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Measuring the Impact of Insurance on Urban Recovery with Light: The 2011 New Zealand Earthquake

Running title: Impact of Insurance on Urban Earthquake Recovery

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Abstract: We measure the longer-term effect of a major earthquake on the local economy, using night-time light intensity measured from space, and investigate whether insurance claim payments for damaged residential property affected the local recovery process. We focus on the destructive Christchurch earthquake of 2011 as our case study. In this event more than 95% of residential housing units were covered by insurance, but insurance payments were staggered over 5 years, enabling us to identify their local impact. We find that night-time luminosity can capture the process of recovery and describe the recovery's determinants. We also find that insurance payments contributed significantly to the process of economic recovery after the earthquake, but delayed payments were less affective and cash settlement of claims were more affective in contributing to local recovery than insurance-managed rebuilding.

JEL: G22, Q54, R11

Keywords: Earthquake, recovery, disaster, insurance, light

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1. Introduction

New Zealand is prone to earthquakes. Recent destructive earthquakes in 2010, 2011, 2013 and 2016 have demonstrated the seriousness of this risk, and have shown that the local recovery from such events is often not easy. In recent years, numerous papers have looked into the recovery from disasters, often from a microeconomic, single household, perspective, or by focussing on a specific case (Rose et al., 1997; Sawada & Shimizutani, 2008; Chang, 2010; duPont Iv et al., 2015). The availability and reliability of detailed and sufficiently frequent microeconomic data has hindered many attempts to explore the relationship between the exposure to disasters and wellbeing.

Moreover, the insurance sector frequently plays a significant role in recovery post-disaster, but analysis of its precise role and functioning during the recovery process is rarely pursued. Insurance is frequently mentioned as (almost) a panacea for disaster risk, and it is singled out as an important part of international disaster risk reduction efforts as specified in the United Nation's 2015 Sendai Framework for Disaster Risk Reduction. Yet, except for Von Peter et al. (2012) and Poontirakul et al. (2017), there is little research that even attempts to look into this question.

Our aim here is to provide a first attempt at measurement of the longer-term effect of a major earthquake event on the local economy, using satellite night-time light intensity as a proxy measure for economic activity. We also investigate whether insurance claim payments for damaged residential property affect the recovery process of the local economy.

We focus on the destructive Christchurch earthquake of 2011 as our case study. We chose this event due to the availability of the disaster insurance claim data, and specific characteristics of the earthquake and the insurance market in New Zealand detailed in the next section.

Our main findings suggest that the night-time luminosity can capture the earthquake damage and the process of recovery. We find that the insurance pay-out contributed significantly to the process of economic recovery after the earthquake.

This earthquake sequence is an attractive case study for several reasons: First, the event is unique case as more than 95% of residential housing units were covered by insurance. Thus, unlike other instances where the insurance penetration rate is much lower, there is no problem of selection (i.e., households that purchase insurance are different from those that do not). Second, there were really big events, from an insurance perspective. Three of the earthquakes in this sequence are listed as some of the costliest insured events, globally, ever. Several geographic aspects of Christchurch make it especially feasible to conduct the analysis we do using night-time luminosity – especially noteworthy are the fact that the city is composed of mostly low rise, spread out residential neighbourhoods (so that the nightlight sensors are not overwhelmed with intense light) and there are many nights of low or no cloud cover (making the measurements more consistent).

We first verify that the reduction in the night-time light intensity between 2010 and 2011 can be used to estimate the immediate direct impact of earthquakes on local economic activity, also using the EQC claim payment data as a direct earthquake damage indicator. We next explore the role of EQC payments on the recovery trajectory in the Greater Christchurch region in the medium run. We use the quarterly change in the nightlight radiance values, which were observed between 2012 and 2016 as a recovery indicator. This data is matched with the quarterly average amount of EQC claim settlements during the same time period.

The remainder of that papers is structured as follows. In the next section we provide some information about the earthquake, the insurance market in New Zealand, and the recovery process. We next discuss the use of nightlight luminosity as a proxy for economic activity and its history of use in the analysis of disaster impact and recovery. After covering these literatures, we describe the data and methodology used in this paper. In the last section , we present our empirical results; and we end the paper with some further comments about future research.

2. The Christchurch Earthquake of 2011

On 4th September 2010, a M7.1 earthquake occurred epi-centred close to Darfield village, a rural area not far from the city of Christchurch (the biggest city in the South Island of New Zealand, with a population of about 400,000). The earthquake damaged the nearby townships and the eastern suburbs of the city which were vulnerable to liquefaction. Many old unreinforced masonry and heritage buildings were affected as well. This event was followed by, a M6.3 earthquake to the southeast of the city on 22th February 2011. This event resulted in intense reserve fault motions which were directed toward the city centre (GeoNet, 2011). Many buildings in the Port Hills, the Central Business District (CBD) and the eastern suburbs were severely damaged.

There were 185 fatalities in the February 2011 earthquake.[1] Many commercial and residential properties were damaged. More than a thousand commercial buildings were ultimately

[1] The majority of people were killed because of the collapse of two reinforced concrete office buildings – the 1992 Canterbury Television (CTV) building and the 1963 Pune Gould Corporation (PGC) building. Almost all the other deaths occurred when façades of both old and modern commercial buildings in the CBD collapsed.

demolished, and practically all residential buildings in the city experienced at least some minor damage, with many thousands eventually requiring complete rebuilds. The areas around the Avon River that goes through the CBD (from West to East) suffered heavily from subsidence. The flood and liquefaction risk of this area was eventually found to be unacceptably high, and the government decided to no longer zone it for residential use by buying the properties from their owners. Similarly, in the Port Hills east of the city, there were areas where the risk to life safety and land remediation was deemed to be too high due to the risk of cliff collapse. In total, around 8,000 residential properties were declared uninhabitable and defined as residential red zones by the government. Following all this, there were numerous aftershocks in 2011-2012, which mostly led to additional destruction to already damaged buildings, and to delays in reconstruction.

This Canterbury Earthquake Sequence (CES) was the most devastating catastrophe in New Zealand's history (Simpson, 2013). New Zealand has very high insurance penetration ratio, with more than 95% of residences being insured for earthquakes (Nguyen and Noy, 2017).[2] This led to high losses to both the overall economy and insurance industry; up to USD 32 billion and USD 21 billion, respectively.[3] EQC (2017) reports that the scheme has settled over 167,000 and 73,000 valid dwelling and land claims respectively. These claim settlements would cost EQC program approximately USD 4.6 billion. In the private insurance section, there

[2] Nguyen and Noy (2017) emphasize the uniqueness of New Zealand's earthquake insurance in term of penetration rate and the extent of coverage by comparing it with other international earthquake insurance schemes. The authors claim that if a similar-sized earthquake event had happened in other earthquake prone developed countries such as Japan, their citizens would receive much less compensation.

[3] Currency are converted to USD, based on the 2016 IRS yearly average exchange rate.

was USD 5.3 billion paid for commercial claims[4] and USD 3 billion for residential claim[5] (ICNZ, 2014).

The New Zealand Earthquake Commission (EQC) is a public entity providing the first layer of residential insurance for earthquakes (for those properties who are further insured privately). The EQC was liable for residential claims that cover dwelling damage up to USD 68,000, content damage up to USD 13,600, and some land damage (liability capped at the market value of the land).[6] The over-cap and out-of-scope claims for damages (for example to pools, driveways or fences) were provided by the private insurers. Based on the EQC data we analyse in this paper, approximately 25,561 residential building structure over-cap claims were transferred to private insurers to be resolved.

The number of submitted claims was twice as large as the EQC expected from a 'worst foreseeable event.' Private insurance companies also had limited experience handling such a large number of claims prior to this event, and almost no experience coordinating their work with the EQC. Further complications were the large number of aftershocks, many previously unacknowledged ambiguities in insurance contracts, complex cover for land damage that is not available in other jurisdictions, and a legal system that was also overwhelmed post-earthquake. Overall, the insurance settlement process has taken over six years to complete, and only now in 2018 are the last remaining claims being settled.

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[4] Vero insurance is one of the main commercial insurers. It received over 31,000 claims, valued at USD 3.3 billion.
[5] Including Southern Response.
[6] The local currency cap amounts are 100,000 NZ$ for dwelling damage, and 20,000 NZ$ for contents.

The delays in claim settlements meant that many homeowners had to go through anxiety-inducing long periods of time in which they were unable to live in their partially ruined dwelling but also unable to have them fixed or move away with the proceeds of their claims (King et al., 2014).

Our study is the first empirical work, as far as we know, that investigates the role of insurance claim settlement on local recovery by exploiting the variations in the timing of the insurance payments in Greater Christchurch (the city and its satellite towns and suburban neighbourhoods). We also rely on the availability of a proxy measure for recovery (night-time luminosity) in both the spatial and temporal detail that are required for accurate identification of the recovery patterns we investigate.

Several other research projects have looked at the CES and it is worthwhile to briefly describe their findings as they pertain to our focus on residential areas' recovery. Similar to residential properties, commercial insurance claim settlement also faced delays due to the scale of claim handling, the complexity of claims, the ongoing seismicity, and the lack of experienced loss assessors. Additional reasons for delay in the assessment process include poor information management, slow decision-making by claimants and the use of brokers for claims settlement (Brown et al., 2013; Seville et al., 2014; Brown, Seville, et al., 2016).

Stevenson et al. (2011) found that business closure was influenced by the time owners waited for the damage assessment. From surveys, Stevenson et al. (2011) also find that affected organisations financed their recovery primarily with their organizational cash-flow instead of from the proceeds of their claim payments.[7] Using these surveys, Poontirakul et al. (2017) find no short-run difference in business survival between the insured and uninsured firms. However, later on, firms which had prompt and full claim payment experienced better recovery in terms of performance and profitability than those that had inadequate or delayed claim settlements. Interestingly, they find the latter firms performed marginally worse than uninsured firms.

3. Insurance and Earthquake Recovery Elsewhere

The literature on the economics of disaster has grown significantly in recent years, especially in its investigation of the varied impacts of disasters. Yet, relatively less is known about the post-disaster recovery process and the factors that shape it. Platt et al. (2016) use a wide range of data sources to identify the speed and the quality of recovery after major earthquakes. These sources include satellite imagery, crowd-sourced geographic information, ground surveys, household surveys, official publications and statistics, and insurance data. They conclude that remote sensing seems to provide accurate and reliable information, but not that this approach is costly and time-consuming.

Few papers have closely looked at the role of insurance post disaster. The insurance sector itself has concentrated more on estimating disaster loss and resolving claim settlements than it has on measuring its role in the recovery process (Kusuma et al., 2017). Melecky and Raddatz (2015) find that high- and middle- income countries, which have high insurance

[7] Clement (2012) and Muir-Wood (2012) claim that the costs of demolition, debris removal and demand surges post-earthquake for the professional and construction services were excluded in the insurance compensation, so that compensation was anyway insufficient to fully fund reconstruction.

penetration, are affected less and experience better economic recovery following a disaster; similar findings are reported in Von Peter et al. (2012). Sawada (2012) focuses on a specific case, and concludes that housing insurance payments contributed significantly to the rapid recovery of Yamakoshi following a 2004 earthquake.[8]

4. Night-time Luminosity in Economic Research

In the past decade, night-time light has been used widely in the social science literature as an indicator for economic activity and human development. Because most consumption and household activities require illumination in the evening, using changes in light intensity as a proxy for GDP per capita growth appears to be appropriate. When household income increases, its light usage also increases (i.e., lighting is a normal good). Studies showing the relationship between night-time luminosity and socioeconomic information include: (Sutton & Costanza, 2002; Doll et al., 2006; Sutton et al., 2007; Elvidge, Sutton, et al., 2009; Ghosh et al., 2009; Ghosh et al., 2010; Chen & Nordhaus, 2011; Kulkarni et al., 2011; Michalopoulos & Papaioannou, 2013; Hodler & Raschky, 2014a; Pinkovskiy & Sala-i-Martin, 2016).[9] In all these projects, night-time illumination data is obtained from DMSP/OLS or VIIRS DNB satellites, and provide useful estimates of high frequency and high spatial resolution for economic outcomes.[10]

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[8] Housing earthquake insurance penetration rate in Yamakoshi before the earthquake was over 80 per cent. Most households participated in an insurance program offered by farmers' cooperatives (Ichimura et al., 2007).

[9] Using panel data of over 100 middle- and low- income countries, Henderson et al. (2012) argue that the elasticity of change in night-time lights with respect to income growth is close to one. In contrast, Bickenbach et al. (2016) claim that the elasticity of regional GDP with respect to night light tends to be unstable for both developed and developing countries.

[10] See the data appendix for more detail about the luminosity data.

Luminosity data has been used to measure economic wealth with spatial detail that is never available from statistical agencies. It has been used to measure wealth at the sub-national level at various grid-cell sizes (Besley & Reynal-Querol, 2014; Montalvo & Reynal-Querol 2016; Storeygard, 2016; Bruederle & Hodler, 2017; Henderson et al., 2017), projected onto cities and municipal boundaries (Brown, Guin, et al., 2016), and for administrative regions (Hodler & Raschky, 2014a, 2014b; Bickenbach et al., 2016). The correlation between the night-time light and economic activity tends to be weaker at very small unit levels (e.g., one pixel), so some aggregation is necessary. For example, Mellander et al. (2015) find that night-time light at fine spatial level is a better proxy for night-time population than day-time business activity or total wage incomes. The authors also confirm that light is a better within-country indicator of urbanization, as it captures population density, rather than the population count.

Moreover, social scientists have used night-time light in order to investigate the economic losses and recovery post disaster event. For instance, Klomp (2016) explores how large-scale disasters affect economic activity, using night-time light intensity and historic data on 1000 natural adverse events between 1992 and 2008. He finds that geophysical and meteorological events reduce night-time illumination in developed countries while hydrological and climatic disasters lead to a short-term decline in the light intensity in developing countries. Klomp concludes that earthquakes have prolonged negative effects on the economy. On average, a single earthquake event can cause damages that are roughly 2.5 times larger than losses from the major drought and flood. Several research papers have used night-time light to capture the immediate economic impact of floods, typhoon and other climate disasters (Tanaka et al., 2000; Bertinelli & Strobl, 2013; Elliott et al., 2015; Mohan & Strobl, 2017).

In contrast, few studies estimate a post-earthquake recovery process using luminosity data. Hashetera et al. (1999) use the illumination intensity before and after the 1999 Marmara earthquake in Turkey to identify the impacted areas and provide information for the initial emergency response. Kohiyama et al. (2004) assess the immediate impact of the 2001 Gujarat earthquake using night-time light intensity, and claim that the estimated loss from the night-time illumination intensity is consistent with their fieldwork information. Gillespie et al. (2014) use household survey data (2004-2007) in Sumatra after its 2004 earthquake/tsunami and reveal the link between night-time luminosity and spending per capita at the community level. They suggest that satellite night-time imagery is a useful tool for assessing the recovery path post disaster event.

5. Data

We restrict our research area to Greater Christchurch only; the region contains three districts: Waimakariri, Christchurch City, and Selwyn. According to the 2006 Census, the regional resident population count was nearly 425,000 with 82% of living in Christchurch City. We aggregate and analyse all the data at the Area Unit level.[11] Based on the 2016 Geographic Boundary of Statistics New Zealand, there are 183 Area Units (AU) in Greater Christchurch, containing 125 AUs in the city. In comparing the AUs in Christchurch city and the two other districts, Table 1 shows that the AUs of the former are much smaller in area, but have higher population densities. Similarly, household income density (income per km^2) in Christchurch is

[11] Area Units (AU) are aggregation of meshblocks (the smallest geographical unit used by Statistics New Zealand). AUs are non-administrative areas intermediate in size between meshblocks and territorial authorities. In urban areas, AUs are often a collection of city blocks while in rural areas, AUs may be similar to localities or communities according to Statistics NZ.

nearly double than in Waimakariri and Selwyn districts, though mean household income was lower in the City.

5.1. Night-time Light Data

We use night-time light data derived from images taken by DMSP/OLS and VIIRS DNB.[12] We convert the images to integer format to obtain nightlight brightness at the pixel level, and clip these processed images to the Greater Christchurch boundary, which is available from the Statistic New Zealand. Because each AU can cover several pixels, we calculate the average nightlight intensity within each AU polygon.

The scales of nightlight pixel and area unit are illustrated in Figure 1. The figure shows the geographic boundaries of Cashmere West and Cashmere East, which are located in the south of Christchurch City. It is easy to observe from this figure that even within the city each AU may contain more than 10 pixels; less densely populated AUs may contain even more pixels.

Figures 2 and 3 present the night-time light images of Greater Christchurch from the 2016 cloud-free composite DMSP/OLS and VIIRS DNB products, respectively. The brightly lit area in the figures corresponds to Christchurch City. It is noticeable that the DMSP data have saturation centred on the city area while the VIIRS product shows more spatial detail. The latter has a better spatial resolution (about 750m) than the 2.7km- resolution of the former (NOAA, 2013). The spatial area for an area unit in Greater Christchurch is approximately 54.7 km^2 on average. Due to the difference in time horizon of the two products, both night-time

[12] More explanations about the data and its sources are available in the appendix. We used ArcGIS software to extract the light data from the TIFF night-time light raster images; which are available to download on the NOAA website.

light datasets are used in this paper. More specifically, the DMSP data of satellite F18, from 2010 to 2013, are used to capture the reduction in nightlights as the indicator of short-run disaster impact.[13] For each AU, the average annual light intensity is recorded in digital number ranging from 0 to 63, with higher values representing higher brightness. In addition, we use the quarterly VIIRS DNB data for the period from 2012 to 2016 for each AU. This composite cloud-free night-time light data is used to estimate the recovery process of localities in the Greater Christchurch region following the CES.

As noted earlier, we aggregate the radiance value of each pixel to the AU level. Figure 4 shows this AU-level aggregated data for 2013. This figure is directly comparable to Figure 3 that shows the same data still at the pixel level, before aggregation to AU. As elsewhere, night-time lights are much brighter in urban centres such as Christchurch City. Especially the Christchurch CBD (Centre Business District), where most office buildings are located. Its light intensity is constantly at the highest level, compared to other areas in Greater Christchurch. AUs that are closer to the CBD have higher light brightness, though the AUs are not fully saturated (at the highest possible luminosity measure).

Henderson et al. (2012) express a concern that light emission is filtered away in low light intensity pixels in the older satellites, so that these might be inappropriately set to zero by the process of screening and filtering. In our sample, less than 5 per cent of the AUs contain

[13] Due to the lack of on-board calibration, satellite shift and sensor degradation across different DMSP satellites (F10- 1992/94, F12- 1994/99, F14- 1997/03, F15- 2000/07, F16- 2004/09 and F18- 2010/13), the obtained digital number of night-time light series cannot be directly used to detect the temporal dynamics over a long period (Elvidge, Ziskin, et al., 2009; Zhang et al., 2016; Li & Zhou, 2017). Hence, in this paper, we only use the light intensity derived from the F18 satellite imageries, even though the F16 product is also available. This data is only available in annual frequency.

only pixels with zero radiance value. This is consistent in both datasets. We interpret that the AUs that have no nocturnal light emission are accurate, as the new satellite we use for the recovery measure is able to detect dimmer lighting using nocturnal airglow emitted by the ionosphere (Miller et al., 2012). For some summer months, the VIIRS DNB data are unavailable for the region. In our analysis, we have to discard the images for 4 months.[14]

Figure 5 graphs the aggregate average night light intensity in the Greater Christchurch region, derived by DMSP and VIIRS over time. The time series observations of the F18 DMSP satellite unsurprisingly show that there was a reduction in night-time luminosity observable in 2011. The average light intensity has increased in 2012. However, it was still lower than the light level pre-earthquakes. The figure also shows the annual night-time light, extracted from the monthly VIIRS DNB imagery. The average annual light intensity increases steadily from 2012 to 2015 before declining in 2016. It is noticeable that comparing between the DMSP and VIIRS DNB data, the nightlight changed in opposite direction during their overlapped years 2012 - 2013. It seems that the two satellite products are incomparable. Even after radiometric inter-calibration undertaken by NOAA, we may be unable to compare between them as the imageries were acquired at different time of day; we consequently cannot link the two datasets.[15]

[14] The monthly DNB data are unobtainable for November-December 2012, January and December 2013. The graph of the monthly VIIRS light intensity series is available in Appendix Figure 1.
[15] See Appendix

5.2. *Insurance Claim Data*

To measure the payments delivered by the insurance sector in the recovery of the Greater Christchurch region, we use the claim payment data that was geo-coded by EQC. The dataset includes individual claims for earthquake events during the 2010-2011 CES. For each insured event, EQC claim data provides the actual amount that EQC have spent on each property and the estimated total damage cost [16] as it was apportioned for each earthquake event. Nguyen and Noy (2017) provide further details about the earthquake residential insurance scheme in New Zealand and more detail about EQC claim data. In this study, we have records of approximately 220,000 valid CES claims for nearly 100,000 properties in Greater Christchurch. More than 85 per cent of these claims came from Christchurch city. Three fourths of the claims are for building structure and the rest are for land and content exposure.

Figure 6 provides the breakdown of EQC claim across districts and the separate earthquakes included in the CES event (2010 – 2011). Unsurprisingly, the Darfield earthquake and Lyttleton earthquakes were the main cause of the earthquake damage to residential property and claim submission in Greater Christchurch. Even though the epicentre of the first event was located further away from Christchurch City, the number of valid claims for the first large earthquake is nearly as high as the latter's figure. However, in Christchurch city, there are fewer claims for the Darfield earthquake relative to the Lyttleton aftershock. For these two earthquakes, the number of residential claims are 67,000 and 72,000, respectively.

[16] This estimated damage cost is the total insurance payment that EQC and private insurers would have transferred to the claimants (as insurance liability was based on replacement costs rather than the value of incurred damage).

Insurance claim payments across asset exposures (building structure, land and content) are highly correlated. Table 2 reveals that the correlations between the insured exposures are more than 0.6. There is usually more than one claimed exposure for each lodged claim.

Table 3 provides summary statistics of quarterly claim payment data for the CES at the AU level. In Greater Christchurch, the average total of quarterly claim payments for each exposure per AU are USD 462,696, USD 17,347, and USD 60,240 for structure, content and land, respectively. By far most of the claim payments are for building structure claims. The number of valid building claims for the CES is high and their claimed amount is typically higher than the other two types of payments.[17]

The standard deviation of total land claim payment is high relative to its mean. There are claims with very high land remediation cost due to land movement, rock fall and cliff collapse, in particular for the Port Hills area. EQC does not only covered for the visible land damage, but the scheme has also been found liable for ground improvement works or long-term reduction of property values due to increased flood and liquefaction vulnerabilities.[18]

We also exploit other information in the EQC data; in particular we focus on two variables: time to settlement, and proportion of cash in settlement. The first is the average number of days to claim settlement, since the day the claim was launched, for each quarter in each AU.

[17] In Christchurch, the value of exposed assets for building structures is much higher than for contents and land values.

[18] Following the CES, many properties have suffer from IFV (Increased Flood Vulnerability) and ILV (Increased Liquefaction Vulnerability) land damage. As far as we know, EQC is the only insurance scheme globally that offers compensation for such risks.

The second variable is the proportion of cash payment amount relative to the total claim settlement in each AU.

Table 3 illustrates that 90 per cent insurance settlement amounts for the CES were in form of cash, while the number of cash-paid claims is only 60 per cent (EQC, 2017). As discussed above, it took between 1 to 4 years for a claim to be resolved (average is nearly 3 years).

5.3. Other Variables

We also use data from Statistics New Zealand, which provides information regarding dwelling and household at the AU level from the census conducted in 2006 and 2013. Essentially, in this paper, the EQC claim data and Statistics NZ census data were processed and matched with the NOAA night-time light data at the AU level. Table 4 illustrates the correlation between the VIIRS non-saturated nightlight and control variables in quarterly dataset at the area unit level from 2012 - 2016. There are positive correlations between light brightness and most explanatory variables. Nightlight is a measure of economic activity and human development. Hence, we expect that nightlight is positively correlated with population and the number of occupied dwellings at the AU level. However, the correlation and the explained variation of the relationships are not as high as the estimates from other previous nightlight research at regional or country level.

Table 4 also shows that light intensity captures the density variables better. For instance, the correlation between nightlight and population is 0.328, which could be compared with the correlation between nightlight and population density (0.409). Interestingly, the nightlight is negatively correlated with household income while there is positive relationship between light brightness and income density. The explanation for this phenomenon is that some wealthy AU may only have a few households live in (as they are typically single-houses with larger plots of land). These AUs have high average household income, which may not represent the economic activity of the area units as the income density does. As a result, the correlation between nightlight and income density is positive and higher. We also find that the nocturnal light is negatively correlated with the distance between the AUs to the epicentre. This variable could be considered as an earthquake damage indicator. We expect that if the units are closer to the earthquakes' epicentre, the earthquake damage might be higher. Hence, during the CES, the loss in nightlight should be higher for these AUs.

6. Methodology

We now turn to the regression analysis where we explore the change in night-time light in the Greater Christchurch region, during and after the CES. In all of our empirical estimations, we exclude the CBD area because the area was cordoned off for two years, and its redevelopment was subject to a very different, complex, and contentious, regulatory regime.[19]

We present two set of results. The first is intended to examine the short-term impact of earthquake damage on local economic activity in Great Christchurch. The second aims to estimate the effect of insurance payments on the recovery of local residential areas in the region.

[19] The CBD area is mainly commercial buildings, which therefore does not capture the economic activity of households. In addition, because the main exposure in the centre district is from commercial buildings, the residential claim payment variable we use is likely to mismeasure the actual impact of the earthquakes.

6.1. *Earthquake Damage and the Loss in Night-time Light*

As already shown in figure 3, the average DMSP nightlight digital value of AUs has declined between 2010 and 2011 and started recovering since 2012. We begin to use the immediate reduction in light brightness post- earthquakes as an indicator of the loss in economic activity in Greater Christchurch. The variable is calculated as follows

$$Economic\_Loss_i^{eq} = \Delta NTL_i^{2010-2011} = \ln(NTL_{i,2010}) - \ln(NTL_{i,2011}) \quad (1)$$

where NTL_i is our economic development indicator based on the DMSP nightlight value (taken in logarithms) in AU *i*. We next aggregate the insurance claim payments over the whole period, to the AU level, to indicate the financial loss experienced by each AU due to earthquake damage. We create a damage ratio variable from these aggregate figures (in equations 2).

$$Damage\_ratio_{i,k} = ln(\frac{\sum_k Claim\_payment_{i,k}}{\sum_k Asset\_value_{i,k}}) \quad (2)$$

Damage_ratio represents the total earthquake financial loss on all exposures (*k* = structure, content and land) as a ratio of the total exposure value for all dwellings for which there were claims in the area unit *i.*[20] The property value data is the New Zealand quotable value (QV) data which insurance assessors used in their damage assessment process.

In the first set of results, we use *ΔNTL* as a dependent variable indicating the change in economic activity due to the earthquakes. We hypothesize that AUs that have high *ΔNTL*

[20] As almost all houses were insured, the deductible was very low, and almost all houses incurred some damage (even if minor), this sum approximates quite closely the total value of residential assets.

experienced large economic losses because of the large amount of damage to property (assets), as follows:

$$Economic\_Loss_i^{eq} = \alpha + \beta_k Damage_{i,k} + \gamma X_i + \varepsilon_i \quad (3)$$

Where $Damage\_ratio_{i,k}$ is earthquake damage as a ratio of exposed value for each AU as specified in equations (2). We use robust standard errors in order to control for the heteroskedasticity in the error terms. In addition, for robustness we include several control variables[21] (X_i) that might also affect the measured economic loss in our regressions such as household income, night-time population, number of bedrooms, surface area and distance to the Christchurch CBD (taken in logarithms).

6.2. Insurance settlement and Christchurch recovery

In the second set of regressions, we estimate the effect of insurance payments on local recovery in the Greater Christchurch region, following the earthquakes. In this regression, we use the VIIRS DNB night-time light dataset from April 2012 to August 2016. We convert the nightlight data from monthly to quarter frequency *t* for AU *i*. In order to identify the economic recovery in Greater Christchurch, we take the proportional change in the night-time radiance value for each quarter. In the specification, the variable is used as dependent variable.

$$Economic\_Recovery_{i,t}^{Post} = \Delta NTL_{i,t}^{2012-2016} = \ln(NTL_{i,t+1}) - \ln(NTL_{i,t}) \quad (4)$$

Similar to the damage variables in the first set, we then use either the insurance payments as a ratio of exposed assets value at quarter *t*, in AU *i* (as described in equations (5)).

[21] The correlations between damage ratio and other variables are shown in the appendix table.

$$Ins\_Income_{\ i,t,k} = ln(\frac{\sum_k Claim\_payment_{i,t,k}}{\sum_k Asset\_Value_{i,t,k}}) \quad (5)$$

The regression model is written as follow:

$$Economic\_Recovery_{\ i,t}^{\ Post} = \alpha_i + \ \beta_k Ins_{i,t,k} + \ \gamma X_{i,t} + \varepsilon_{i,t} \quad (6)$$

Where $Ins_{i,t,k}$ is one of the measures of insurance payments described in equations (5). In this regression set, we hypothesize that the insurance payments may explain the quarterly change in nightlight in the years following the earthquakes (Q2 2012 – Q3 2016). In order to test the robustness of our results, we include control variables $X_{i,t}$ in our fixed and random effects specifications with robust standard error to control for heteroskedasticity. In this case, we also include year dummies to control for uniform changes across time. Other included insurance-related variables are 'settlement time', and 'proportion cash settlement amount' discussed in the previous section. In addition, because there are quarters in which no claim was resolved, we include a binary indicator for these quarters.[22] We also investigate the interaction term between insurance payment and settlement time (assuming that delayed payments may have a different impact than the prompt ones). This may help to identify areas of variation explaining the recovery process, which needs further analysis.

The GLS – random-effect model controls several additional time-invariant variables which are collected from the 2006 Census (pre-quake level). These household income, number of bedrooms, proportion of fulltime employment, proportion of people owning their residence and proportion of people who aged over 65. Furthermore, we also use the outcome variable

[22] In some AUs, there are quarters without claim payment. The value of the insurance related variables are set as zero for these observations.

of the first regression set to control for the economic loss in each AU caused by the earthquakes.

7. Results

For the first set of regressions, examining whether earthquake damages explain the reduction in economic activity in Greater Christchurch, results are shown in table 5. The damage ratio variable is the main explanatory variable in the regressions. In columns 1-2 of the table, we estimate the effect of residential building damage on the economic activity in the aftermath of the earthquake events. Other columns focus on the damage for content, land and total damage (sum of the three asset classes). In these specifications, the coefficients of damage variables are almost always positive and significant. For instance, in column 1 of table 5, the economic loss will be 1.09 percent higher, when the residential buildings damage over property value increases by 1 per cent. When controlling for other variables (taken in logarithms), the damage indicators are still statistically significant, except for the content and land regressions (columns 4 and 6). Maybe not surprisingly, overall, the earthquakes' residential building damage appears to explain the economic loss immediately after the disaster; and it is the only variable that consistently has explanatory power.

In addition, the variable household income has negative and significant coefficient across regressions of all asset classes. Previously, we thought that high income households are more likely to have high disaster exposure and hence experience more impact relative to the less wealthy one. The regression finding points out that low income localities (AUs in the east side of Christchurch city) experience higher economic loss due to the earthquakes.

For the second main set of regressions, we examine the effect of insurance payment on local economic recovery post-earthquakes. Table 6 provides the results for the estimations of equation (6) including AU fixed effects.[23] The insurance payment variables are estimated for each exposure separately (columns 1-6). The estimated coefficients are always positive and are statistically significant especially for the largest exposure (building damage). Not surprisingly, payments for damage to contents, which are anyway quite small, do not have any statistically discernible impact on recovery. When the insurance payment density and payment/income for building damage increase by 1 percent, the economic recovery increases by about 2.46 percent on average. Noticed that the magnitude of the estimation coefficients is slightly higher when other insurance related variables are included in the regressions. This finding is important. It is the first time, as far as we know, that detailed post-catastrophe insurance payments are empirically linked with better local economic performance.[24]

The time to settlement variable and the interaction term between insurance payment and settlement time have negative coefficients - delays in claim payments slow down local recovery in residential areas.[25] The adverse effect on the recovery process is quite large, and estimated at over 20 per cent for 1 per cent increase in the claim processing duration, *ceteris paribus*. Maybe less expected is the finding that the positive impact of the claim amount is reduced when the settlement process was delayed – i.e., delayed payments are less helpful in generating increased economic activity. This might be because with delayed payments the

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[23] The regressions include observations of up to 177 AUs in Greater Christchurch over 15 quarters (Q2 2012 – Q4 2015) in total.
[24] Von Peter et al. (2012), in a widely cited paper, found an association between overall insurance coverage and post disaster GDP growth.
[25] Delays in insurance settlements are frequently mentioned as a reason for delays in reconstructing business districts such as the Christchurch CBD.

owner of delayed claims may have already moved elsewhere or has fixed her house without insurance monies but to a lower standard.

The coefficient of the proportion of cash settlement variable is generally statistically insignificant, except for the land payments where it is negative (higher proportion of cash settlement means lower recovery). This latter finding about land payments is most likely because cash settlements for land damage were usually undertaken when it was decided it is too costly to 'fix' the land and the plot was abandoned. It is not therefore surprising that in these cases the AU shows slower recovery. Alternatively, there might be other reasons why direct land remediation work leads to better economic performance (for example, because of the spending by workers who are employed doing the remediation).

It was suggested that cash payments for building damage (by far the biggest payments) enable recipients to move away and not rebuild. Our regression results do not show any evidence to support this contention.[26] In these specifications, we also control for the variations across time using the year dummies.

To further test the robustness of our results, we re-ran similar specifications using random effects – this allows us to add additional time-invariant control variables that account for average household characteristics in each AU[27] and also control for the more direct economic loss associated with the earthquake (the change in nightlight between 2010 and 2011).

[26] Though, of course, we cannot refute this argument; we just fail to find evidence to support it.
[27] These variables are retrieved from the New Zealand Census 2013 and linked with the EQC claim payment data at area unit level.

As shown in Table 7, the findings on the insurance related variables variable are similar to the fixed effect regression results. However, the measures of insurance payments for building damage are positive but statistically insignificant. Time to settlement of insurance claims is, as was the case in previous specifications, negative, statistically significant, and large (including the payment*time interaction term does not change this result materially).

As reported earlier, the proportion of cash settlement is positive for building damage payments (columns 1-2) and negative for land damage payments (columns 5-6) – the reasons that are most likely driving these results were discussed above.

The economic loss variable, measured as the decrease in night-time light between the averages for 2010 and 2011, is not statistically significant in most specifications in table 7 (except for the land payments specifications in columns 6). Since the coefficient is statistically insignificant in the contents regressions (columns 3-4), we do not really see these results as robust. We are surprised that the initial decline in economic activity is not a determinant of subsequent recovery, but of course there are several reasons that might be explaining this lack of association. The statistically significant results for the land regressions may imply that the earthquake damage to land had more significant long term impact on local recovery than damages to man-made assets (building and contents) as these are more easily replaceable.

The effects of household characteristics on the economic recovery are more difficult to identify, as none of these variables is consistently statistically significant and estimated to be similar across the different specifications in table 7. Household income positively explains the economic recovery in all regressions - higher income density implies more recovery; in itself not a very surprising finding that households with more resources at their disposal recover faster. The coefficients of the population density, proportion of full time employment, and median age are all only sporadically statistically significant, leading us to conclude that these probably do not have a statistically discernible impact on the strength and speed of recovery.

Areas where a larger proportion of residents owned their home have experienced better recovery. It seems intuitive that homeowners have stronger incentives to repair/rebuild quickly after an earthquake event, than renters or their agents might. This phenomenon appears to be an issue in the TC3 area in Christchurch city, which may bode ill for the future trajectory of these areas.

8. Conclusion

Quite a few research projects have explored how disasters affected short-run economic dynamics in high- and low-income countries. Few papers, however, have examined economic recovery in the longer-term, and none have looked at the role of insurance post-disaster, in facilitating recovery at the local level. This was mainly due to the limited availability of the required data or its proxies at the appropriate frequency and over the longer term. Recently, a number of studies have used night-time light intensity as a proxy for economic activity and have used this measure to examine short-term post-disaster economic recovery.

Our contribution to the empirical literature is twofold: First, we estimated the immediate economic impact and the economic recovery of local areas after the sequence of earthquakes in Canterbury (2010 - 2011) using the change in night-time luminosity. Second, we used insurance claim payment data to examine the effectiveness of these payments in facilitating local recovery.

We found that the earthquake damage significantly reduced the nightlight radiance in the immediate aftermath of these events (the following year), and that the amount of lights bounced back and even increased in the years that followed. Using the insurance payment information, we found that building and land claim payments contributed significantly to local residential recovery in the years following the earthquakes. However, prolonged settlement delays (in cases when these occurred) reduced the benefits of these insurance payments. We also found that settling claims in cash was more conducive to faster recovery for building claims while the repair/remediation option was better for claims for damage to land (an insurance cover unique to New Zealand). The effect of land damage seems to be longer-lasting. Our results also suggest that localities with households with higher incomes and owner-occupied properties experienced better recovery in the medium run.

New Zealand has much higher earthquake insurance coverage rates than other high-risk countries, and much of the disaster damage cost was ultimately covered by international reinsurers. As such, it should be worthwhile to examine other jurisdictions that have experienced similar catastrophic events (e.g., Chile in 2010 and Japan in 2011) and identify the differences in the ways their insurance sectors assist or hinder recovery.

Similarly of note is the question of settlement duration. As far as we are aware, this problem was unusually acute in Christchurch as almost every residential property that was damaged (and almost all were) was also insured. As other countries increase their insurance penetration rates, this problem may manifest itself more acutely in other jurisdictions as well.

It is also important to note that while public earthquake insurance is less prevalent, and less often used, there are many publicly funded programs for flood insurance in many different countries (and not only in high-income countries). Flood insurance programs may suffer from the same vulnerability as the risk is correlated on even larger spatial areas than earthquake risk is. The recent events associated with the 2017 Atlantic Hurricane season (especially

Hurricanes Harvey and Maria) have amply demonstrated that, and the role of insurance in the recovery of Houston and Puerto Rico from these events (respectively), should currently be of concern to policymakers and the residents there.

Appendix

1. Night-time Light

Satellites from the U.S Air Force Defense Meteorological Satellite Program (DMSP) have been recording anthropogenic light present at the earth's surface with their Operational Linescan System (OLS) sensors by NOAA since 1970s. This digital information has been detected and recorded by OLS low light imagery from 1992 to 2013. The DMSP satellites observed the lights of all surfaces on the planet between 8:30pm to 9:30pm every night (Elvidge et al., 2001). However, the DMSP cloud-free composited stable light data appears to have a number of weaknesses: only annual frequency, limited spatial resolution, saturation on bright lights (mostly metropolitan areas), no on-board calibration, and lack of low light spectral bands for discriminating different types of lighting (Elvidge et al., 2007; Elvidge et al., 2010).[28]

In contrast, following the launch of the Suomi National Polar-orbiting Partnership (Suomi-NNP) satellite of NASA and NOAA in 2011, the day-night band (DNB) of the Visible Infrared Imaging Radiometer Suite (VIIRS) offered many improvements. This new generation night-time light data was released in 2012 and surpass its predecessor in term of radiometric accuracy, radiance range, on board calibration system, and spatial resolution (Baugh et al., 2013; Jing et al., 2016).[29] The overpass time of Suomi-NPP is midnight to 1:30am. Although there is a decline in outdoor lighting for urban areas after 10:00pm, the VIIRS DNB still detects plenty of lighting indicated by human development (Elvidge et al., 2013). The monthly DNB composite data is increasingly used in social science research. Li et al. (2013) suggest that VIIRS DNB nightlight data has a stronger capacity to proxy for gross regional product than the DMSP-OLS data, using a case study of counties and provinces in China. See also: (Ma et al., 2014; Shi et al., 2014).

[28] The DMSP cloud-free composited stable light product capture the lights from urban areas, towns and places with persistent bright lighting. The noises of the background are detected and replaced with zero value. DMSP digital values range from 0-63. The lighting value for areas with no cloud-free observations within a year are set as 255.

[29] DNB can be considered as a radiometer. It has an onboard calibration system to generate the radiances for Earth observations. In contrast, DMSP/OLS only has an image sensor and does not equip the onboard calibration.

2. Appendix table - Correlation table between Damage ratio and other variables

VARIABLES	Damage ratio			
	Building	**Content**	**Land**	**Total**
Settlement time	0.154***	0.151***	0.0885***	0.130***
Prop. Cash settlement	-0.147***		-0.0421	-0.139***
Change in NTL 2010-2011	0.0783***	0.0502*	-0.204***	0.0600***
Night-time population	0.129***	0.00522	-0.349***	0.0999***
Household Income	0.0680***	-0.0236	-0.298***	0.0427*
Number of bedrooms	-0.258***	-0.0912***	0.109***	-0.240***
Number of occupied properties	0.161***	0.0359	-0.206***	0.140***
Weekly rent paid	-0.156***	-0.108***	-0.120***	-0.150***
Distance to CBD	-0.320***	-0.0382	0.173***	-0.281***
Prop. Fulltime employment	-0.0392*	0.0190	0.124***	-0.0229
Prop. Maori descent	0.137***	0.115***	-0.0554*	0.127***
Prop. Owned dwelling	-0.164***	0.0552*	0.119***	-0.135***
Prop. Age above 65	-0.0237	-0.0126	0.169***	-0.0169

***/**/* Indicating the significance levels of respectively 1%, 5% and 10%.

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Figure 1 - Example of area unit polygons in south Christchurch and the DMSP/OLS light intensity pixels

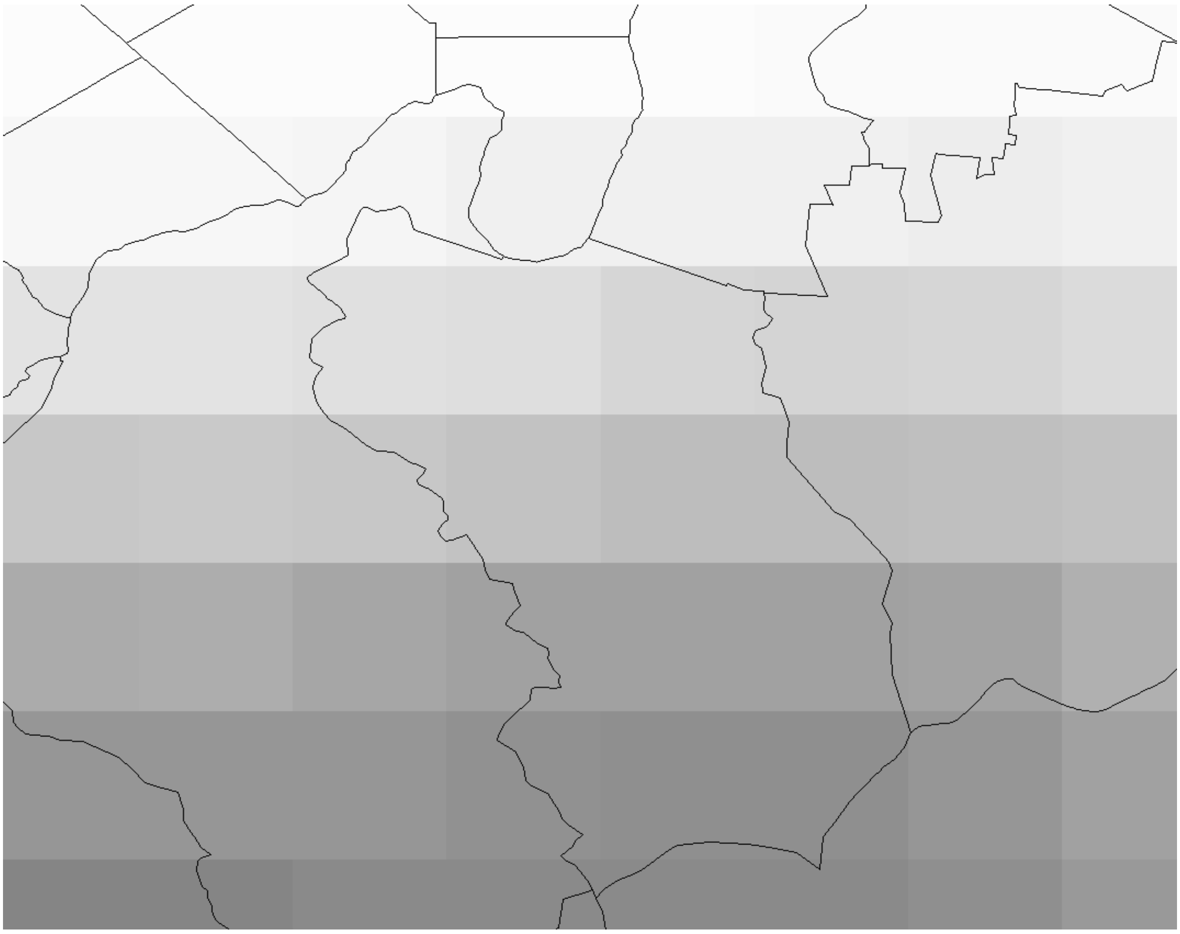

Figure 2 - Raw image of night-time light in 2013, produced by DMSP/OLS

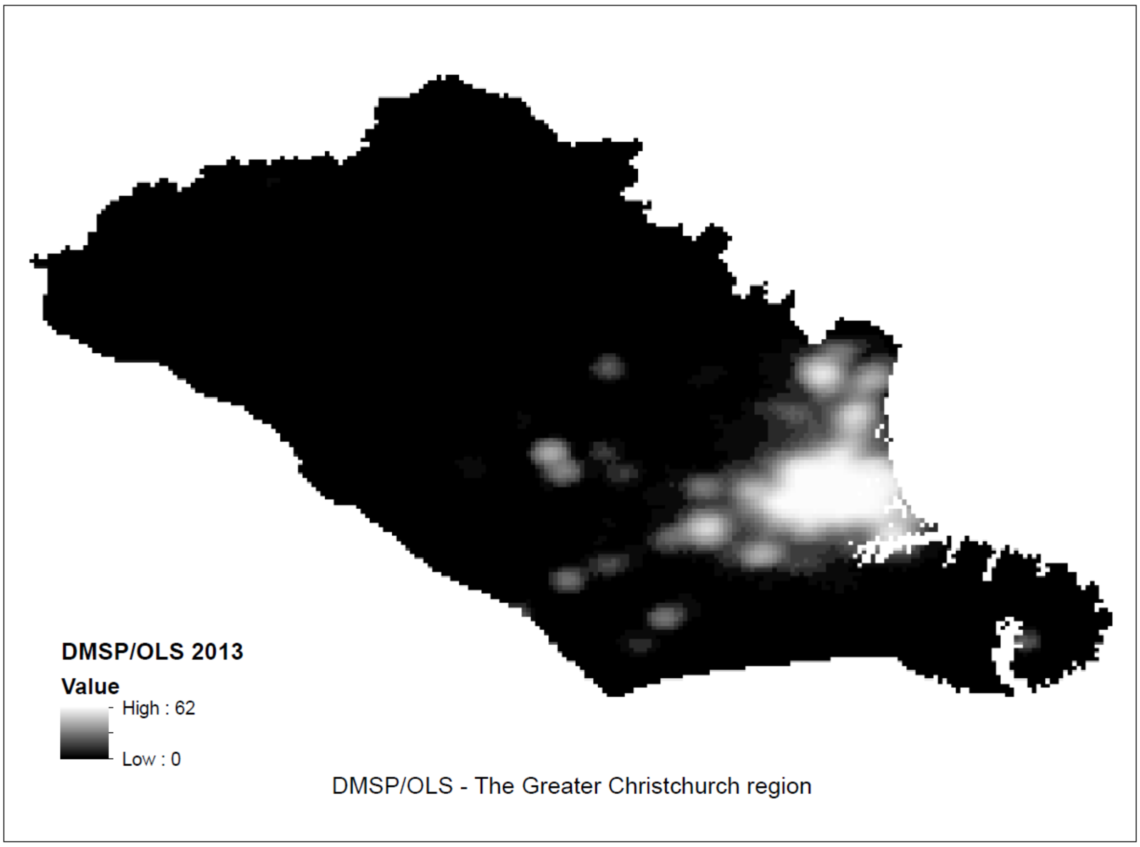

Figure 3 - Raw image of night-time light in 2013, produced by VIIRS DNB

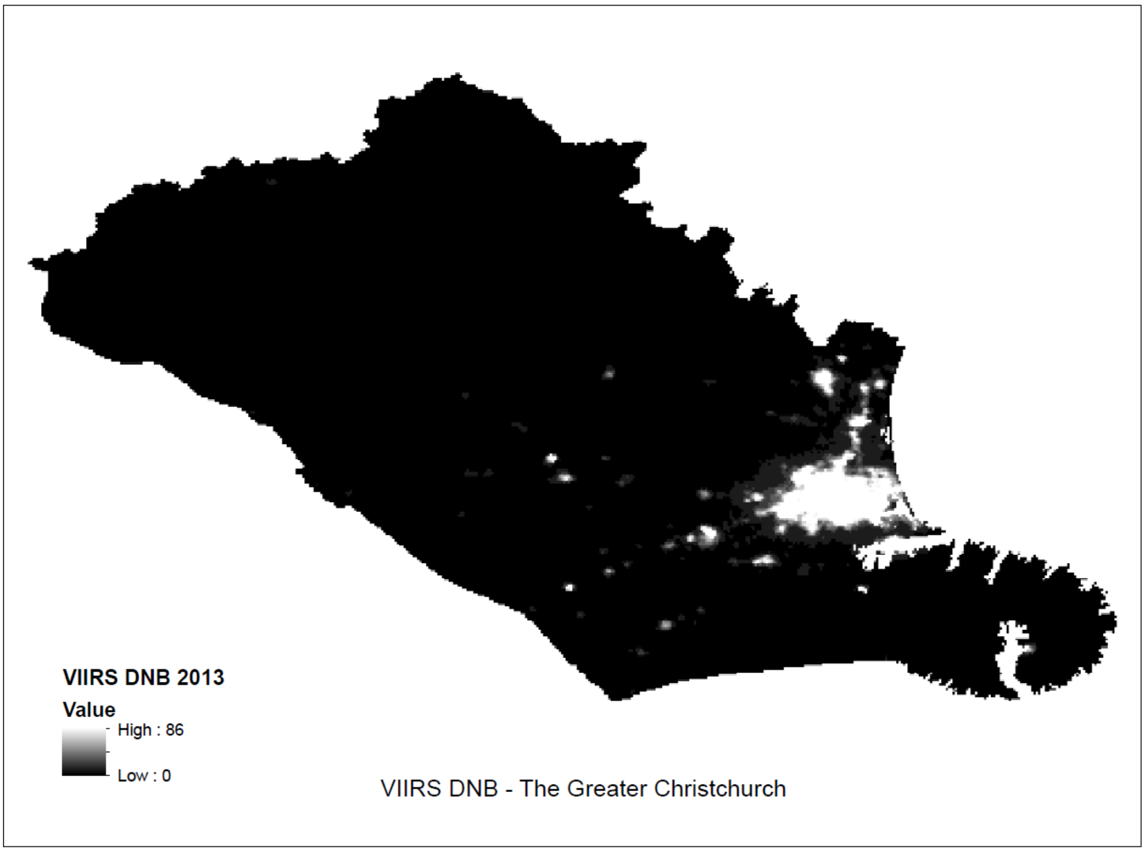

Figure 4 - Average annual night-time light in 2013 at the area unit level

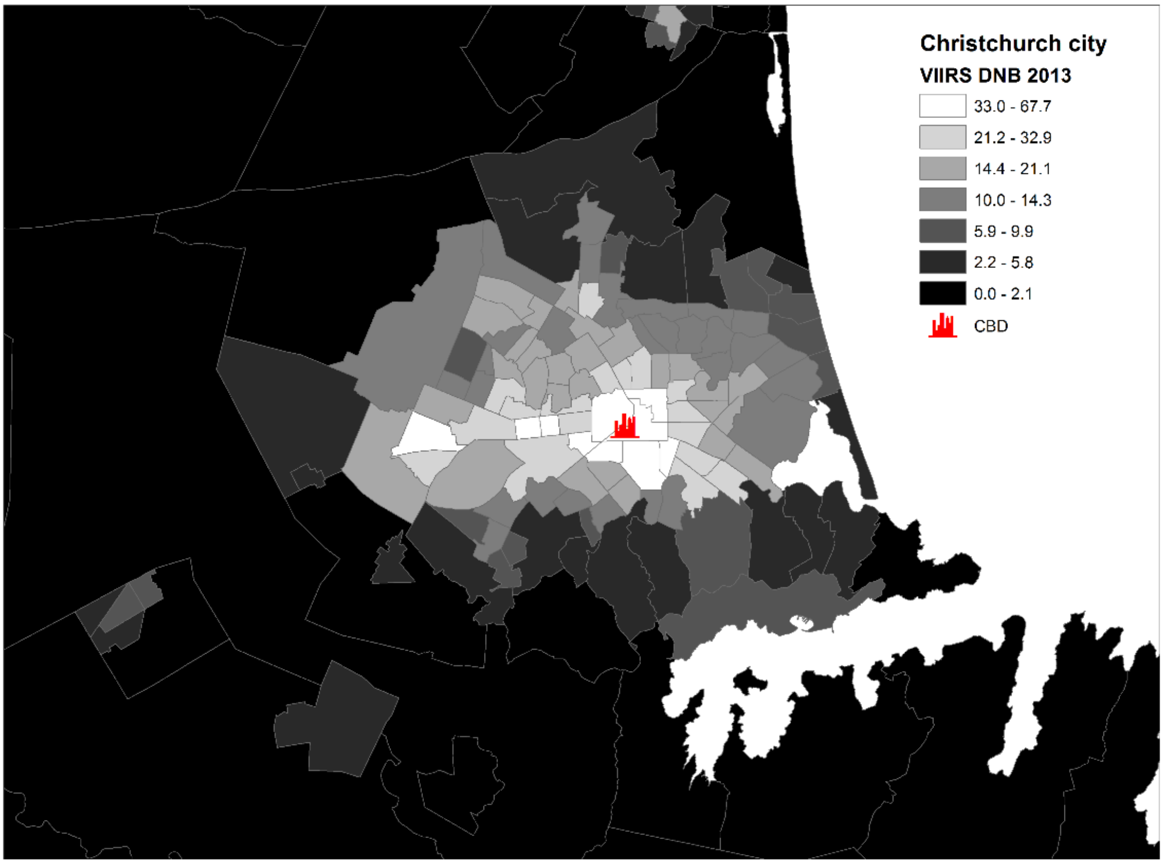

Figure 5 - Average annual night-time light for area units in Greater Christchurch 2010 - 2016

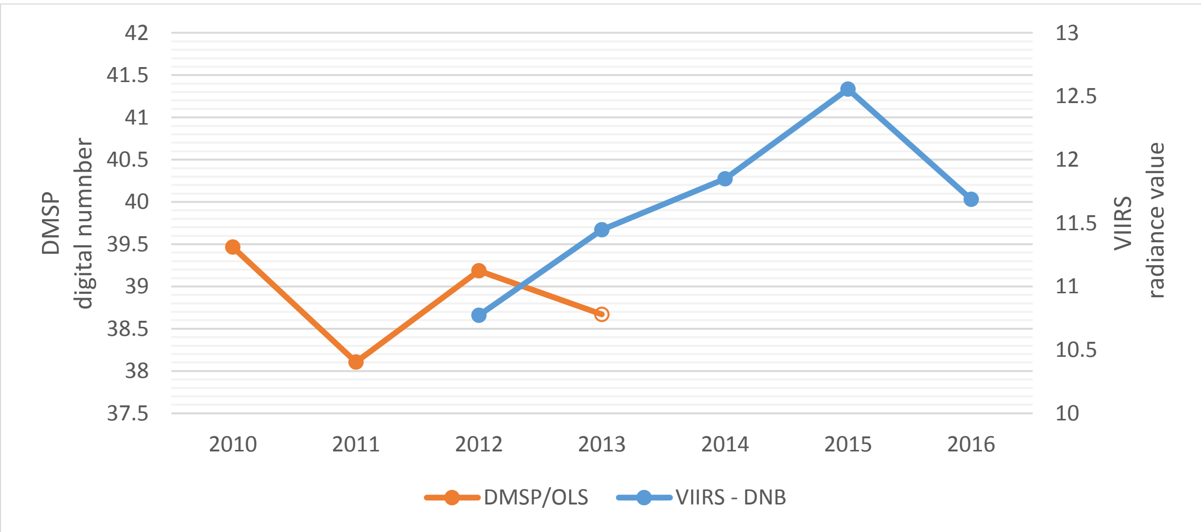

Figure 6 - Histogram of residential claims with respect to different aftershock event in the CES

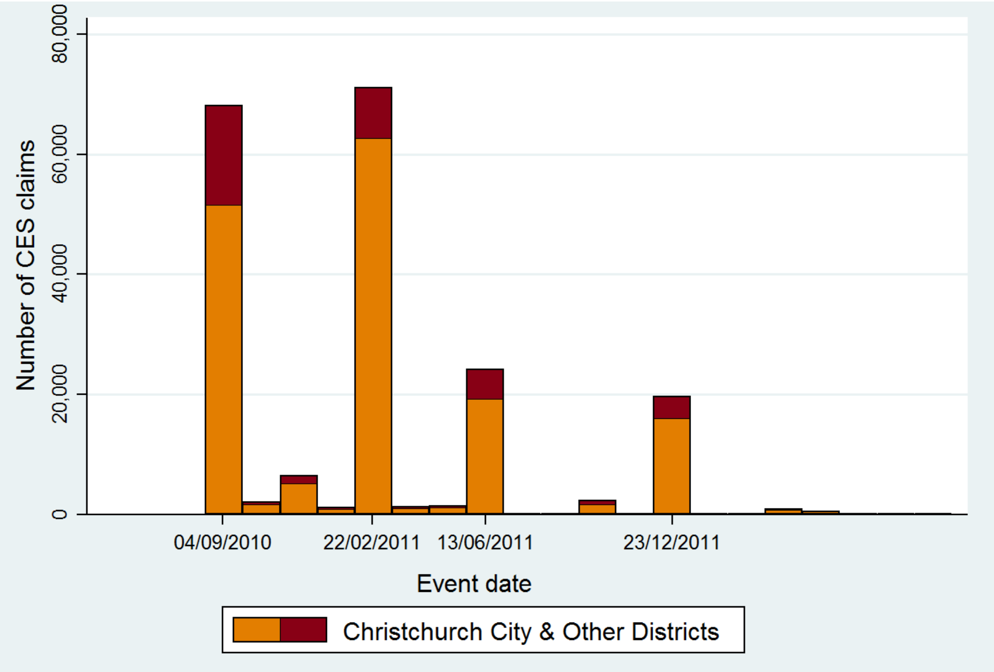

Table 1 - Summary statistics of Greater Christchurch

VARIABLES	Christchurch city		Waimakariri and Selwyn	
	Mean	**St. Dev.**	**Mean**	**St. Dev.**
Area in squared km	11.3	44.0	148.2	612.4
Night-time population	1,755	1,183	1,643	1,255
Night-time population density	2,802	1,296	514	698
Household income	68,420	18,220	74,171	18,345
Household income density	40,893	28,853	25,097	29,778

Note: Household income and night-time population are measured using 2006 and 2013 Censuses. The density variables are per km^2.

Table 2 - Correlation between different insured exposures

	Building	**Content**	**Land**
Building	1		
Content	.845**	1	
Land	.645**	.639**	1

Table 3 - Summary statistics - Quarterly claim payment data at the AU level in Greater Christchurch

VARIABLES	Building (N = 143,545)		Content (N = 68,324)		Land (N = 73,123)		Total (N = 220,898)	
	Mean	**St.d.**	**Mean**	**St.d.**	**Mean**	**St.d.**	**Mean**	**St.d.**
Total claim payment (USD)	462,695	696,423	17,347	43,840	60,240	1,424,564	540,284	1,642,358
Total exposed value of the assets (USD)	6,680,840	7,645,051	274,319	520,982	694,532	2,844,193	7,651,877	9,406,143
Proportion of cash paid/total settlement	0.85	0.17	1.00	0.00	0.85	0.26	0.90	0.33
Time to settlement (days)	845	538	489	439	688	514	984	542

Note: Summary statistics of variable “Time to settlement” are calculated at the individual claim level

Table 4 – Correlations between night-time light and control variables

VARIABLES	Night-time light	
	Correlation	**% of the variation explained**
Night-time population	.328**	10.78
Night-time population density	.409**	16.79
Household income	-.275**	7.57
Household income density	.357**	12.78
No. occupied dwellings	.326**	10.61
No. occupied dwellings density	.407**	16.59
Distance from epicentres	-.446**	19.88

Table 5 - Short run economic impact of the earthquakes using the damage ratio variable

VARIABLES	Dependent variable: Change in night-time light between 2010 and 2011							
	Building		**Content**		**Land**		**Total**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Damage ratio	1.097***	0.741***	1.631**	1.037	0.044	0.141	0.776**	0.471*
	(0.329)	(0.272)	(0.690)	(0.700)	(0.192)	(0.193)	(0.371)	(0.263)
Household Income		-0.209***		-0.220***		-0.218**		-0.213***
		(0.072)		(0.082)		(0.085)		(0.078)
Night-time Population		0.0112		0.00864		0.0136		0.0108
		(0.024)		(0.024)		(0.022)		(0.023)
Distance to CBD		-0.005		-0.0161		-0.018		-0.012
		(0.021)		(0.022)		(0.023)		(0.022)
Number of bedrooms		0.203		0.232		0.217		0.209
		(0.174)		(0.195)		(0.202)		(0.188)
Area square km		-0.013		-0.011		-0.013		-0.012
		(0.011)		(0.011)		(0.011)		(0.011)
Constant	-0.122***	1.917***	-0.108***	2.132**	-0.059***	2.133**	-0.101***	2.044**
	(0.028)	(0.728)	(0.028)	(0.834)	(0.015)	(0.858)	(0.027)	(0.789)
Observation	177	176	177	176	177	176	177	176
R-squared	0.053	0.151	0.032	0.143	0.001	0.141	0.030	0.142
Adj. R-squared	0.047	0.121	0.027	0.113	-0.005	0.110	0.024	0.111

***/**/* Indicating the significance levels of respectively 1%, 5% and 10%. Robust standard errors are shown in parentheses. All regressions are estimated with OLS.

Table 6 - Economic recovery following the earthquakes (Claim payment) – AU fixed effects

VARIABLES	Dependent variable: Quarterly change in night-time light							
	Building		**Content**		**Land**		**Total**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Claim payment	2.330***	2.469**	0.0577	-0.553	0.371*	0.873*	2.252**	2.497**
	(0.888)	(1.021)	(0.465)	(0.751)	(0.215)	(0.463)	(0.871)	(1.010)
Settlement time		-22.79***		-3.996***		-1.460		-21.23***
		(4.612)		(1.179)		(1.106)		(4.173)
Prop. Cash settlement		19.48***				-11.80***		13.65***
		(6.931)				(2.309)		(5.041)
Ins. payment* Settlement time		-7.070		-4.044		-6.806**		-8.290
		(9.499)		(4.977)		(2.967)		(9.167)
No payment indicator	-17.10	-136.8***	2.411	-15.12	1.235	-13.96***	-15.22	-124.0***
	(13.35)	(48.08)	(4.155)	(16.23)	(2.073)	(4.826)	(13.24)	(44.05)
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observation	3186	3186	3186	3186	3186	3186	3186	3186
N.o Area Units	177	177	177	177	177	177	177	177
R-squared	0.058	0.072	0.055	0.057	0.057	0.062	0.058	0.069

***/**/* Indicating the significance levels of respectively 1%, 5% and 10%. Robust standard errors are shown in parentheses. All regressions are estimated with AU fixed-effects.

Table 7 - Economic recovery following the earthquakes (Claim payment) – Random effects

VARIABLES	Dependent variable: Quarterly change in night-time light							
	Building		Content		Land		Total	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Claim payment	0.0786	0.0894	0.130	0.230	0.859***	0.866***	0.206	0.254
	(0.330)	(0.368)	(0.327)	(0.338)	(0.298)	(0.311)	(0.273)	(0.304)
Settlement time	-20.62***	-23.01***	-2.768**	-3.066***	1.483	1.480	-17.99***	-19.84***
	(4.637)	(4.637)	(1.135)	(1.119)	(0.893)	(0.927)	(3.918)	(3.912)
Prop. Cash settlement	18.58***	18.52***	0.606	0.937	-11.39***	-11.39***	13.81***	13.49***
	(6.470)	(6.592)	(2.439)	(2.600)	(2.139)	(2.159)	(4.606)	(4.628)
Ins. payment* Settlement time	-3.077**	-3.887***			-6.114***	-6.383***	-3.224***	-3.653**
	(1.202)	(1.403)			(2.120)	(2.239)	(1.241)	(1.419)
Change in NTL 2010-2011		1.715		1.406		-2.239*		1.744
		(1.695)		(1.656)		(1.276)		(1.591)
Household Income		2.648*		2.157**		2.527***		3.570**
		(1.621)		(1.075)		(0.890)		(1.583)
Number of bedrooms		-4.873		0.552		-3.962*		-3.872
		(3.734)		(2.752)		(2.274)		(3.871)
Prop. Fulltime employment		-3.579		2.926		-2.914		-2.950
		(4.226)		(4.009)		(3.694)		(4.776)
Prop. Owned dwelling		-1.955		-0.984		-0.837		-1.743
		(2.479)		(1.232)		(1.045)		(2.559)
Prop. Age above 65		-2.456		-0.458		-3.254		0.560
		(4.027)		(3.910)		(3.535)		(4.113)
Prop. Maori descent		12.60		5.327		8.928		9.298
		(9.443)		(8.854)		(7.767)		(9.360)
No payment indicator	-140.0***	-160.8***	-15.60	-17.40	-11.97***	-12.67***	-127.0***	-142.9***
	(34.30)	(34.93)	(12.87)	(12.98)	(4.367)	(4.406)	(30.37)	(30.77)
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observation	3168	3168	3168	3168	3168	3168	3168	3168
N.o Area Unit	176	176	176	176	176	176	176	176
R-squared	0.071	0.075	0.056	0.058	0.062	0.064	0.068	0.071

***/**/* Indicating the significance levels of respectively 1%, 5% and 10%. Robust standard errors are shown in parentheses. All regressions are estimated with GLS - Random effects.

TE WHARE WĀNANGA O TE ŪPOKO O TE IKA A MĀUI

VICTORIA

UNIVERSITY OF WELLINGTON