CESifo WORKING PAPERS

7031
2018

May 2018

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
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Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

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CESifo *Working Paper No. 7031*
Category 9: Resource and Environment Economics

Measuring the Impact of Insurance on Urban Recovery with Light: The 2010-2011 New Zealand Earthquakes

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 Canterbury Earthquake Sequence (CES) 2010 -2011 as our case study. Uniquely for 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 effective than insurance-managed repairs in contributing to local recovery.

JEL-Codes: G220, Q540, R110.

Keywords: earthquake, recovery, disaster, insurance, light.

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April 2018
We thank QuakeCoRE and the Resilience National Science Challenge for providing funding that supported this work.

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 attempts to shed more light on the dynamics of recovery over time.

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 the role of the sector in recovery.

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 how insurance claim payments for damaged residential property affect the recovery process of the local economy.

We focus on the destructive Canterbury Earthquake Sequence (CES) in 2010 - 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 that allow us to clearly identify its impact. These are 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 also find that the insurance pay-out contributed significantly to the process of economic recovery after the earthquake; and further identify the importance of the timing of payments, and comparing cash payments versus insurance-led repair.

This earthquake sequence is an attractive case study for several reasons: First, the event is unique 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, these 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 2009 and 2011 can be used to estimate the immediate direct impact of earthquakes on local economic activity, using the insurance claim payment data as a direct earthquake damage indicator. We next explore the role of 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 insurance claim settlements during the same time period.

The remainder of this paper is structured as follows. In the next section we provide 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 the history of its 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 penultimate section , we present our empirical results; and we end the paper with some further comments about future research.

2. The Canterbury Earthquake Sequence 2010 - 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 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 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 re-zone it for non-residential use only by buying the homes from their owners. Similarly, in the Port Hills east of the city, there were areas where the risk to life safety 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 public insurance scheme has settled over 167,000 and 73,000 valid dwelling and land claims respectively. These claim

[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.

[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.

settlements would cost the public program approximately USD 4.6 billion. In the private insurance sector, USD 5.3 billion were paid for commercial claims[4] and USD 3 billion for residential claims[5] (ICNZ, 2014).

The New Zealand Earthquake Commission (EQC) is the public entity providing the first layer of residential insurance for earthquakes (only 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 driveways or fences) were provided by the private insurers. Based on the EQC data we analyse in this paper, approximately 25,561 residential building over-cap claims were transferred to private insurers to be resolved.

The number of submitted claims was twice as large as the EQC expected and planned for 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 seven years to complete, and only now in 2018 are the last remaining claims being settled.

[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 waiting for their claims to be resolved.

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 likelihood of business survival between the insured and uninsured firms. However, later on, firms which had prompt and full claim payment

[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.

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 immediate impacts of disasters. Yet, relatively less is known about the post-disaster recovery process and the factors that shape it. Platt et al. (2016) describe the use of 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 note that this approach is costly and time-consuming.

Very 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 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, a rural Japanese township, following a 2004 localised earthquake.[8]

[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).

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 feasible. 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 are numerous (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 of economic outcomes.[10]

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

[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 appendix 1 for more detail about the luminosity data.

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.

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; Del Valle et al., 2018).

Fewer 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 the Greater Christchurch region. This includes Christchurch city and its satellite towns. 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 158 AUs in the residential areas.

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 Statistic New Zealand. Because each AU has different size and can cover several pixels, we calculate the nightlight intensity weighted mean 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

[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.

[12] More explanations about the data sources and extraction procedures are available in the appendix 2. 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.

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. The spatial area for an area unit in Greater Christchurch is approximately 54.7 km^2 on average.

Figures 2 and 3 present the night-time light images of Greater Christchurch from the 2016 cloud-free composite DMSP/OLS and VIIRS DNB satellites, 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). Due to the difference in time horizon of the two products, both night-time light datasets are used in this paper. More specifically, the DMSP data of satellite F16 and F18, from 2009 to 2012, 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.

We use the VIIRS DNB data for the period from 2012 to 2016 for each AU. This data is available in monthly frequency, and we aggregate it to quarterly data. 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-

[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 of time (Elvidge, Ziskin, et al., 2009; Zhang et al., 2016; Li & Zhou, 2017). In order to obtain comparable nightlight time series data for 2009-2012, we apply the inter-calibration procedure, suggested by Elvidge et al. (2014). This data is only available in annual frequency.

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 region of interest, all the AUs have the average nightlight intensity higher than zero. This is consistent in both datasets. We conclude that the AUs that have low nocturnal light emission are accurately measured, as the new satellite 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 whole 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 region of interest, derived by DMSP/OLS over time. The Elvidge-corrected time series unsurprisingly show that there was a reduction in night-time luminosity observable in 2010. The average light intensity started increasing in 2011. However, it was still lower than the light level pre-earthquakes. Figure 6 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 slightly in 2016.

[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 1.

It seems that the DMSP/OLS and VIIRS DNB data are not comparable. Even after radiometric inter-calibration undertaken by NOAA, comparison is impossible as the imageries were acquired at different time of night. We consequently do not link the two nightlight datasets.[15]

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 the 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 as it was apportioned for each earthquake event.[16] 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

[15] See Appendix 1

[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).

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.

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.[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 generated by the earthquakes.[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 percent amount EQC and private insurers paid to CES claimants, 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 households at the AU level from the census conducted in 2006 (pre-treatment). 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 2006 nightlight and control variables from the 2006 Census in the research area. 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.[19]

Table 4 also shows that light intensity captures the density variables better. For instance, the correlation between nightlight and population is 0.587, which could be compared with the correlation between nightlight and population density (0.709). Interestingly, the nightlight is negatively correlated with household income while there is positive relationship between light brightness and income density. The explanation for this is that wealthy AU have fewer

[19] However, the correlation in levels are not as high as the estimates from other previous nightlight research at more aggregate regional or country level.

households (as they are typically single-houses with larger plots of land). These AUs have higher average household income, which may not represent the economic activity of the AUs 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 and the city centre. If the AU is closer to the CBD, it will have higher night-time glow.

The last data we use here are Shakemaps for the September 2010 and February 2011 earthquakes, offered by the USGS Earthquake Hazard Program.[20] These maps provide the spatial distribution of the physical intensity for major earthquakes. We aggregate these macro-seismic intensities to AU level and use them in our empirical models. 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.[21]

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. 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.

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[20] Seismologists have started to produce detailed shake maps for major earthquakes. The maps capture the exact spatial extend of earth surface movements and their decay in magnitude across space (that decay is not linear in distance and depends on surface conditions). Appendix 4 provides the physical intensity map of February 2011 earthquake.

[21] 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 5, the Elvidge corrected 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

$$Economic\_Loss_i^{eq} = \Delta NTL_i^{2019-2011} = \ln(NTL_{i,2009}) - \ln(NTL_{i,2011}) \tag{1}$$

where NTL_i is our economic development indicator based on the DMSP nightlight value (taken in logarithms) in each 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. A number of papers in the literature have stressed that earthquake damage is correlated with income per capita (Kahn, 2005; Toya & Skidmore, 2007; Felbermayr & Gröschl, 2014). Hence, even in the spatially confined study at hand, cross-AU heterogeneity in damage may be driven by cross-AU differences in income per capita. To reduce the endogeneity of the financial loss indicator, we create a damage ratio variable from these aggregate figures (in equations 2).

$$Damage_{i,k} = \frac{\sum_k Claim\_payment_{i,k}}{\sum_k Asset\_value_{i,k}} \tag{2}$$

$Damage_{i,k}$ 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*.[22] The property value data is the New Zealand quotable value (QV) data which is used by local authorities in their assessments of property tax liabilities.

[22] 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.

In the first set of results, we use $Economic\_Loss_i^{eq}$ as a dependent variable indicating the change in economic activity due to the earthquakes. We hypothesize that AUs that have high *ΔNTL* experienced large economic losses because of the large amount of damage to property (assets), as follows:

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

Where $Damage_{i,k}$ is earthquake damage as a ratio of exposed value for each AU as specified in equations (2). We use AU cluster-robust standard errors in order to control for the heteroskedasticity in the error terms. In addition, for robustness we include several control variables[23] (X_i) that might also affect the measured economic loss in our regressions such as household income, night-time population, number of bedrooms and surface area (taken in logarithms).

The next robustness check for endogeneity leads us to implement a two-stage least squares (2SLS) method in the specifications. We use the earthquakes' physical intensity measure (Z_i) as an instrumental variable for $Damage_{i,k}$. We expect that the 2SLS method will give us a similar finding as the main regression. The correlations between damage ratio measured by property damage and the macro-seismic intensity of February 2011 earthquake are over 50%, except for land damage.[24] Thus, we expect to have strong first stage where the instrument is highly correlated with the endogenous variable.[25] Moreover, we make an assumption that the effect of earthquakes' physical intensity (Z_i) on $Economic\_Loss_i^{eq}$ only come from our endogenous explanatory variables - $Damage_{i,k}$.

[23] The correlations between damage ratio and other variables are shown in the appendix 3.

[24] See Appendix 3

[25] When we run the tests of endogeneity, the null hypothesis (H_0: damage ratio variable is exogenous) get rejected at 5% and 1% significance level.

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, due to the limited availability of the VIIRS DNB data, we use the 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.

$$Economic\_Recovery\,_{i,t}^{Post} = \Delta NTL_{i,t}^{Q2.2012-Q3.2016} = \ln\,(NTL_{i,t}) - \ln\,(NTL_{i,t-1}) \quad (4)$$

The main explanatory variable is the insurance payment. It is the total insurance claim pay-out which an AU received at quarter t, as described in equations (5).

$$Ins_{i,t,k} = \ln\,(\textstyle\sum_k Claim\_payment_{i,t,k}) \quad (5)$$

The regression model is written as follow:

$$Economic_{Recovery}\,_{i,t}^{Post} = \alpha_i + \tau_t + \beta_k Ins_{i,t,k} + \gamma X_{i,t} + \varepsilon_{i,t} \quad (6)$$

Where $Ins_{i,t,k}$ is our measure 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). We included AU and quarter fixed-effects to control for unobserved variations across individual AUs and over time. In order to test the robustness of our results, we also include AU cluster-robust standard errors to control for heteroskedasticity. Insurance-related variables such as 'settlement time', and 'proportion cash settlement amount' are included in the regression, as discussed in the previous section.

In some AUs, there are quarters without claim payments. The value of the insurance related variables are in this case set as one.[26] 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.

In addition, we carry out spatial panel data analysis. Spatial econometric modeling helps us control for spatial specific effects. Thus, spatial panel models may reduce the unobserved estimation bias which arise from both spatial and time dependence. More importantly, spatial regression methods permit us to identify spillover effects coming from neighbouring AUs over time (Anselin et al., 2008; Lee & Yu, 2010; Elhorst, 2014). Spatial models have been used in economic geography, urban and regional science (Baltagi & Li, 2004; Kelejian & Piras, 2014; Firmino et al., 2016; Noy et al., 2016).

Following this literature, we implement four different spatial specifications including Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM) and Spatial Autocorrelation Model (SAC).[27] We employ spatial panel Maximum Likelihood estimation for the set of regression models with AU and quarter fixed effects as described below.

SAR) $$Y_{i,t} = \alpha_i + \tau_t + \rho W Y_{i,t} + \beta X_{i,t} + \varepsilon_{i,t} \tag{7}$$

SEM) $$Y_{i,t} = \alpha_i + \tau_t + \beta X_{i,t} + \vartheta_{i,t} \quad \text{where} \quad \vartheta_{i,t} = \lambda W \vartheta_{i,t} + \varepsilon_{i,t} \tag{8}$$

[26] So that their log value will be equal to zero.

[27] We exclude the general nesting spatial (GNS) model, which include all the interaction effects' types, due to concerns of overfitting and the over-identification (Manski 1993; Elhorst, 2014).The GNS model is seldom used in applied spatial research (LeSage & Pace, 2009).

SDM) $$Y_{i,t} = \alpha_i + \tau_t + \rho WY_{i,t} + \beta X_{i,t} + WX_{i,t}\theta + \varepsilon_{i,t} \quad (9)$$

SAC) $$Y_{i,t} = \alpha_i + \tau_t + \rho WY_{i,t} + \beta X_{i,t} + \vartheta_{i,t} \quad \text{where} \quad \vartheta_{i,t} = \lambda W\vartheta_{i,t} + \varepsilon_{i,t} \quad (10)$$

These models include three different types of interaction effects among units: (i) endogenous spatial interaction effects among the dependent variable ($WY_{i,t}$); (ii) exogenous spatial interaction effects among the explanatory variables $(WX_{i,t})$; and (iii) spatial interaction effects among the error terms ($W\vartheta_{i,t}$). The parameter ρ is the spatial autoregressive coefficient, while θ and λ are the spatial-response and spatial-autocorrelation coefficients, respectively.

W is referred to the non-negative spatial weighted matrix ($N \times N$) that describes the spatial structure of dependence between AUs in the sample. In this study, we employ the row-standardized contiguity weighted matrix. The elements ω_{ij} of matrix W equals to 1/ the number of neighbours of AU i if AU i and j share the border, otherwise $\omega_{ij} = 0$. Our spatial models, therefore, emphasize the geographical contiguity between AUs, rather than physical distance. The next section describes the results of these empirical models.

7. Results

For the first set of regressions results, examining whether earthquake damages explain the reduction in economic activity in Greater Christchurch, are shown in table 5. The damage ratio variable is the main explanatory variable in the regressions. In columns 1-3 of the table, we estimate the effect of residential building damage on the economic activity in the immediate 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 0.559 percent higher, when the residential buildings damage over property value increases by 1 percent. When controlling for other variables (taken in logarithms), the damage indicators are still statistically significant, except for the land regressions (columns 5 - 9). 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.

The control variables household income and number of bedrooms, which indicates the size of the dwelling, have small and insignificant coefficient across regressions of all asset classes. Moreover, when using earthquakes' physical intensities as instrument variables, the 2SLS regressions[28] (column 3, 6, 9 and 12) provide us a similar result to the OLS regressions. The magnitude of the damage ratio coefficient is stronger for building and total assets regressions. For instance, 1 percent increase in the total asset damage over its value is associated with 0.91 percent reduction in economic activity on average.

For the second set of regressions, our primary focus in this paper, 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 and quarter fixed effects.[29] The insurance payment variables are estimated for each exposure separately (columns 1-6). Their estimated coefficients are small and insignificant when other insurance variables are not included (columns 1,3, 5, and 7). Nevertheless, the insurance payment variables become positive and significant when controlling for other variables (columns 2, 4, 6 and 8). The estimated

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[28] The 1st stage R-squared of the regressions are between 0.4 – 0.5 for different asset classes.

[29] The regressions include observations of up to 158 AUs in residential areas in the Greater Christchurch region over 17 quarters (Q2 2012 – Q3 2016) in total.

coefficients are positive and are statistically significant especially for the largest exposure (building damage). Not surprisingly, payments for damage to contents, which are quite small, do not have any statistically discernible impact on recovery. When the insurance payment for building damage increase by 1 percent, the economic recovery increases by about 0.36 percent on average. 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 recovery.[30]

The effect of the settlement time variable on the outcome variable is small and insignificant. However, the interaction term between insurance payment and time to settlement has negative and significant coefficient - delays in claim payments slow down local recovery in residential areas.[31] In other word, 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 owner of delayed claims may have already moved elsewhere or has fixed her house without insurance monies but to a lower standard.

The coefficients of land claim payment (column 6) have smaller magnitude, compare to building claims results (column 2). This difference may be partially explained by the difference in cash settlements patterns.

The coefficient of the proportion of cash settlement variable[32] is positive and statistically significant for building structure and total assets. It was suggested that cash payments enable

[30] Von Peter et al. (2012), in a widely cited paper, found an association between overall insurance coverage and post disaster GDP growth at the national level.
[31] Delays in insurance settlements are frequently mentioned as a reason for delays in reconstructing business districts such as the Christchurch CBD.
[32] The variable is excluded in the content specification because all the content payments were settled in cash.

recipients to move away and not rebuild. Our regression results show evidence that does not support this contention. In these specifications, we also control for the variations across time using the quarter dummies. The coefficients of the quarter dummies are large and volatile for the first 2 years after the CES, their coefficient estimates become smaller in absolute term from 2014 onward. Economic recovery occurred mainly in 2012 and 2013 and the recovery rate thus declines as time passes.

To further test the robustness of our results, we re-ran similar specifications using spatial panel models– this allows us to control for the spatial dependencies in the regression set.[33] Table 7 and 8 report the estimation results explaining the effect of insurance payment on local recovery for the different spatial econometric models (SAR, SEM, SAC and SDM). The finding is similar to the results of the non-spatial regressions. Building and land specifications have significant coefficients, while content regressions do not. The building payment coefficients' magnitude is slightly higher, except for the SAC model. The payment*time interaction term is, as was the case in previous specifications, negative and statistically significant.

We carry out model selection tests (Anselin et al., 1996; Olivia et al., 2009; Belotti et al., 2016; Noy et al., 2016).[34] The diagnostic tests support the SDM model specification, except for land regression. In addition, we also implement the Hausman test for the spatial panel model to test whether random effect models are preferred. Table 7 and 8 shows that the null

[33] The Moran's I statistics for the dependent and independent variables are around 0.3 – 0.6 and their *p*-values are approximately zero. This indicates the existence of the spatial autocorrelation in our variables.
[34] The null hypotheses include: If $\theta = 0$ the model is a SAR, while if $\theta = -\beta\rho$ the model is SEM. The tests' chi-squared statistics are between 10 – 19. And the *p*-values are approximately zero. Except for the land regressions, the null hypotheses cannot be rejected. The model selection is more toward SAR and SEM models than SDM for land payment.

hypothesis is rejected as Hausman chi-squared is large and the fixed effect models is preferred.

Importantly, the spatial autoregressive (ρ) and autocorrelation (λ) coefficients are significant. This reconfirms the existence of the spatial dependencies in our models. The economic recovery of an AU is positively influenced by the recovery of other surrounding AUs. In the SAC model, the point estimate of ρ is higher than its coefficient in SAR and SDM models.

Because the estimation coefficients of the specifications cannot be compared with each other, we derive the direct and spillover effects[35] from these coefficient estimates, reported in Table 9. In general, a 1 percent increase in insurance payment directly leads to 0.4 – 0.5 percent increase in economic recovery. However, this direct positive effect would be eliminated when the claim settlement was delayed.

If the spatial regression models include the endogenous interaction term $\left(WY_{i,t}\right)$, the direct effects contain the feedback effects in their estimates[36]. The feedback effects occur when the impact goes through neighbouring AUs and back to the initial AU (LeSage & Pace, 2009). In our result, when taking the difference between direct effect and point estimate, the feedback effect only accounts for about 10 - 12 percent of the direct effect. In the SMD model, this feedback effect becomes smaller but is negative when the spatial exogenous interaction effects are controlled $(WX_{i,t})$.

In the indirect effects, the discrepancies are substantial across different spatial models. The bottom half of Table 9 shows that the spillover effect in the SAR and SAC models are similar

[35] To obtain the direct and spillover effects estimates, we use the variation of 500 simulated parameter combinations drawn from the multivariate normal distribution implied by the Maximum Likelihood estimated. This procedure is widely used in spatial statistic inferences (LeSage & Pace, 2009; Vega & Elhorst, 2015).

[36] The SEM model does not contain the endogenous interaction effect. Hence, the point estimates of its explanatory variables is equal the direct effects. See Table 9.

to the direct effect's finding. Higher insurance payment received in an AU does not only lead to better economic recovery at its local area, but it also increases the economic growth in neighbouring AUs. The spillover effect of the delay in claim payment is also observable in these spatial econometrics models. The interaction term between payment and time is negative and significant. In other word, the positive indirect effect of insurance payment is reduced when the settlement time is longer.[37]

In contrast, the indirect effects of insurance payment and its interaction term with time in the SDM are not significant. But the effect of the settlement time and proportion cash payment variables are significant.[38] The delay in claim settlement in an AU would impact the recovery of other neighbouring AUs. The spillover effect of cash payment for building structure is positive and its magnitude is over 3 times larger than its direct effect. This is an intuitive finding because cash payment is highly mobile and the money can be used for other economic activities outside the AU. Most residential relocations occurred within Canterbury, migration net outflow was only 2% of population before and after earthquakes (MBIE, 2013). Hence, the insurance cash payments most likely circulated in the region without leaving to other areas. The finding of strong positive spillover effect of cash payment on the local recovery is therefore expected.

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

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[37] Interestingly, the magnitude of the spillover effects in the SAC regression are even higher than the direct effects itself.

[38] From the econometrics- theoretical viewpoint, the SDM model is global spillover specification and has less restrictions on the magnitude of spillover effects, we obtain different result, compared to other spatial models (Kirby & LeSage, 2009; Vega & Elhorst, 2015).

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 a sequence of earthquake disasters 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 treatment years), 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 no conclusive finding for the effect of land remediation/ or cash payment (an insurance cover unique to New Zealand). Moreover, we identify the positive spillover effects of insurance payout and cash payment to the recovery of other surrounding AUs.

As far as we are aware, the average time it took to settle claims was unusually long in Christchurch as almost every residential property that was damaged (and almost all were) was also insured. Yet, it is by no means unique. Complaints about the time it takes to settle claims appear after almost every large well-insured event. As other countries increase their insurance penetration rates, this problem may further exacerbate 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 which was more heavily insured) have amply demonstrated that. The role of insurance in the recovery of Houston should clearly be of concern to policymakers and the residents there, and unfortunately, in future events that are bound to occur.

Appendix - 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 the 1970s. 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 that NOAA makes available appear to have several weaknesses: only annual frequency, limited spatial resolution, saturation in bright metropolitan areas, no on-board calibration, and absence of low-light spectral bands for discriminating different types of lighting (Elvidge et al., 2007; Elvidge et al., 2010).[39]

In contrast, 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).[40] 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).

[39] 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.

[40] 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.

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

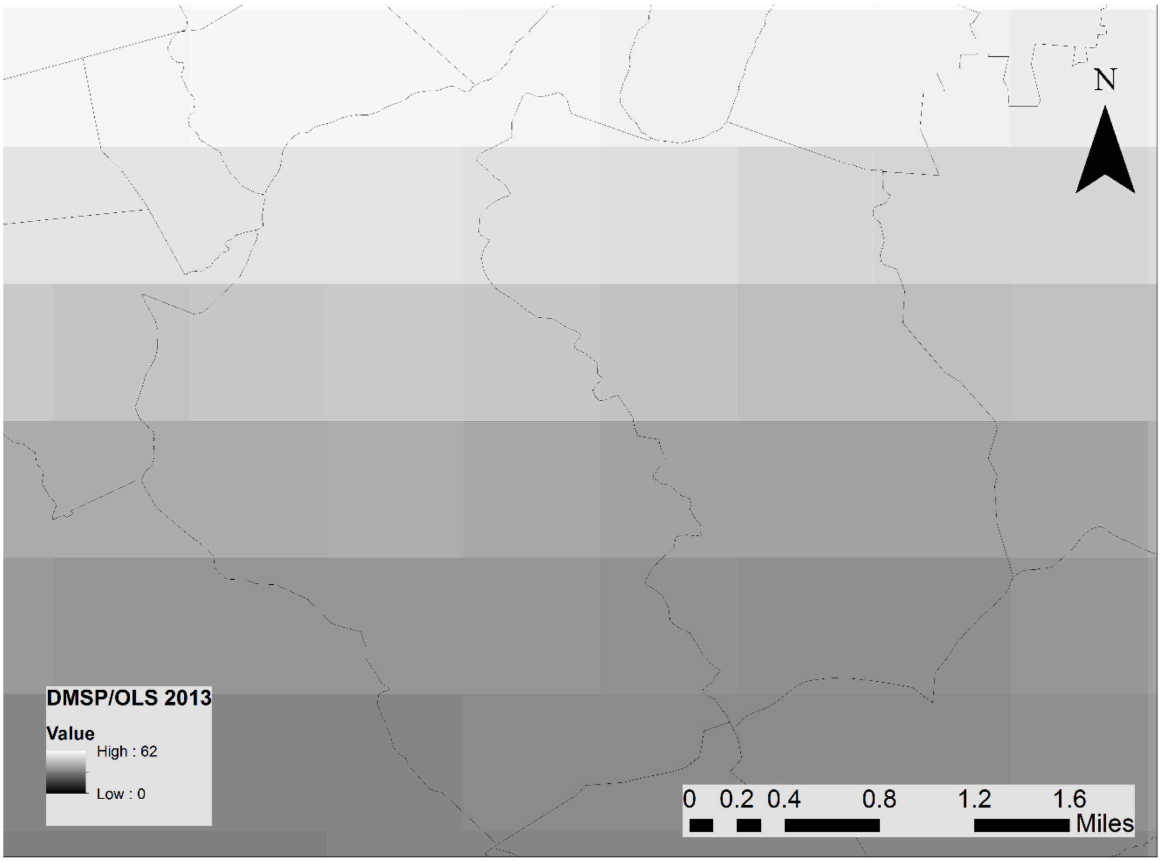

Figure 2 - Raw image of night-time light in 2013, produced by DMSP/OLS

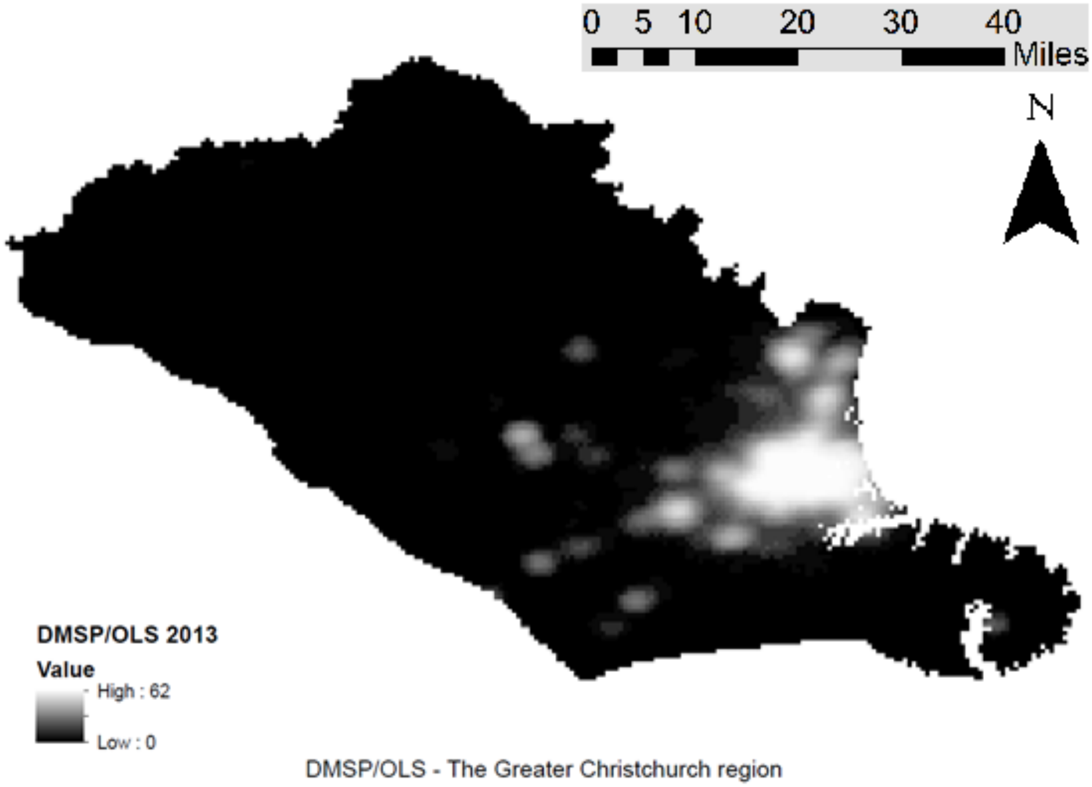

Figure 3 - Raw image of night-time light in 2013, produced by VIIRS DNB

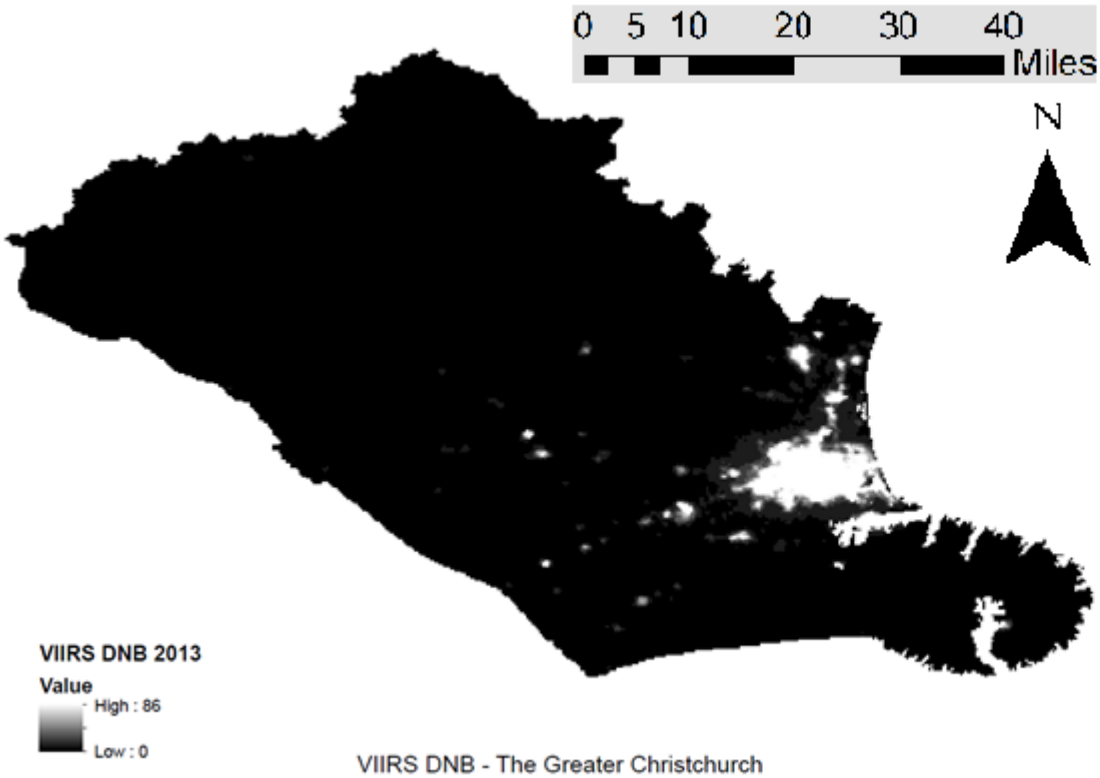

Figure 4 - Average annual night-time light in 2013 at the area unit level

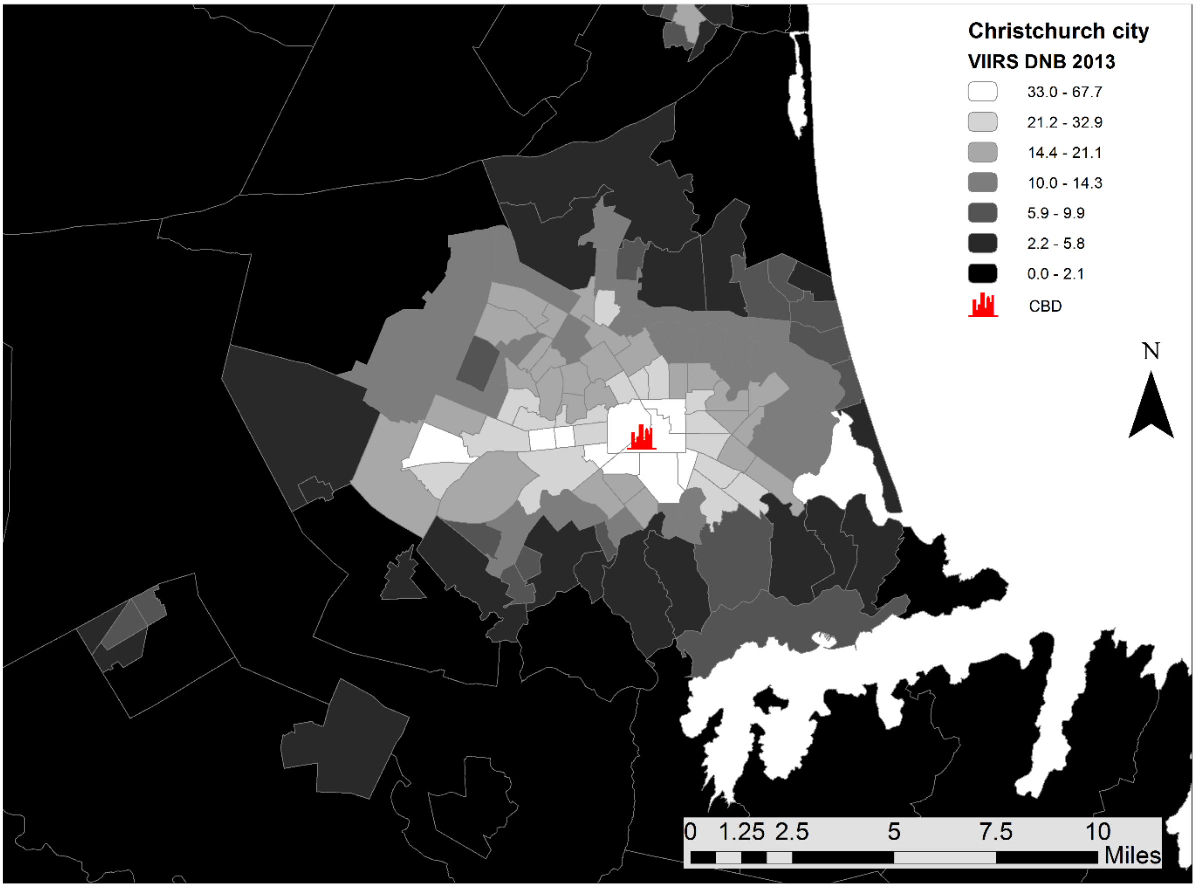

Figure 5 - Average annual nightlight DMSP/OLS for area units in Christchurch 2006 - 2012

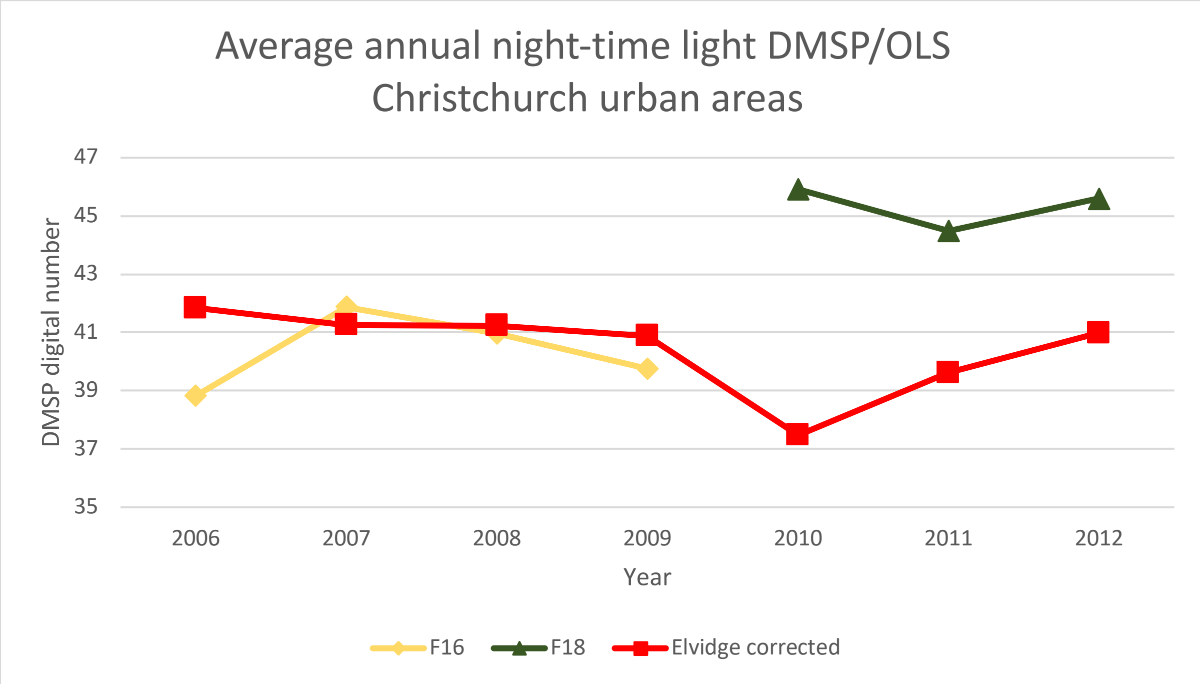

Figure 6 - Average annual nightlight VIIRS –DNB for area units in Christchurch 2012 - 2016

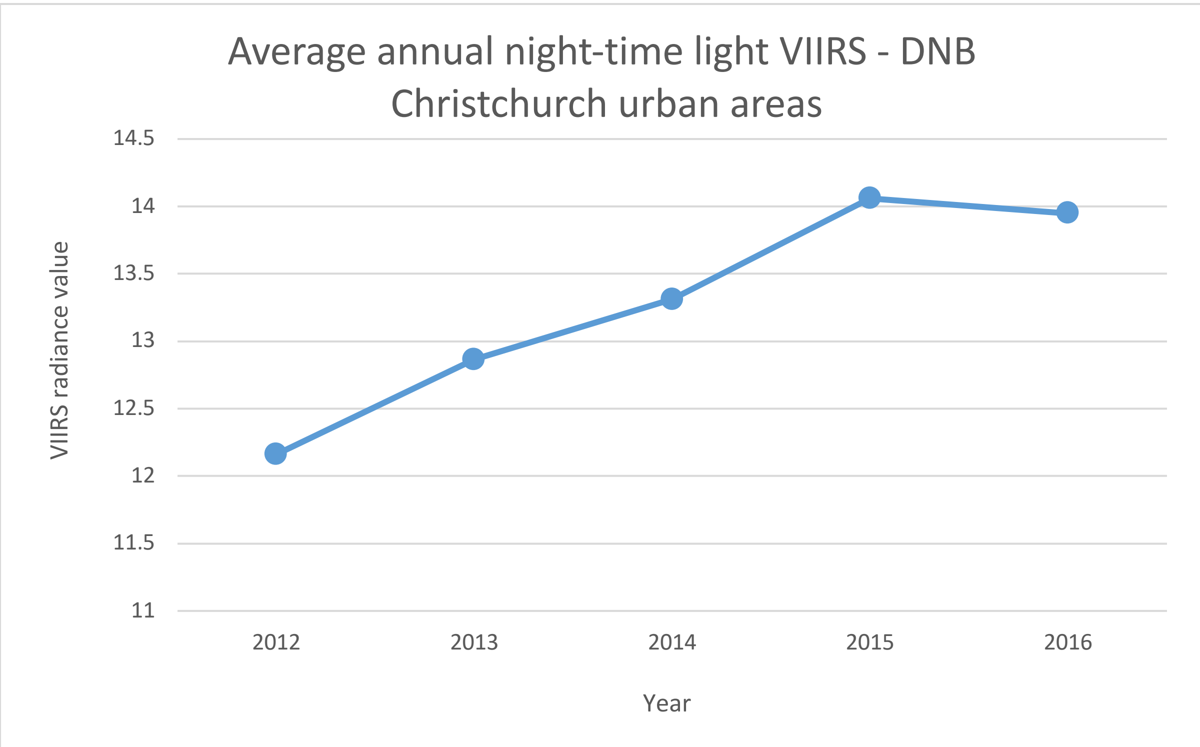

Figure 7 - Histogram of residential claims with respect to different aftershock event in the CES

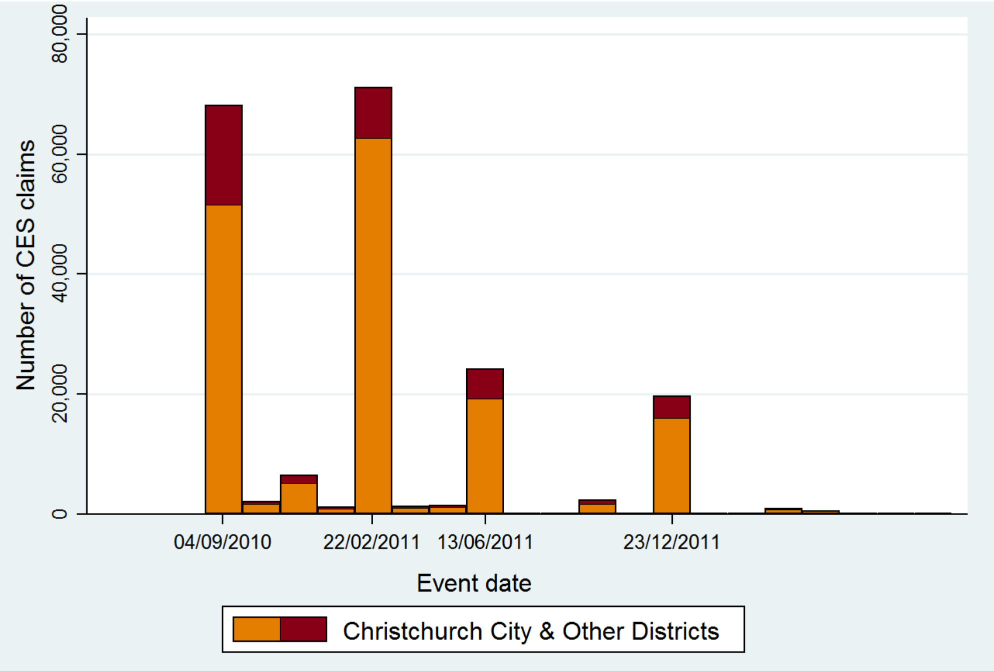

Table 1 - Summary statistics of Greater Christchurch

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 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 intensity	
	Correlation	**% of the variation explained**
Night-time population	.587**	34.47
Night-time population density	.709**	50.29
Household income	-.299**	8.94
Household income density	.479**	23.01
No. occupied dwellings	.585**	34.23
No. occupied dwellings density	.727**	52.86
Distance from CBD	-.831**	69.05

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)	(9)	(10)	(11)	(12)
Damage ratio	0.559***	0.416**	0.957**	0.757**	0.379	0.379	0.016	-0.006	0.747	0.474***	0.343**	0.912**
	(0.186)	(0.171)	(0.401)	(0.367)	(0.389)	(0.389)	(0.051)	(0.068)	(0.493)	(0.181)	(0.162)	(0.415)
Household Income		0.008	0.003		0.007	0.007		0.012	-0.025		0.007	-0.000
		(0.037)	(0.045)		(0.036)	(0.036)		(0.038)	(0.049)		(0.037)	(0.041)
Night-time Population		0.018	0.017		0.019	0.019		0.019	0.021*		0.019	0.017
		(0.012)	(0.012)		(0.012)	(0.012)		(0.012)	(0.012)		(0.012)	(0.012)
Number of Bedrooms		-0.060	-0.019		-0.071	-0.071		-0.093	0.023		-0.061	-0.011
		(0.094)	(0.119)		(0.092)	(0.092)		(0.092)	(0.144)		(0.092)	(0.114)
Area square Km		0.006	0.005		0.006	0.006		0.006	-0.012		0.005	0.003
		(0.008)	(0.008)		(0.008)	(0.008)		(0.009)	(0.018)		(0.008)	(0.009)
Constant	-0.086***	-0.237	-0.251	-0.076***	-0.210	-0.210	-0.052***	-0.228	0.011	-0.079***	-0.224	-0.221
	(0.016)	(0.312)	(0.367)	(0.016)	(0.301)	(0.301)	(0.008)	(0.309)	(0.362)	(0.0151)	(0.305)	(0.335)
Observation	158	158	158	158	158	158	158	158	158	158	158	158
R-squared	0.045	0.097	0.058	0.022	0.079	0.079	0.000	0.074	0.031	0.037	0.093	0.043
IV			40.349			35.301			3.171			22.328

***/**/* Indicating the significance levels of respectively 1%, 5% and 10%. AU cluster - robust standard errors are shown in parentheses. All regressions are estimated with OLS. IV is the robust Kleinbergen-Paap *rk* Wald F statistic for test of weak instruments. IV regressions have overidentification's *p*-value approximately equal to zero, except for land regression.

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

VARIABLES	Dependent variable: Quarterly change in night-time light							
	Building		**Content**		**Land**		**Total**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Insurance payment	-0.017	0.363**	-0.005	-0.034	-0.001	0.158***	-0.019	0.389**
	(0.0225)	(0.154)	(0.007)	(0.075)	(0.006)	(0.049)	(0.023)	(0.176)
Settlement time		0.001		-0.007		0.022		-0.0205
		(0.050)		(0.028)		(0.021)		(0.054)
Prop. Cash settlement		0.629***				-0.079		0.609***
		(0.226)				(0.101)		(0.216)
Ins. payment* Settlement time		-0.405***		0.031		-0.150***		-0.417***
		(0.140)		(0.075)		(0.045)		(0.158)
Constant	1.180***	1.261***	1.009***	1.006***	0.972***	0.956***	1.207***	1.258***
	(0.292)	(0.284)	(0.101)	(0.094)	(0.090)	(0.092)	(0.308)	(0.299)
Observation	2686	2686	2686	2686	2686	2686	2686	2686
N.o Area Units	158	158	158	158	158	158	158	158
R-squared	0.653	0.705	0.651	0.653	0.651	0.672	0.652	0.705

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

Table 7 - Economic recovery following the earthquakes (Claim payment) – Spatial panel AU and quarter fixed effects

VARIABLES	Dependent variable: Quarterly change in night-time light											
	SAR				**SAC**				**SEM**			
	Building	**Content**	**Land**	**Total**	**Building**	**Content**	**Land**	**Total**	**Building**	**Content**	**Land**	**Total**
Main												
Insurance payment	0.407***	-0.057	0.128***	0.461***	0.336**	-0.048	0.106**	0.365**	0.456***	-0.061	0.130***	0.536***
	(0.149)	(0.072)	(0.048)	(0.165)	(0.144)	(0.067)	(0.045)	(0.161)	(0.157)	(0.076)	(0.046)	(0.173)
Settlement time	0.034	0.013	0.015	0.013	0.003	0.003	0.011	-0.011	0.061	0.032	0.015	0.042
	(0.042)	(0.026)	(0.020)	(0.045)	(0.040)	(0.025)	(0.018)	(0.045)	(0.045)	(0.025)	(0.022)	(0.045)
Prop. Cash settlement	0.401**		-0.052	0.408**	0.426***		-0.056	0.421***	0.277		-0.033	0.292
	(0.188)		(0.088)	(0.170)	(0.165)		(0.079)	(0.149)	(0.199)		(0.092)	(0.182)
Ins. payment* Settlement time	-0.440***	0.034	-0.117**	-0.482***	-0.363***	0.035	-0.097**	-0.384**	-0.490***	0.024	-0.119***	-0.558***
	(0.138)	(0.072)	(0.045)	(0.151)	(0.138)	(0.067)	(0.042)	(0.153)	(0.143)	(0.072)	(0.044)	(0.157)
Spatial												
ρ	0.468***	0.469***	0.467***	0.468***	0.664***	0.670***	0.665***	0.666***				
	(0.040)	(0.041)	(0.040)	(0.041)	(0.076)	(0.073)	(0.077)	(0.073)				
λ					-0.327**	-0.333**	-0.329**	-0.328**	0.469***	0.468***	0.467***	0.469***
					(0.150)	(0.146)	(0.150)	(0.145)	(0.040)	(0.041)	(0.040)	(0.040)
Observation	2686	2686	2686	2686	2686	2686	2686	2686	2686	2686	2686	2686
N.o Area Units	158	158	158	158	158	158	158	158	158	158	158	158
R-squared	0.706	0.707	0.705	0.706	0.706	0.703	0.704	0.705	0.705	0.706	0.705	0.707
Hausman chi-sq	181.7	168.84	189.86	178.33					165.36	181.16	198.26	170.68

***/**/* Indicating the significance levels of respectively 1%, 5% and 10%. AU cluster - robust standard errors are shown in parentheses. Rho ρ is the spatial autoregressive coefficient and Lambda λ is the spatial autocorrelation coefficient. All regressions are estimated with AU and quarter fixed effect. All models have Hausman p-value equal to zero.

Table 8 - Economic recovery following the earthquakes – Spatial panel AU and quarter fixed effects

VARIABLES	SDM Building	Content	Land	Total
Main				
Insurance payment	0.394**	-0.071	0.128***	0.454***
	(0.155)	(0.073)	(0.048)	(0.166)
Settlement time	0.043	0.029	0.014	0.028
	(0.043)	(0.026)	(0.021)	(0.044)
Prop. Cash settlement	0.357*		-0.042	0.330*
	(0.194)		(0.090)	(0.178)
Ins. payment* Settlement time	-0.426***	0.035	-0.114**	-0.476***
	(0.143)	(0.072)	(0.046)	(0.152)
Wx				
Insurance payment	-0.322	0.086	-0.032	-0.591**
	(0.337)	(0.173)	(0.055)	(0.300)
Settlement time	-0.253***	-0.159***	-0.012	-0.239***
	(0.086)	(0.053)	(0.045)	(0.076)
Prop. Cash settlement	0.799**		-0.118	0.696**
	(0.324)		(0.171)	(0.330)
Ins. payment* Settlement time	0.358	0.0374	0.030	0.628**
	(0.335)	(0.163)	(0.055)	(0.301)
Spatial				
ρ	0.465***	0.468***	0.468***	0.467***
	(0.040)	(0.040)	(0.041)	(0.040)
Observation	2686	2686	2686	2686
N.o Area Units	158	158	158	158
R-squared	0.706	0.705	0.707	0.708
Hausman chi-sq	245.26	173.51	199.19	221.89

***/**/* Indicating the significance levels of respectively 1%, 5% and 10%. AU cluster - robust standard errors are shown in parentheses. Wx is the spillover effect coefficients and Rho ρ is the spatial autoregressive coefficient. All regressions are estimated with AU and quarter fixed effect. All models have Hausman *p*-value equal to zero.

Table 9 - Economic recovery following the earthquakes (Claim payment) – Direct and Indirect effects

VARIABLES	Dependent variable: Quarterly change in night-time light															
	SAR				**SAC**				**SEM**				**SDM**			
	Building	**Content**	**Land**	**Total**	**Building**	**Content**	**Land**	**Total**	**Building**	**Content**	**Land**	**Total**	**Building**	**Content**	**Land**	**Total**
Direct effect																
Insurance payment	0.434***	-0.057	0.136***	0.491***	0.389**	-0.051	0.122**	0.422**	0.456***	-0.061	0.130***	0.536***	0.387**	-0.063	0.132**	0.421**
	(0.161)	(0.078)	(0.052)	(0.178)	(0.167)	(0.078)	(0.050)	(0.186)	(0.157)	(0.076)	(0.046)	(0.173)	(0.172)	(0.077)	(0.052)	(0.184)
Settlement time	0.0336	0.0140	0.0153	0.0122	0.00239	0.002	0.012	-0.014	0.062	0.032	0.015	0.042	0.016	0.013	0.013	0.001
	(0.0432)	(0.0268)	(0.020)	(0.046)	(0.0449)	(0.028)	(0.020)	(0.050)	(0.044)	(0.025)	(0.022)	(0.045)	(0.042)	(0.027)	(0.020)	(0.045)
Prop. Cash settlement	0.444**		-0.0454	0.449***	0.508***		-0.055	0.501***	0.277		-0.0330	0.292	0.485**		-0.048	0.444**
	(0.190)		(0.0892)	(0.171)	(0.185)		(0.087)	(0.169)	(0.199)		(0.0922)	(0.182)	(0.195)		(0.087)	(0.177)
Ins. payment* Settlement time	-0.469***	0.034	-0.125**	-0.513***	-0.420***	0.038	-0.112**	-0.443**	-0.490***	0.024	-0.119***	-0.558***	-0.417***	0.039	-0.118**	-0.440***
	(0.148)	(0.077)	(0.049)	(0.163)	(0.160)	(0.079)	(0.048)	(0.176)	(0.143)	(0.072)	(0.044)	(0.157)	(0.161)	(0.077)	(0.049)	(0.170)
Indirect effect																
Insurance payment	0.332**	-0.044	0.104**	0.376**	0.663*	-0.087	0.194**	0.715*					-0.208	0.088	0.045	-0.627
	(0.136)	(0.061)	(0.043)	(0.150)	(0.361)	(0.150)	(0.092)	(0.402)					(0.583)	(0.285)	(0.096)	(0.525)
Settlement time	0.026	0.011	0.018	0.010	0.002	-0.001	0.020	-0.0284					-0.388***	-0.247***	-0.005	-0.382***
	(0.034)	(0.021)	(0.016)	(0.036)	(0.084)	(0.057)	(0.038)	(0.0957)					(0.149)	(0.094)	(0.073)	(0.135)
Prop. Cash settlement	0.338**		-0.0318	0.343**	0.896*		-0.0852	0.880*					1.665***		-0.243	1.465**
	(0.156)		(0.0677)	(0.141)	(0.489)		(0.156)	(0.472)					(0.588)		(0.290)	(0.583)
Ins. payment* Settlement time	-0.358***	0.0273	-0.096**	-0.393***	-0.718**	0.0695	-0.179**	-0.752*					0.240	0.093	-0.041	0.668
	(0.129)	(0.060)	(0.041)	(0.142)	(0.363)	(0.156)	(0.089)	(0.396)					(0.591)	(0.277)	(0.093)	(0.535)

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