objective for longer-term analysis is to investigate the direct role of insurance claim in supporting firms' recovery.

As we are constrained by the types of the survey questions, the outcome variables of interest are all binary. Therefore, a non-linear model, a logistic regression, is used for analysis (Gujarati, 2003). As heteroscedasticity is likely to present in the model, we use White's standard errors for robustness. The model to estimate the effect of insurance on business recovery is as follows:

$$\Pr(Y_i = 1 | INS_i, X_i) = F(\alpha + \tau\, INS_i + \beta X_i)$$

Where Y_i is the outcome variable denoting 1 if the response to the survey question was positive, and 0 otherwise. X_i is a vector of control variables. The list of outcome variables and independent variables are listed in Table 8.1. τ is the estimated average treatment effect of insurance on the outcome variable. β is a vector of the estimated coefficients of X_i. F is the cumulative distribution function of logistic distribution.

The probability of successful outcome (P_i) conditional on X covariates can be written as:

$$P_i = F(\alpha + \tau\, INS_i + \beta X_i) = \frac{e^{\alpha + \tau\, INS_i + \beta X_i}}{1 + e^{\alpha + \tau\, INS_i + \beta X_i}}$$

The slope coefficients of the logit model can be interpreted as the change in the log of the odds ratio given a unit change in the regressor, holding other things constant. The logit model can be written as:

$$L_i = \ln\left(\frac{P_i}{1 - P_i}\right) = \alpha + \tau\, INS_i + \beta X_i + u_i$$

Where L_i is the Logit, and $\left(\frac{P_i}{1 - P_i}\right)$ is the odds ratio.

In this case, the marginal effect is given by:

$$\frac{\partial \Pr(Y = 1)}{\partial (z_i)} = \frac{e^{z\beta}}{(1 + e^{z\beta})^2} \frac{\partial (z\beta)}{\partial (z_i)} = \frac{e^{z\beta}}{(1 + e^{z\beta})^2} \beta$$

Where z_i is the regressors and $z\beta$ is $(\alpha + \tau\, INS_i + \beta X_i + u_i)$.

Chapter 7

Data Description

The insurance section in the questionnaire asks firms if they plan to finance their recovery through insurance; what type of insurance they had at the time of the earthquake; whether they have submitted claims; whether they believe their insurance coverage is adequate; and what proportion of their claim was already paid out.

The longer-term survey was undertaken in 2013.[19] The sample was selected based on two criteria. First, the participants must have one or more premises located in the districts that experienced serious physical damage by the 2011 earthquake: Christchurch city, Selwyn, and Waimakariri districts. Secondly, the participants were sampled from 19 different sectors defined by Australian and New Zealand Standard Industrial Classification (ANZSIC).

The questionnaire was initially sent to 2,176 unique organizations (a branch of an organization was treated as a representation of one unique organization). The response rate was approximately 25%. As shown in Table 1.2, there are 541 returned responses but after removing non-valid responses, we were left with 461 participants. Non-valid responses were duplicate responses, surveys with missing information for some of the key questions, and responses from public sector. Table 7.11 compares the number of firms in our sample against the nationwide numbers. Half of our sample employs less than 10 people with the majority of organizations employing between 1 to 5 people. The mean and standard deviation of total employees are 86 and 468 respectively.

Table 7.2 presents the number of insured organizations classified by types of insurance they have. The definition of each type of insurance is described earlier in chapter 4. Out of 461 valid responses, 432 observations are insured with property damage insurance and 288 observations are insured with both property damage and business interruption insurance. With this being the case, we chose the insured observations for the analysis in order to prevent any unobserved differences between insured and uninsured firms. Therefore, the total number of

[19] See Brown et al. (2014) for detailed description of the survey.

observation in this study is 432 insured firms. As shown in Table 7.3, 67% of our sample also had Business Interruption insurance (BI).

Table 7.1 Comparison of number of employees between nationwide and longer-term survey

Number of employees	[1]Nationwide			[2]Longer-term Survey		
	No. of Enterprise	%	Cum.%	No. of Enterprise	%	Cum.%
0	323,935	69%	69%	5	1%	1%
1-5	97,888	21%	90%	140	30%	31%
6-9	19,571	4%	94%	73	16%	47%
10-19	15,980	3%	97%	90	20%	67%
20-49	8,420	2%	99%	69	15%	82%
50-99	2,489	1%	100%	30	7%	88%
100-499	1,739	0%	100%	41	9%	97%
500+	324	0%	100%	13	3%	100%
Total	470,346	100%		461	100%	

Source: [1]Ministry of Economic Development of New Zealand (2011), [2]Author's calculation

Table 7.2 Number of observations classified by types of insurance

Type of Insurance	Obs.	% of Total
Property Damage (PD)	432	100%
Business Interruption (BI)	288	67%

Table 7.3 Descriptive statistics of insurance section from the survey

Definition	M	SD
Adopted business interruption insurance	0.67	0.47
Filed insurance claim	0.7	0.46
Believe coverage is adequate	0.55	0.5
Received over 80% of claim payout	0.44	0.5
Adequately Insured with Payout over 80%	0.38	0.49

Since all observations are insured and affected by the earthquake, it is interesting that only 70% of them had filed a claim, as shown in Table 7.3. Two plausible explanations are that their insurance does not cover for damage they incurred and/or the cost of damage for these organizations may be lower than the deductible (the initial amount of loss that is required to be absorbed by the insured). Notably, only half of the sample believe their insurance is adequate. Of those that submitted a claim, nearly half had received almost full insurance payout. However, only 38% of the total sample received payout over 80% and believe that their coverage is adequate.

Table 7.4 The distribution of observations between core variables and outcome variables

Description	**BI**		**No BI**		**Adequately Insured**		**Not Adequately Insured**	
	Obs.	**%**	**Obs.**	**%**	**Obs.**	**%**	**Obs.**	**%**
Operating	281	65.0%	142	32.9%	161	37.3%	262	60.6%
Not Operating	7	1.6%	2	0.5%	2	0.5%	7	1.6%
Profitable	208	48.1%	92	21.3%	121	28.0%	179	41.4%
Not Profitable	80	18.5%	52	12.0%	42	9.7%	90	20.8%
Increased Productivity	158	36.6%	57	13.2%	80	18.5%	135	31.3%
Not Increased Productivity	130	30.1%	87	20.1%	83	19.2%	134	31.0%
Better-off	127	29.4%	53	12.3%	72	16.7%	108	25.0%
Not Better-off	161	37.3%	91	21.1%	91	21.1%	161	37.3%

In this study, we emphasize two insurance questions: whether the firm adopts business interruption insurance, and whether the firm is adequately insured and received payout over 80%. Table 7.4 shows the distribution of observations between our core variables and main outcome variables of interest. Note that 1% of sample had BI and do not continue their operations while 0.5% of sample stops their operations even though they are adequately insured. Since we do not have much variation in terms of number of firms that are operating, this variable cannot be used. While most firms also adopted business interruption insurance, a large share of them reported that their insurance coverage is inadequate, even when they receive nearly full payout. Henceforth, for easy reference, we use ‘adequately insured’ to refer to the firms that reported that they are adequately insured and received insurance payout over 80%.

In term of profitability, 48% of sample are firms with BI and are profitable. Notwithstanding, only 28% of sample indicated that they are adequately insured and profitable. We use profitability as a proxy that indicates whether firms had recovered from the disaster. Overall, there are more profitable firms in the sample than unprofitable. Unfortunately, the level of profitability is not known.

In term of increased productivity, 37% of sample had BI and increased their productivity in the aftermath. Comparatively, only 19% of sample are adequately insured. There are roughly equal number of firms that increased their productivity level versus otherwise (decreased or unchanged). Some firms also reported that their productivity has decreased after the earthquake. In the survey, there is one question asking whether the firm is better off after the earthquake. Approximately 30% of firms are better off with BI while only 17% of firms are better off while adequately insured. The number of observations is detailed in Table 7.5 which also presents the total number of observations in different categories classified into firms that had business interruption insurance and firms that are adequately insured with nearly full payout.

For the industry sector, a large share of firms in our sample are in retail and wholesale trade, and manufacturing sector while the sector with the least amount of sample are in financial services and insurance industry. Note that the original survey has a total of 19 different sectors but we use only 6 sectors for analysis. Some sectors are not included due to small number of observations (less than 10), uninsurable for property and business interruption insurance (e.g. agriculture), and no literature of economic implications of disaster impact (e.g. arts). In addition, some sectors are left out of the model because the overall model is better fit without (higher pseudo R^2). The six sectors are health care and social assistance, manufacturing, construction, accommodation, financial services and insurance, and retail and wholesale trade. Within each industry, the majority of firms also adopted business interruption insurance except in construction business which has approximately equal share of firms with BI versus without BI.

Table 7.5 Total number of observations in different categories classified into firms that had business interruption insurance and firms that are adequately insured

Definition	Total Obs.	Had BI		No BI		Adequately Insured			
						Yes		No	
		Obs	%	Obs	%	Obs	%	Obs	%
Industry Sector									
Health Care And Social Assistance	44	31	70.5%	13	29.5%	15	34.1%	29	65.9%
Manufacturing	78	60	76.9%	18	23.1%	33	42.3%	45	57.7%
Construction	41	20	48.8%	21	51.2%	10	24.4%	31	75.6%
Accommodation	46	38	82.6%	8	17.4%	26	56.5%	20	43.5%
Financial Services And Insurance	21	17	81.0%	4	19.0%	12	57.1%	9	42.9%
Retail And Wholesale Trade	79	57	72.2%	22	27.8%	25	31.6%	54	68.4%
Ownership Structure									
Sole Proprietorship	66	43	65.2%	23	34.8%	22	33.3%	44	66.7%
Partnership	34	21	61.8%	13	38.2%	15	44.1%	19	55.9%
Private Limited Liability Company	262	184	70.2%	78	29.8%	101	38.5%	161	61.5%
Public Limited Liability Company	14	10	71.4%	4	28.6%	4	28.6%	10	71.4%
Size of Organization									
10 Employees Or Less	216	133	61.6%	83	38.4%	68	31.5%	148	68.5%
Greater Than 50 Employees	73	59	80.8%	14	19.2%	30	41.1%	43	58.9%
Disruption by the EQ									
Structural Damage	162	110	67.9%	52	32.1%	67	41.4%	95	58.6%
Non-Structural Damage	201	137	68.2%	64	31.8%	85	42.3%	116	57.7%
Difficult Access to Premises	127	78	61.4%	49	38.6%	49	38.6%	78	61.4%
Financial Status									
Currently have High Debt	36	24	66.7%	12	33.3%	13	36.1%	23	63.9%
Finance its Recovery with Organizational Cash Flow	197	49	72.1%	19	27.9%	86	43.7%	111	56.3%
Located in CBD	316	214	67.7%	102	32.3%	125	39.6%	191	60.4%
Had Emergency Plan in Place	308	210	68.2%	98	31.8%	122	39.6%	186	60.4%
For-Profit Organization	398	272	68.3%	126	31.7%	146	36.7%	252	63.3%
Own The Current Property	188	120	63.8%	68	36.2%	70	37.2%	118	62.8%

With regard to the ownership structure of our sample, the majority of firms are private limited liability companies (limited liability companies that are not listed on the stock exchange). We also categorize ownership structure as sole traders, partnership organization, and public limited liability company (listed firms). The majority of firms in each category adopted business interruption insurance while most of them are inadequately insured.

With regard to the size of organizations, the mean (standard deviation) of total number of employees is 86 (468) with a range between 0 and 7000 people. We also have two dummy variables to represent the firms that employ less than 10 people and firms that employ more than 50 people.

Regarding the damage from the earthquake, most firms experienced damage and loss but not all of them reported that their business operations were also disrupted. Three main statistics are presented including structural damage, nonstructural damage and difficulties accessing the premises. The business operations of most firms were disrupted by nonstructural damage, approximately 47% of the total sample, which includes damage to furniture, fixture, fittings, inventory, motor, equipment, and machinery breakdown. Approximately 38% of the total sample also experienced structural damage. In addition, 29% of firms were disrupted because of difficulties of getting access to the business sites.

With regard to the financial situation, there are 197 firms that have financed their recovery with organizational cash flow – 72% of them had BI insurance. In addition, 35 firms said they had moderate to high debt but the definition of the level of debt is subjective. Additionally, a large number of firms in the survey located in the Central Business District (CBD) of the city of Christchurch. 92% of our sample are for-profit organizations. Roughly the same number of firms own their domicile and rent it.

Chapter 8

Empirical Results

The first section lists the outcome variables, the core variables, and the control variables from the longer-term survey. The second section discusses the correlation among the outcome and the core variables. It is followed by the results of the logit regression estimations.

8.1 Variables

In this study, there are three outcome variables, two core variables of interest, and a number of control variables. Table 8.1 lists the variables and their definition. Each variable is detailed below.

8.1.1 Outcome Variables

All three outcome variables are binary. The first is the profitability of firms after disaster. This variable represents the financial status of each organizations following the earthquake. Current positive financial status of the affected organizations after a disaster is a proxy to measure how well a firm is performing after the disaster. As there are both for-profit and not-for-profit organizations in this study, we use the status of financial surplus for the not-for-profit organizations instead of profitability. For for-profit organizations, this variable equals 1 if the current organization's profitability is moderate or high. For not-for-profit organizations, this variable equals 1 if the organization has a financial surplus, either low or high, at the time of the survey. There are 6 missing values for this variable and they are coded as 0 for analysis. These missing values are assumed to be *missingness at random* where the probability of missing is supposedly due to information availability (by reviewing the responses to other questions); it is generally coded missing values in this case as zero for logistic regression (Gelman and Hill, 2006).

Table 8.1 Variable description

Variable	Definition	M	SD	Min	Max
Core Variables					
BI	1 = had business interruption insurance	0.67	0.47	0	1
CADQ	1 = claim payout over 80% and the coverage is adequate	0.38	0.49	0	1
Outcome Variables					
YPROF	1 = moderately/highly profitable for commercial and 1 = financial surplus for non-profit organizations	0.69	0.46	0	1
YPROD	1 = slight/greatly increased productivity level	0.5	0.5	0	1
YBETO	1 = slightly/significantly better-off	0.42	0.49	0	1
Level of Disruption by the EQ					
DSTRUC	1 = moderately/highly disrupted by structural damage	0.38	0.48	0	1
DNONST	1 = moderately/highly disrupted by non-structural damage	0.47	0.5	0	1
DPREM	1 = moderately/highly difficulties accessing premises	0.29	0.46	0	1
Industry Sector					
SHEA	1 = health care and social assistance	0.1	0.3	0	1
SMAN	1 = manufacturing	0.18	0.39	0	1
SCON	1 = construction	0.09	0.29	0	1
SACC	1 = accommodation	0.11	0.31	0	1
SFIN	1 = financial services and insurance	0.05	0.22	0	1
SRW	1 = retail and wholesale trade	0.18	0.39	0	1
Ownership Structure					
OSOLE	1 = sole proprietorship	0.15	0.36	0	1
OPART	1 = partnership	0.08	0.27	0	1
OPRIV	1 = private limited liability company	0.61	0.49	0	1
OPUB	1 = public limited liability company	0.03	0.18	0	1
Size of Organization					
ELE10	1 = employ 10 employees or less	0.5	0.5	0	1
EGR50	1 = employ greater than 50 employees	0.17	0.38	0	1
Location					
LCBD	1 = located in CBD	0.73	0.44	0	1
LCANT	current number of locations in Canterbury	1.61	3.52	0	70
LNZ	current number of locations in New Zealand	6.49	29.08	0	452
OWN	1 = own the current property	0.44	0.5	0	1
Financial Status					
FREVC	% revenue from Canterbury prior to the EQ	66.79	35.18	0	100
FDEBT	1 = currently have high/very high debt	0.08	0.28	0	1
FOCF	1 = finance recovery with organizational cash flow	0.46	0.5	0	1
NYR	number of years operating before the EQ	18.17	21.6	0	155
EMG	1 = had emergency plan in place	0.71	0.45	0	1
PROF	1 = for-profit organization	0.92	0.27	0	1

The second outcome variable is the level of productivity of firms after the disaster. This variable represents changes in the firm's operation after the earthquake. The question asks firms if their current productivity greatly/slightly increased, decreased or remained the same. It equals 1 if the organization's level of productivity has slightly or greatly increased after the earthquake and 0 otherwise. There are three missing values for this variable which are coded as 0. These missing values are also the case of *missingness at random* which is often coded as zero for logistic regression (Gelman and Hill, 2006). The ability to expand productivity level after a natural disaster could potentially be a good measure for successful recovery. The third outcome variable is whether the firm is better-off as a result of the earthquake. Even though this question is especially subjective, it would be informative to see the relationship of this variable with insurance variables. This variable equals 1 if the firm is significantly or slightly better off as a result of the earthquake and 0 otherwise.

8.1.2 Core variables

There are two core variables of interest for us. The first is whether the organization had business interruption insurance at the time of the earthquake. This variable is a binary choice that equals 1 if the firm had business interruption insurance coverage at the time of the earthquake and 0 otherwise. Since all units in this study had property damage insurance (which includes insurance coverage for furniture, fixture, fitting, contents, equipment, and machinery breakdown), this variable captures the impact of business interruption insurance.

Business interruption insurance (BI) covers loss of revenue and/or increased cost of working following a damage to the insured property. The claim payout from BI is mainly expected to lower the adverse impact of the loss of revenue. The increased cost of working coverage provides support for increased expenditures such as hiring temporary stuff, and renting a temporary warehouse and office spaces. Note that the coverage for increased cost of working is an add-on option with additional premium. We are not able to identify which type of BI coverage is available for each firm.

The second core variable is whether the firm had received insurance payout over 80% and believe the amount of insurance coverage is adequate. This variable is a binary indicator that equals 1 if the firm had received insurance payout over 80% and it believes the amount of insurance coverage is adequate and 0 otherwise. This variable exhibit the extent of supportive role of insurance in aiding recovery when the affected organization is adequately insured.

In our dataset, there are some firms that have received insurance claim in full but the amount of coverage is deemed inadequate compared with the amount of loss they had experienced. Also, there are some firms that responded that they are adequately insured but it is not necessarily reliable because the claims have not yet been paid and we are not able to verify the adequacy of the amount covered. Under these circumstances, the role of insurance is not explicit because any positive effect to the affected firm in the aftermath of the earthquake would be due to other factors, not insurance, because the insurance claim has not been fully paid and/or the cover is not adequate. We, therefore, combine the adequacy of insurance and the proportion of claim payout into one variable to examine the role of insurance once the claim is adequately insured.

8.1.3 Control Variables

There are a total of 25 control variables in this study which can be categorized into five main categories. All the variables are hypothesized to have an impact on business recovery (Webb et al., 2002). The first category is industry sector. We use six binary variables to represent industry sectors: health care and social assistance, manufacturing, construction, accommodation and food services, financial and insurance services, and retail and wholesale trade. We include these as we hypothesize that different industry sectors would respond and recover differently after a natural disaster.

We use four variables to represent ownership structure: sole proprietorship, partnership organizations, private limited liability company, and public limited liability company. Ministry of Business, Innovation & Employment of New Zealand (2014) defines four types of business ownership structure in New Zealand: Sole traders, Partnerships, Companies, and others. We use two dummy variables to capture the first two types. We separate “Companies” into two: privately held Limited Liability Company and publicly held Limited Liability Company.

The third category is the size of organizations measured by the number of employees: organizations with less than 10 employees, and more than 50 (the use of dummy variables to represent a single attribute requires that we subtract one dummy variable out; therefore, the dummy represents organizations that employ between 10 and 50 people are left out of the model). We have the precise number of employees of each firm but using dummy variables to represent the size of organizations allows us to better capture the effect of different organization's size. The fourth category is the causes of disruption brought about by the earthquake. We have three variables capturing different causes of business disruption after the earthquake: whether the firm was disrupted by structural damage, by non-structural damage, and whether the firm had difficulties accessing their business premises (these are not mutually exclusive).

We have three variables to capture the financial situation of each firm. The first is the proportion of the firm's revenue coming from the Canterbury region prior to the earthquake. The firm which solely operates in Canterbury (i.e. earn 100% revenue from Canterbury) is more likely to suffer than the firm which diversified its business operations to several places. The second variable is whether the firm has high outstanding debt. The third variable is whether the firm finances its recovery by spending from its own sources: its cash flow (for company or partnership) or personal savings (for sole traders).

In addition, two variables capture total number of locations of each firm classified, separately, into the total number of locations in Canterbury and the total number of locations in New Zealand (excluding Canterbury). If the affected firm had other locations to operate, they could quickly recover by moving from the Canterbury location to the other locations. Additionally, we have one continuous variable that captures the number of years that the firm had been operating prior to the earthquake; one variable that captures whether the organization is for-profit organization; and, one that captures whether the firm had emergency plans in place at the time of the earthquake.

8.1.4 Correlation

Table 8.2 Correlation matrix of core variables and outcome variables

Variables	Adequately Insured	Profitability	Productivity	Better-off
BI	.165**	.085	.144**	.070
Adequately Insured		.081	-.011	.040
Profitability			.218**	.265**
Productivity				.605**

Significance level 0.01***, 0.05**, 0.1*

Table 8.2 shows the correlations of outcome variables and core variables. For the outcome variable, there is a correlation of 0.605 (0.05 significance) between whether the firm is positively impacted by the earthquake and increased productivity level, and a correlation of 0.265 (0.05 significance) between whether the firm is positively impacted by the earthquake and firms' profitability. Profitability and increased productivity also are positively correlated at 0.218 (0.05 significance).

For the core variables, business interruption insurance coverage is significantly correlated with productivity of 0.144 (0.05 significance). The claim adequacy is not significantly correlated with any outcome variables. The BI also positively correlated with insurance adequately of 0.165 at 0.05 significance level.

8.2 Empirical Results

The regression of core variables without any control variables have 432 observations. However, there are some missing values as there were missing responses for some of the survey questions. Therefore, we were left with 416 observations for the regression when including the control variables. We discuss the sign of the coefficients of each core variable below. The average marginal effects of each core variable will be discussed in a separate section.

8.2.1 Results of Adopting Business Interruption Insurance

As discussed earlier, the first core variable is whether the firm had adopted business interruption insurance at the time of the earthquake. Table 8.3 displays the results of the logit regression with White's standard errors for each outcome variables. When regressing without any control variables, business interruption insurance seems to significantly affect profitability and productivity of firms. However, when adding control variables, the BI significantly (statistically) impacts the productivity level of firms and possibly leads firms to be better off after the earthquake.

The overall model is fit at 0.01 significance level for all three outcome variables with pseudo r^2 of 13.25%, 13.93%, and 13.97% for profitability, productivity, and the firm's better off respectively.[20] In contrast with productivity, business interruption insurance seems to have minimal impact on profitability. While we are not directly testing the various channels through which the presence of BI insurance can generate an increase in productivity, it may be because BI payouts provide additional funding for investment in productivity. Although the increase of productivity after the earthquake may depend on various factors such as the change in demand, our model does show that business interruption insurance (statistically) significantly leads to increased productivity. The result is robust with and without control variables with slight difference in the magnitude of the coefficients. For the third outcome variable, the result suggests that business interruption insurance significantly leads firms to be better off.

In any case, the result suggests that the adopting business interruption insurance has a positive impact on all outcome variables. It significantly supports the increased productivity level and positively affect firms after the earthquake.

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[20] The pseudo r^2 is also known as McFadden's r^2. It is defined as $R^2 = 1 - \frac{\ln \hat{L}(M_{Full})}{\ln \hat{L}(M_{Intercept})}$, where $\hat{L}$ is the estimated likelihood, M_{Full} is model with predictors, and $M_{Intercept}$ is model without predictors. Note that the pseudo r^2 for logit regression is not interpreted as same as the r^2 for OLS. The pseudo r^2 is used to evaluate the goodness-of-fit of a model, however, it has no meaning when used independently or compared with different datasets. They are only useful when comparing multiple estimation models predicting the same outcome on the same dataset (Long & Freese, 2006).

Table 8.3 Logit regression results of adopting Business Interruption (BI) insurance

Variables		Profitability Coef. (S.E.)		Productivity Coef. (S.E.)		Better-off Coef. (S.E.)	
No Control Variables							
BI	1 = had business interruption insurance	0.39	*	0.62	**	0.31	
		(0.22)		(0.21)		(0.21)	
	_cons	0.58	***	-0.43	**	-0.55	**
		(0.18)		(0.18)		(0.18)	
With Control Variables							
BI	1 = had business interruption insurance	0.20		0.76	**	0.44	*
		(0.27)		(0.25)		(0.25)	
	Industry Sector						
SHEA	1 = health care and social assistance	-0.46		-0.27		-0.88	**
		(0.42)		(0.37)		(0.44)	
SMAN	1 = manufacturing	-0.40		-0.66	*	-0.83	**
		(0.35)		(0.36)		(0.35)	
SCON	1 = construction	0.67		1.89	***	1.22	**
		(0.47)		(0.43)		(0.42)	
SACC	1 = accommodation	0.36		1.17	**	1.53	***
		(0.47)		(0.46)		(0.44)	
SFIN	1 = financial services and insurance	2.03	**	0.19		-0.18	
		(0.88)		(0.52)		(0.54)	
SRW	1 = retail and wholesale trade	0.22		0.14		0.04	
		(0.33)		(0.3)		(0.3)	
	Ownership Structure						
OSOLE	1 = sole proprietorship	0.58		-0.15		0.06	
		(0.59)		(0.52)		(0.53)	
OPART	1 = partnership	0.67		0.35		-0.26	
		(0.64)		(0.6)		(0.61)	
OPRIV	1 = private limited liability company	0.20		0.61		0.27	
		(0.51)		(0.46)		(0.46)	
OPUB	1 = public limited liability company	1.79	*	0.03		-0.03	
		(1.01)		(0.73)		(0.75)	
	Size of Organization						
ELE10	1 = employ 10 employees or less	-0.59	**	-0.40		-0.32	
		(0.29)		(0.27)		(0.27)	
EGR50	1 = employ greater than 50 employees	-0.43		-0.07		-0.62	
		(0.4)		(0.38)		(0.39)	

Variables		Profitability		Productivity		Better-off	
		Coef. (S.E.)		Coef. (S.E.)		Coef. (S.E.)	
	Level of Disruption by the EQ						
DSTRUC	1 = disrupted by structural damage	-0.34		-0.02		0.05	
		(0.32)		(0.3)		(0.29)	
DNONST	1 = disrupted by non-structural damage	0.30		0.35		0.52	
		(0.3)		(0.28)		(0.28)	
DPREM	1 = difficulties accessing premises	-0.62	**	-0.26		-0.32	
		(0.31)		(0.3)		(0.31)	
	Financial Status						
FREVC	% revenue from Canterbury prior to the EQ	-0.01		0.01		0.01	**
		(0.01)		(0.01)		(0.01)	
FDEBT	1 = currently have debt	-1.92	***	-1.09	**	-1.21	
		(0.4)		(0.42)		(0.48)	
FOCF	1 = finance its recovery with organizational cash flow	0.01		-0.24		-0.43	
		(0.26)		(0.24)		(0.25)	
LCANT	current number of locations in Canterbury	0.04		-0.08		-0.03	
		(0.05)		(0.09)		(0.03)	
LNZ	current number of locations in New Zealand	0.01		-0.01		0.01	
		(0.01)		(0.01)		(0.01)	
LCBD	1 = located in CBD	0.40		-0.21		0.08	
		(0.27)		(0.26)		(0.25)	
NYR	number of years operating before the EQ	0.01		0.01		-0.01	
		(0.01)		(0.01)		(0.01)	
EMG	1 = had emergency plan in place	k0.44		-0.19		-0.02	
		(0.28)		(0.27)		(0.27)	
PROF	1 = for-profit organization	1.03	*	0.24		0.69	
		(0.63)		(0.54)		(0.57)	
OWN	1 = own the current property	-0.23		-0.55	**	-0.20	
		(0.26)		(0.23)		(0.24)	
_cons		-0.15		-0.66		-1.63	
		(0.69)		(0.66)		(0.67)	
	Log pseudolikelihood	-222.74299		-248.06692		-242.67464	
	Wald χ^2	63.94		63.15		61.62	
	P-value	0.000	***	0.000	***	0.000	***

	Pseudo R^2	0.1325	0.1393	0.1397

Significance level 0.01***, 0.05**, 0.1*
Total observations for core-variable-only regression is 432 organizations.
Total observations for regression with control variables is 416 organizations

8.2.2 Results of Adequately Insured

The second core variable is the adequacy of insurance. As we detailed earlier, we use the combination of whether the proportion of claim paid is over 80% and whether the insured consider the coverage adequate. Table 8.4 shows the logit regression results with White's standard errors of each outcome variables. Without control variables, the core variable only significantly (statistically) affect the profitability of firms after the earthquake. However, when adding control variables, the core variable does not significantly affect any of the outcome variables. The adequate cover positively impacts the firm's profitability and general performance while it has a slight negative impact on the increased in productivity level.

Table 8.4 Logit regression results of adequately insured

Variables		**Profitability**		**Productivity**		**Better-off**	
		Coef. (S.E.)		**Coef. (S.E.)**		**Coef. (S.E.)**	
No Control Variables							
CADQ	1 = claim payout over 80% and the coverage is adequate	0.38	*	-0.05		0.17	
		(0.23)		(0.2)		(0.21)	
	_cons	0.69	***	0.01		-0.40	***
		(0.13)		(0.13)		(0.13)	
With Control Variables							
CADQ	1 = claim payout over 80% and the coverage is adequate	0.25		-0.10		0.16	
		(0.26)		(0.24)		(0.24)	
	Industry Sector						
SHEA	1 = health care and social assistance	-0.42		-0.18		-0.82	*
		(0.42)		(0.38)		(0.44)	
SMAN	1 = manufacturing	-0.39		-0.56		-0.79	**
		(0.34)		(0.34)		(0.35)	

Variables		Profitability Coef. (S.E.)		Productivity Coef. (S.E.)		Better-off Coef. (S.E.)	
SCON	1 = construction	0.67		1.71	***	1.18	**
		(0.46)		(0.42)		(0.41)	
SACC	1 = accommodation	0.35		1.37	**	1.58	***
		(0.46)		(0.47)		(0.44)	
SFIN	1 = financial services and insurance	2.00	**	0.36		-0.13	
		(0.87)		(0.52)		(0.55)	
SRW	1 = retail and wholesale trade	0.26		0.21		0.09	
		(0.33)		(0.3)		(0.3)	
	Ownership Structure						
OSOLE	1 = sole proprietorship	0.58		-0.12		0.05	
		(0.59)		(0.55)		(0.55)	
OPART	1 = partnership	0.64		0.37		-0.28	
		(0.64)		(0.61)		(0.62)	
OPRIV	1 = private limited liability company	0.19		0.64		0.28	
		(0.51)		(0.49)		(0.47)	
OPUB	1 = public limited liability company	1.82	*	-0.03		-0.03	
		(1.03)		(0.73)		(0.76)	
	Size of Organization						
ELE10	1 = employ 10 employees or less	-0.57	**	-0.46	*	-0.32	
		(0.29)		(0.26)		(0.27)	
EGR50	1 = employ greater than 50 employees	-0.40		0.02		-0.58	
		(0.41)		(0.39)		(0.4)	
	Level of Disruption by the EQ						
DSTRUC	1 = disrupted by structural damage	-0.33		-0.01		0.06	
		(0.32)		(0.3)		(0.29)	
DNONST	1 = disrupted by non-structural damage	0.29		0.37		0.51	*
		(0.3)		(0.28)		(0.28)	
DPREM	1 = have difficulty accessing premises	-0.62	**	-0.31		-0.35	
		(0.31)		(0.3)		(0.31)	
	Financial Status						
FREVC	% revenue from Canterbury prior to the EQ	-0.01		0.01		0.01	**
		(0.01)		(0.01)		(0.01)	
FDEBT	1 = currently have debt	-1.93	***	-1.08	**	-1.23	**
		(0.4)		(0.43)		(0.48)	
FOCF	1 = finance recovery with organizational cash flow	-0.02		-0.23		-0.44	*
		(0.27)		(0.24)		(0.25)	

Variables		Profitability Coef. (S.E.)		Productivity Coef. (S.E.)		Better-off Coef. (S.E.)	
LCANT	current number of locations in Canterbury	0.04		-0.07		-0.03	
		(0.05)		(0.09)		(0.03)	
LNZ	current number of locations in New Zealand	0.01		-0.01		0.01	
		(0.01)		(0.01)		(0.01)	
LCBD	1 = located in CBD	0.40		-0.16		0.10	
		(0.27)		(0.26)		(0.25)	
NYR	number of years operating before the EQ	0.01		0.01		-0.01	
		(0.01)		(0.01)		(0.01)	
EMG	1 = had emergency plan in place	0.42		-0.13		-0.01	
		(0.28)		(0.27)		(0.26)	
PROF	1 = for-profit organization	1.13	*	0.37		0.80	
		(0.62)		(0.56)		(0.58)	
OWN	1 = own the current property	-0.24		-0.54	**	-0.20	
		(0.26)		(0.23)		(0.24)	
_cons		-0.20		-0.35		-1.51	**
		(0.7)		(0.64)		(0.66)	
	Log pseudolikelihood	-222.57614		-252.77679		-243.98353	
	Wald χ2	61.32		58.21		60.20	
	P-value	0.000	***	0.000	***	0.000	***
	Pseudo R2	0.1332		0.1230		0.1351	

Significance level 0.01***, 0.05**, 0.1*
Total observations for core-variable-only regression is 432 organizations.
Total observations for regression with control variables is 416 organizations

8.2.3 Marginal Effects

Logit regression result cannot directly interpret the estimated coefficients as marginal effects. Table 8.5 displays the average marginal effects of the core variables on the outcome variables. Business interruption insurance has an average marginal effect of 3.5 (8.11) with (without) control variables on profitability. The result is significant without control variables. This means that having business interruption insurance, holding other things equal, increases the probability of being profitable by 8.11 percentage point.

Table 8.5 Average marginal effects of core variables

Variables	**Profitability**	**Productivity**	**Better-off**
Adopting business interruption insurance			
- No Control Variables	0.0811 *	0.1513 **	0.0734
- With Control Variables	0.0350	0.1558 ***	0.0860 *
Adequately insured			
- No Control Variables	0.0782 *	-0.0111	0.0401
- With Control Variables	0.0438	-0.0201	0.0317

Regarding the increased productivity of firms, business interruption insurance has a significant impact on productivity. It has an average marginal effect of around 0.15 both with and without control variables. When a firm adopted business interruption insurance, it has increased probability of increasing its productivity level by 15 percentage point. This results show robust estimation for the effect of adopting business interruption insurance on increased productivity level of firms in the aftermath of the earthquake.

Regarding whether firms are subjectively better-off, business interruption insurance shows significant result when estimated with control variables. It has an average marginal effect of 0.086. The average marginal effects with and without control variables are slightly different. On average, a firm that has adopted business interruption insurance, has higher probability of being better off after the earthquake by approximately 8.6 percentage point higher, holding other things constant.

The insurance adequacy significantly increase the probability of firm's profitability in the aftermath when regressing without control variables but the result is not significant when adding additional covariates. It has an average marginal effect of 0.0782 which means that being adequately insured increases the probability of profitable by 7.82 percentage point, holding other thing constant.

In addition, insurance adequacy seems to increase the probability of being better off in the aftermath; though none of the results is statistically significant. Contrastingly, the marginal effect of being adequately insured on increased productivity level is counter-intuitive; it has a marginal effect of -0.011 (-0.02) with (without) controls. Insurance adequacy decreases the probability of increasing productivity level by 1 to 2 percentage point.

Chapter 9

Conclusion and Discussion

We examine the role of insurance in business recovery following the Christchurch earthquake in 2011 in the *short*- and *longer-term*. The central question we pose, in the short-term analysis, is whether insurance increases the likelihood of business survival in the aftermath of a disaster. We found only weak evidence that those firms that had both property damage and business interruption had higher likelihood of survival post-quake. Whether this failure to find more robust evidence of insurance impact is an attribute of our data, or of problems in the way the sector operated in the immediate aftermath of the Christchurch earthquake remains an open question. For longer-term analysis, our results show a more explicit role for insurance in the aftermath of the disaster. Firms with business interruption insurance have higher probability of increasing productivity and improved performance following the catastrophe. Business interruption insurance significantly increase the likelihood of enhanced productivity – by approximately 15 percentage points. The BI claim undoubtedly supports business recovery in term of productivity and has positive impact on firm's operation.

As the first paper attempting to find a causal effect of insurance on business recovery, we emphasize some caveats. First, we would have preferred to have data on the actual property damage claims and the amount of business interruption claims each firm had (and relative to each firm's size and revenue). In addition, an issue of major concern in the case of the Christchurch was, and still is, the length of time it took insurance firms to settle their clients' claims. Knowing if and when the claims were settled would have allowed us to analyze more deeply the role of insurance in business recovery and further understand how the timing of payments may (or may not) facilitate business recovery. Had we had the actual break-down of BI claims, into loss of revenue and increased cost of working, we would have been able to further provide details on the precise role of business interruption insurance in determining firm performance.

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Appendices

Table 1 Descriptive statistics of total number of employees

Description	Insured		Uninsured	
	Mean (Std.Dev.)	Min-Max	Mean (Std.Dev.)	Min-Max
All employees	56.42 (154.04)	0 - 1200	60.71 (178.08)	0 - 1000
Full-time	45.48 (139.29)	0 - 1200	53.59 (176.09)	0 - 1000
Part-time	8.22 (25.19)	0 - 170	6.27 (18.24)	0 - 90
Temporary staff	2.73 (24.48)	0 - 252	0.86 (2.25)	0 - 10

Figure 1 Histogram of estimated propensity scores, before (up) & after (down) stratification