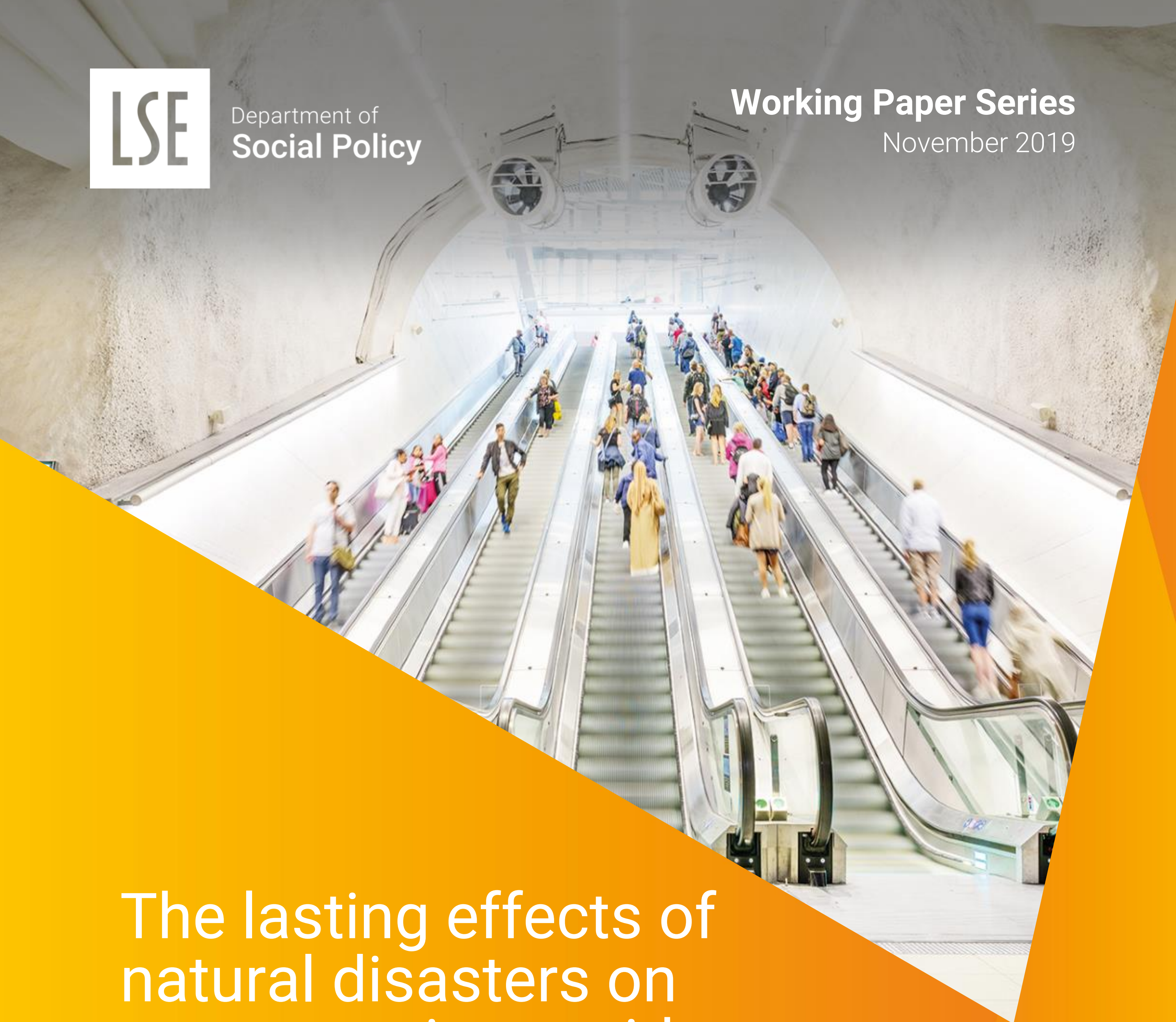

Department of
Social Policy

Working Paper Series
November 2019

The lasting effects of natural disasters on property crime: evidence from the 2010 Chilean earthquake

Working Paper 12-19

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To cite this paper:
García Hombrados, J. (2019),Tthe lasting effects of natural disasters on property crime: Evidence from the 2010 Chilean Earthquake, Social Policy Working Paper 12-19, London: LSE Department of Social Policy.

Abstract

Natural disasters cause human losses, destroy economic assets and are often followed by widespread looting and altruistic behaviours of many individuals; affecting ambiguously the long-term benefits and costs of committing crime. Using household data from victimisation surveys and a difference in difference strategy, the analysis shows that municipalities exposed to the 8.8 Richter magnitude earthquake that struck Chile in February 2010 experienced lasting reductions in the prevalence of property crime. The analysis reveals that the drop in property crime in these areas is closely linked to the positive effect of the earthquake on the strength of community life and the subsequent adoption of community-based crime prevention measures.

Key words: Natural disasters; crime; social capital.

JEL Codes: K4; H8.

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Acknowledgments

Declarations of interest: none. The research that led to this paper was funded by an ESRC-DTP scholarship and by the European Research Council starting grant 336475 (COSTPOST) to Mikko Myrskylä. This paper received close guidance from Andy McKay and Edoardo Masset. The paper also received comments from Marcos Vera-Hernandez, Vikram Pathania, Sam Marden, Rocco D'Este and from anonymous reviewers from the Economic Journal and the American Economic Journal: Applied Economics. I declare that I have no relevant or financial interests that relate to the research described in this paper.

1 - Introduction

Aside from the images of destruction, one aspect often displayed by televisions and newspapers in the aftermaths of natural disasters are scenes of chaos and looting. The evidence suggests that the disorders that followed natural disasters such as the Katrina hurricane or the 2010 Haiti earthquake seem to be closely linked to power cuts and to the collapse of the police, decreasing temporarily the cost of participating in criminal activities [Frailing and Harper, 2007, Friesema et al., 1979, Kolbe et al., 2010].

Although the *break in the social contract* often found in the aftermath of natural disasters is usually limited to a few days or even hours [Quarantelli, 2001], temporary reductions in the cost of committing crime could lead to lasting effects on crime rates if the personal cost of engaging in criminal activities is a decreasing function of the number of previous crimes committed. Similarly, the negative effects of disasters on employment [Belasen and Polachek, 2008] could also decrease persistently the opportunity cost of crime. On the other hand, some studies suggest that natural disasters strengthen community links [Dynes and Quarantelli, 1980, Bailey, 2009], facilitating cooperation among neighbours and the adoption of community-based crime prevention strategies, eventually affecting the cost of committing crime and the demand for crime prevention. With mixed effects on the supply of crime and the demand for crime prevention, the medium- and long-term impact of natural disasters on property crime is theoretically ambiguous and is therefore an empirical question.

I provide evidence on the lasting effects of natural disasters on property crime using as a case study the 8.8 Richter magnitude earthquake that struck the Centre-South of Chile in 2010. This earthquake caused 547 fatalities and economic damages estimated at USD 15-30 billions [UNEP, 2011]. In the aftermath of the catastrophe, the most affected areas experienced looting episodes that involved hundreds of people and in response, the Chilean government deployed the army and declared a curfew in these municipalities. The main estimations presented in this study rely on difference in difference models comparing crime rates in municipalities close and far away from the epicentre and use pre- and post-earthquake data from 7 rounds of a household victimisation survey that sampled every year more than 25,000 urban households in Chile.

The results of the study reveal that, depending on the specification, exposure to a *very strong* earthquake intensity decreased the incidence of home burglary the year of the earthquake by 15%-30% relative to areas not directly affected by the disaster and that this effect remained constant over the 4 post-earthquake years studied. The results hold for other types of property crime such as larcenies or non-home burglary and also when crime data from police records are examined, ruling out the possibility of crime displacement from home burglary towards other types of property crime. The results are also robust to the use of alternative earthquake intensity thresholds to define treatment and control municipalities, and to the use of a continuous measure of exposure to the earthquake.

I examine different mechanisms for lower property crime in earthquake affected areas. The results suggest that the main channel that drove the lasting contraction in property crime rates was the positive effect of the disaster on the strength of community life. The improvement in social capital at the community level facilitated co-operation among neighbours and boosted the adoption of community-based measures to prevent crime, increasing the cost of illegal activities in earthquake affected areas. Alternative mechanisms such as an increase in the number of policemen, the destruction of assets reducing the expected benefits of committing crime, large population displacements or a reduction in unemployment due to reconstruction activities in areas affected by the earthquake are rejected in the light of the results. Furthermore, the estimates also suggest that the lasting drop in the incidence of property crime was not caused by higher levels of incarceration as a consequence of the institutional efforts in the aftermath of the earthquake to address looting or by a rise in the perceived risk of crime boosting the demand for crime prevention measures. Finally, the analysis shows that the persistent reduction in property crime rates in earthquake affected areas was not driven by a lasting effect of the deployment of the army or the curfew via a temporary increase in the cost of committing crime with long-term consequences.

This study is primarily related with the body of literature that investigates the effect of natural disasters on the incidence of crime. The results are consistent with the informal guardianship theory developed in sociology that argues that natural disasters increase co-operation and the formation of social capital within damaged communities, increasing the provision of informal guardianship in these communities and therefore the cost of committing crime. In this context, the contribution of the study is threefold. First, unlike previous studies that examine the evolution of crime rates over a maximum post-disaster period of 12 months, this study explores for the first time whether the effects of natural disasters are persistent over longer periods of time. In a global context where natural disasters are every year more frequent [UNISDR, 2018], understanding the multidimensional long-term consequences of natural disasters could reveal key for the design of effective social policies following catastrophes. Second, this is the first study that investigates empirically the mechanisms driving the effects of natural disasters on property crime, providing evidence that supports different predictions of the informal guardianship theory. More generally, this suggestive evidence on the informal guardianship theory opens the debate and calls for more research on whether interventions aiming to strength community links can be useful instruments to tackle crime in areas where the capacity of formal institutions to enforce the law is limited. In this sense, this result also contributes to the body of evidence investigating the effects on crime of different forms of social capital such as civic norms, altruism or associational networks [Buonanno, Montolio, and Vanin, 2009, Akcomak and Ter Weel, 2012]. Third, although previous studies assess the effects of natural disasters on crime over shorter periods of time, this is the first study that builds on the use of unaffected areas as a natural control group and uses crime data from victimisation surveys that include information on both crime reported to and unreported to the police. If natural disasters could affect the probability of reporting a crime to the police, the use of data that include crime unreported to the police is crucial to net out effects on true crime rates from effects on crime recorded by the police.

The study is structured as follows. Section 2 introduces the conceptual framework. Section 3 discusses the existing evidence on the link between natural disasters and crime. Section 4 describes the context and the main political and social events that followed the 2010 Chilean earthquake. Section 5 presents the data and section 6 introduces the empirical strategy used to estimate the effect of the earthquake on property crime. Section 7 discusses the main results of the analysis. Then, section 8 expands the analysis using crime data from police records and explores crime and apprehension in the aftermath of the earthquake. Section 9 explores the mechanisms through which the earthquake could have reduced property crime and section 10 concludes.

2 - Conceptual Framework

Mainly developed in the field of sociology, there are two opposing streams of literature that set out different predictions about how crime rates evolve following natural disasters.

On the one hand, some authors hypothesise that crime rates increase following natural disasters. There are three main mechanisms through which this effect might operate. The first of them, known in the field of sociology as the *routine activities theory*, is described in Cohen and Felson [1979]. They argue that natural disasters are followed by a rise in crime rates because catastrophes increase the availability of suitable targets and reduce the presence of capable guardianship. Another mechanism that explain why crime rates could spike following natural disasters is that crime is more prevalent in those places characterised by the incapacity of the community to informally control crime due to factors such as residential instability that might be severely damaged by natural disasters [Zahran et al., 2009]. This argument is interpreted in the context of the *social disorganisation* theory developed in Shaw and McKay [1942]. These two mechanisms can be embedded in traditional economics of crime models that describe crime rates as the intersection between a supply of crime (determined by the costs and benefits of committing crime) and a demand for crime prevention [Becker, 1968, Ehrlich, 1973, Cook, 1986]. Through causing a temporary or permanent obstruction to law enforcement and forcing some households to leave their dwellings, natural disasters decrease the cost of committing crime leading to larger crime rates through affecting crime supply. The third path through which natural disaster may raise property crime is the labour market. If employment represents the opportunity cost of crime, the lasting negative effect of natural disasters on employment documented in Belasen and Polachek [2008] would also affect crime supply boosting the incidence of crime.

The second stream of literature argues that crime rates do not raise and might even decrease following natural disasters. These authors highlight that although natural disasters may decrease the capacity of *formal* institutions such as the police to enforce the law, they also raise pro-social and altruistic behaviours [Quarantelli and Dynes, 1970], fostering co-operation and the formation of social capital within communities, facilitating coordination among neighbours and ultimately increasing the level of informal guardianship in these communities [Cromwell et al., 1995]. The authors argue that the rise in the level of informal guardianship offsets the potential harmful effects of natural disasters on crime arising from a reduced capacity of the police to enforce the law immediately after disasters or from the perverse effect of the disaster on other crime determinants, eventually leading to lower crime rates. In a traditional economics of crime theoretical model, the argument of these authors implies that far from reducing the costs of committing crime, the rise in the provision of informal guardianship in affected communities compensates the reduced capacity of formal institutions to provide capable guardianship, increasing the cost of committing crime in these communities through affecting the supply of crime and the demand for crime prevention in equilibrium.

The two streams propose different channels through which natural disasters can affect lastingly crime rates with opposite directions. In the light of this literature, the effect of natural disasters on crime predicted in theoretical models of economics of crime would be ambiguous, with the sign of the net effect depending on the superiority of some channels over others. Thus, the direction of the net effect of natural disasters on property crime is an empirical question, as it is the investigation of whether this effect vanishes or remains over time.

3 - Related literature

The short-term evolution of crime rates following natural disasters has been empirically investigated in different studies, with mixed results.

Most of the studies addressing this question find that crime rates increase after natural disasters. For example, Roy [2010] exploits district-level panel data in India to investigate the incidence of violent and property crime in districts that experienced a natural disasters the same year. The paper shows that, overall, natural disasters are followed by increases in most types of property and violent crime. Using crime data from police records, Friesema et al. [1979] show large increases in motor vehicle theft in Texas following hurricane Carla. Frailing and Harper [2007] find a spike in the incidence of burglary in New Orleans after hurricane Katrina, and Kolbe et al. [2010] suggest that the large earthquake that affected Haiti in 2010 triggered sexual assaults in the weeks following the disaster. Leitner and Helbich [2011] investigate the link between crime and natural disasters through studying the daily evolution of crime rates before, during and after two hurricanes that affected the city of Houston. The authors state that while burglary and motor-vehicle theft increased immediately before and after hurricane Rita, crime rates did not change before, during or after hurricane Katrina. They argue that the difference in effects might be driven by the fact that while an order of evacuation was issued before hurricane Rita, no such order was issued before or during hurricane Katrina in Houston. The empirical evidence supporting the suggestion that natural disasters are followed by an increase in crime rates is particularly strong for domestic and sexual violence offences such as child abuse [Curtis et al., 2000], sexual assault [Kolbe et al., 2010] or gender violence [Peacock et al., 1997, Enarson et al., 2006].

However, the evidence is not homogeneous and there are some empirical studies that find either a decrease or a stagnation in crime rates after natural disasters. For example, using qualitative data collected one month after hurricane Andrew in Florida, Cromwell et al. [1995] show that although the hurricane increased the number of motivated offenders and unprotected victims, it also boosted informal guardianship leading to sharp decreases in crime rates during the weeks that followed the hurricane. Similarly, Siegel, Bourque, and Shoaf [1999] find that exposure to the 1994 Northridge earthquake in California did not increase the likelihood of suffering a violent or a property crime during the two months that followed the disaster. Although the evidence is mixed, most of the studies that explore the evolution of crime rates in New Orleans and neighbouring parishes after hurricane Katrina suggest that except for burglaries, property crime rates decreased the months following the disaster although the rates converged to pre-hurricane levels one year later [Leitner et al., 2011, Bailey, 2009][1].

Zahran et al. [2009] bring the discussion a step forward arguing that the incidence of different types of crimes might evolve differently after natural disasters. Using county-level panel data from Florida and well-conducted fixed effects techniques, the paper provides evidence that while natural disasters tend to decrease property and violent crime the year of the disaster, they also raise the incidence of domestic violence.

Although the number of studies that explore the short-term effect of natural disasters on crime is large, most of these studies have methodological problems. For example, only two of the studies discussed [Roy, 2010, Zahran et al., 2009] use a counterfactual approach and with one exception [Kolbe et al., 2010], the literature relies on crime data from police records. The use of police records could be problematic because changes in crime recorded by the police after natural disasters could be reflecting an effect of natural disasters on the probability of reporting crime to the police rather than on true crime rates. Furthermore, I am not aware of any previous study investigating whether the effects of natural disasters on crime expand over more than one year. Finally, and although some of the studies discuss them theoretically, this is the first study that explores empirically the mechanisms driving the effect of natural disasters on property crime.

4 - The Context

The early morning of the 27th of February of 2010 an earthquake of 8.8 degrees in the Richter scale shook the Centre-South of Chile. The epicentre was located approximately 90 km north west of Concepción, the second largest Chilean city with a metropolitan population above 1,000,000 inhabitants. The earthquake was followed by a tsunami with waves striking approximately 500 km of the Chilean coast. Although the economic losses affected a total of 6 regions that included the 80% of the Chilean population, the regions of Biobio and Maule were particularly damaged by the earthquake and the tsunami [Larranaga and Herrera, 2010b].

Different reports from the Chilean government, NGOs, universities and international organisations provide an estimation of the economic damages and human losses caused by the earthquake and the tsunami. Nahuelpan and Varas [2011] report that the earthquake and the tsunami that followed caused a total of 547 deaths. Contreras and Winckler [2013] attribute 181 of these deaths to the tsunami. Regarding the direct economic losses caused by the earthquake and the tsunami, UNEP [2011] estimates in USD 15-30 billions the damage caused to public and private assets, including 440,000 houses and numerous roads severely deteriorated [CEPAL, 2010]. Although identifying the losses caused only by the tsunami is in most cases difficult, Contreras and Winckler [2013] argue that it damaged 17,392 houses in 24 different municipalities. The same report also highlights that the tsunami affected many coastal infrastructures including different harbours and piers and approximately 3,000 boats. Table 1 summarises the main losses at the regional level for the six

[1]The evidence on crime dynamics after Katrina hurricane is mixed and some studies also show that crime rates one year after the disaster were larger than pre-hurricane rates, particularly for murder [VanLandingham, 2009].

regions affected by these natural disasters.

The earthquake also caused water, power and telephonic cuts. Power cuts affected the 80% of the population and lasted between a few hours and three days in the most damaged areas of the country [OPM, 2010]. In the aftermath of the earthquake many households in affected areas left their houses for some days and set their tents in front of their dwellings. The delivery of the emergency aid was coordinated with neighbourhood-based groups, fostering cooperation among neighbours. After some looting episodes in the regions of Biobio and Maule, the 28th of February the Chilean government declared the state of emergency for 30 days in these two regions and a curfew in the municipalities that experienced looting episodes. Following the declaration, the army was deployed for almost a month in some of the urban municipalities of these regions where soldiers collaborate in restoring public order[2]. Nonetheless, looting did not completely stop and pillage episodes were occasionally registered during the following week[3]. In total, there were looting events in 33 municipalities [Ormeno, 2010]. Some of these episodes were documented by the media and involved hundreds of looters[4].

Table 1: Fatalities and economic damage of the earthquake/tsunami by region

	Fatalities	% Dwellings severe damage	% Dwellings severe damage (I quintile)	% Dwellings severe damage (V quintile)	% HHs facing problem from earthquake/tsunami	% pop >18 with symptoms post-traumatic stress
Valparaíso	25	7.4	11.3	2.4	51.9	8.3
O'Higgins	53	12.2	12.5	7.5	67	22.3
Maule	280	20.7	26.3	12.8	92.9	21.4
Biobío	145	17.8	25.4	8.5	92.9	23.9
Araucanía	17	5.1	10.2	0.5	59.3	11.5
Metropolitana	27	4.8	6.5	3.0	56	6.5
All regions aff.	547	8.8	12.0	4.6	64.7	12.0

Source: Larranaga and Herrera [2010a]. Information on damages is only provided for the six regions affected by the earthquake. The regions Tarapacá, Arica y Parinacota, Atacama, Coquimbo, Antofagasta, Los Ríos, Los Lagos, Aisén and Magallanes are not included in the survey because the authors concluded that they were not directly damaged by the earthquake or the tsunami.

Qualitative data and media reports point out that the earthquake was followed by social chaos in heavily affected areas that ended with many people participating in looting events mainly towards big supermarkets and shops[5]. However, despite the limited capacity of formal institutions to enforce the law the days following the earthquake, the looting of dwellings and habited places was a very rare event [Grandón et al., 2014, Larranaga and Herrera, 2010b]. Remarkably, these reports also document widespread pro-social and altruistic behaviours in the aftermath of the earthquake

[2] http://internacional.elpais.com/internacional/2010/02/28/actualidad/1267311602_850215.html
[3] http://www.ambito.com/noticia.asp?id=510234
[4] See for example: http://www.24con.com/nota/37127_Saqueos_la_gente_se_lleva_desde_lechehastaplasmas
[5] http://ciperchile.cl/2010/07/19/saqueadores_post_terremoto_ii_la_horda_que_nunca_llego_a_las_casas

and communities organising themselves to overcome earthquake catastrophic consequences. Perhaps influenced by the media coverage of the post-disaster events, the 32% of the urban households interviewed for the 2010 ENUSC survey believed that the earthquake caused an increase in the incidence of crime at the national level during the same year. Interestingly, the percentage of households that reported such perception was higher in the areas far away from the earthquake epicentre (32% in control municipalities) than in municipalities close to it (27% in treatment municipalities).

5 - Data

The crime data used in the main analysis correspond to seven rounds of the Encuesta Nacional Urbana de Seguridad Ciudadana (ENUSC) survey for the period 2007-2013[6]. The ENUSC is a household survey conducted by the Chilean Ministry of Governance and applied every year to a cross section of more than 25,000 urban households living in the largest 101 Chilean municipalities. The survey collects household level information on victimisation in the last 12 months for different types of crimes and on the adoption of individual and community-based measures to prevent crime.

The main advantage of the ENUSC data relative to crime data from police records is that while police records only include those offences recorded by the police, the ENUSC survey captures both the crimes reported to and unreported to the police. On the other hand, the use of this dataset has two drawbacks. First, with the exception of home burglary, the exact location of each crime is not reported. This could be particularly problematic for the metropolitan areas of Santiago and Concepcíon where many individuals work and live in a different municipality. Second, the difference between some types of property crimes such as larcenies, burglaries or robberies is in many cases fuzzy. In consequence, some households might be unable to report reliably some specific types of crime to the enumerator. Thus, and since home burglary is unlikely to be confounded with other crimes by the households interviewed or the enumerator and we know their exact location in the survey, the analysis of the effect of the earthquake on home burglary deserves more confidence. Nonetheless, the paper also reports the effect of the earthquake on the prevalence of robberies, larcenies and motor-vehicle theft using the ENUSC dataset and finding consistent results.

Section 8 tests the robustness of the results to the use of crime data from police records. These records were obtained from the Subsecretaria de Prevención del Delito (SPD) in Chile and they report every month and year (a) the number of crimes recorded by the police in each of the 345 Chilean municipalities by type of crime[7] and (b) the number of individuals apprehended by the police in every municipality. Since Chilean municipalities vary substantially in terms of population, I compute for every municipality, year and type of crime, the number of crimes per 1,000 inhabitants.

[6] The first publicly available ENUSC survey was conducted in 2007.

[7] The crime data are available at: http://www.seguridadpublica.gov.cl/tasa_de_denuncias_y_detenciones.html

The main advantage of this dataset relative to ENUSC is that it includes crime information for all Chilean municipalities (345) and not only for the largest 101.

The dataset on earthquake intensity is constructed using the geographical information provided by the Oficina Nacional de Emergencia del Ministerio del Interior y Seguridad Pública (ONEMI) on the coordinates, magnitude and depth of the earthquake hypocentre. The distance to the earthquake hypocentre is then used to predict the Modified Mercalli Intensity (MMI) at the municipality level using the method described in Barrientos [1980] that predicts earthquake intensity in a given place as a function of the distance from the place to the hypocentre and of the earthquake magnitude at its source[8].

In the main analysis, I define as treatment municipalities those exposed to a predicted $MMI \geq 7.5$. The expected damages associated with a $MMI = 7$ are negligible damage in buildings of good design and construction; slight to moderate in well-built ordinary structures and considerable damage in poorly built or badly designed structures[9]. However, I set the threshold in predicted $MMI \geq 7.5$ because the predicting method developed in Barrientos [1980] seems to overestimate intensities $MMI > 7$ for this particular earthquake [Astroza et al., 2010]. Control municipalities are defined as those exposed to a predicted $MMI < 5.75$. I set this threshold to define control municipalities because the damages associated with a $MMI < 6$ are minimum [Astroza et al., 2010] and Mercalli intensities are usually assigned on a half-point basis in the scale. The municipalities exposed to a predicted $5.75 \leq MMI < 7.5$ are initially dropped from the analysis because although the overall damages caused by the earthquake in these municipalities were small, I cannot rule out the possibility that the earthquake affected poor constructions or generated power cuts in them, affecting the benefits and costs of committing crime. Because the selection of the exact predicted intensity thresholds is to some extent arbitrary, I will examine the robustness of the results to the use of alternative intensity thresholds to define treatment and control municipalities and also to the use of the alternative method to predict earthquake intensity described in Astroza et al. [2010][10]. Finally, and in order to avoid dropping any municipality from the analysis, I also use a continuous measure of exposure to the earthquake equal to the predicted MMI in the municipality, rounded at the 0.5 points in the scale. Because the effect of a higher MMI is unlikely meaningful below a certain threshold, I capped the lower value of the continuous measure of exposure to the earthquake at $MMI = 5.5$.

8 Using data from 945 measurements of earthquake intensity in different places after 73 earthquakes $M_W > 5.5$ that struck Chile between 1906 and 1977, the paper estimates the following function that predicts the intensity of an earthquake in a given location (measured in MMI) as a function of the distance to the hypocentre and of the magnitude of the earthquake measured in M_W.

$$IMMI = 1.3844M_w - 3.7355log_{10}(DistHC) - 0.0006DistHC + 3.8461$$

9 The interpretation of the values in the Mercalli and MSK scales is reported in appendix B.

10 The paper measures MSK in 98 locations after the 2010 earthquake and estimate the MSK as a function of the distance to the closest seismic asperity. They estimate the following equation for the 2010 Chilean Earthquake:

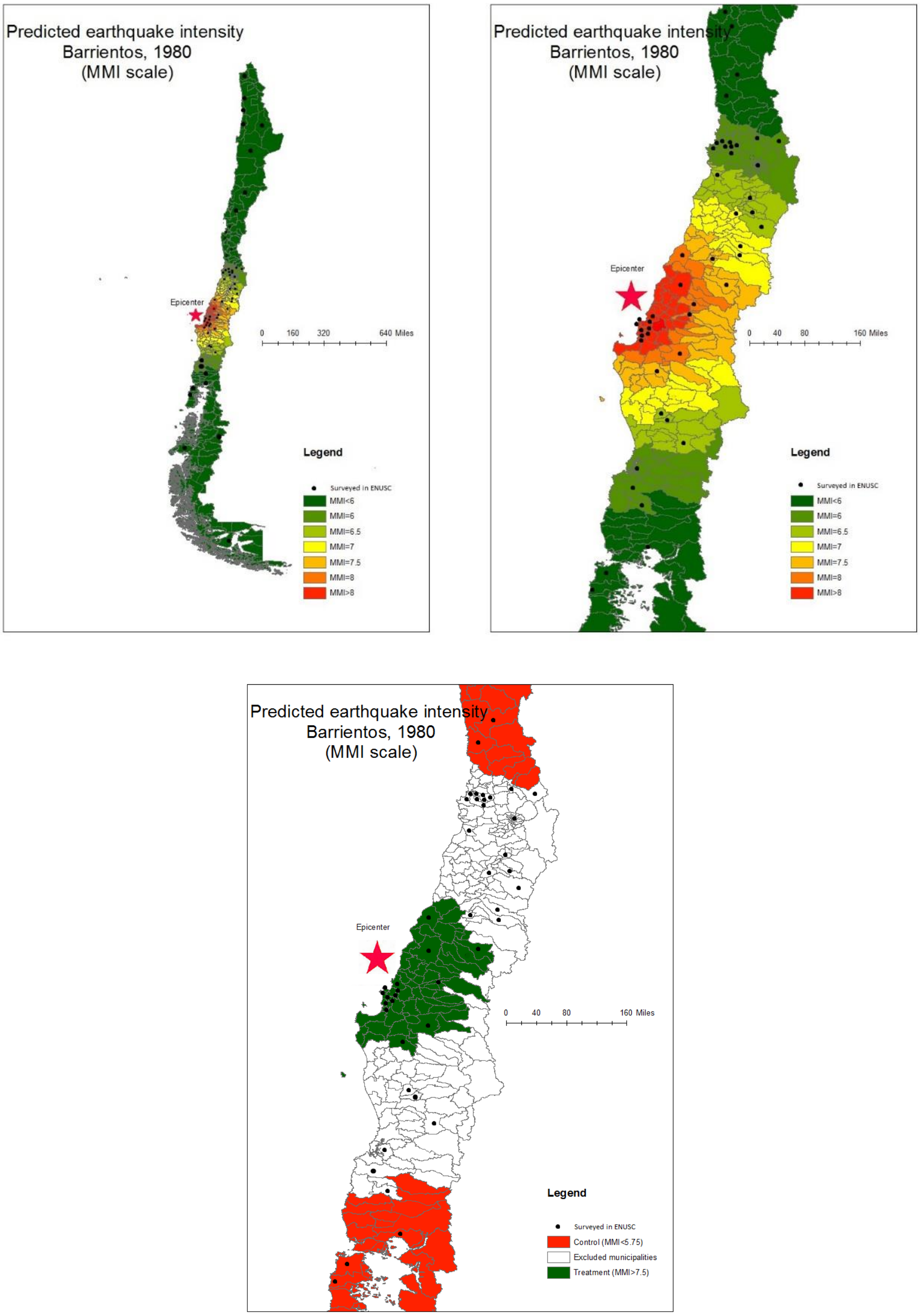
$$IMSK = 43.11 - 18.96log_{10}(DistAs) + 0.0294DistAs$$

Figure 1 shows maps with (a) the predicted earthquake intensities for Chilean municipalities calculated using the method developed in Barrientos [1980] and rounded at the 0.5 points in the MMI scale and with (b) treatment and control municipalities under the default thresholds of $MMI \geq 7.5$ for treatment municipalities and $MMI < 5.75$ for control municipalities. The configuration of treatment, control and excluded municipalities under alternative earthquake intensity thresholds and calculation methods used to predict earthquake intensities are presented in figures C1 and C2 in appendix C.

We use predicted earthquake intensity as a measure of exposure to the earthquake rather than actual intensity or earthquake damages for two reasons. First, there is no information on recorded MMI intensity for many of the municipalities. Second, while the predicted intensity measure only depends on the distance to the hypocentre, the extent of human losses or economic damages in a municipality could arguably be affected by pre-disaster factors that may influence the costs and benefits of committing crime.

Table 2 summarises the data used in the study. Descriptive statistics are provided for three different samples. The first of them includes the municipalities exposed to either a predicted $MMI \geq 7.5 \ or \ MMI < 5.75$ that are also included in the ENUSC database, and therefore, that are used in the main analysis of the effects of the earthquake on property crime. For this sample, the table reports the before-earthquake mean values for the variables of interest for the treatment and control groups. The second sample includes all the municipalities exposed to either a predicted $MMI \geq 7.5 \ or \ MMI < 5.75$ regardless of whether they are included in the ENUSC database. This is the sample of municipalities that is used in the analysis of crime data from police records and in most of the analysis of mechanisms. For this sample, the table reports the before-earthquake mean values for the treatment and control groups. The third sample includes all the Chilean municipalities regardless of their predicted MMI intensity. This sample is used in the analysis conducted using the continuous measure of exposure to the earthquake. For this sample, the table reports the mean values of the variables using only the before-earthquake years and all years available.

Figure 1: Predicted intensity: treatment and control areas



Note: In the maps that display the predicted earthquake intensities, the colour is assigned based on a rounding of the predicted earthquake intensity at the 0.5 points. On the other hand, the construction of the treatment and control groups of municipalities is based on whether the exact value of the predicted earthquake intensity in the municipality is above or below a certain threshold. This is the reason why for example, the municipalities exposed to a predicted earthquake intensity $7.25 \leq$ MMI < 7.5 are coded as MMI 7.5 in the maps that display the predicted earthquake intensities but they are not coded as treatment municipalities in the other map.

Table 2: Descriptive Statistics for variables used in the analysis

	Treatment and Control before earthquake Municip. included in ENUSC data					Treatment and Control before earthquake All Treat and Contr. Municip.					All Chile (345 Munic.)			
	Treatment (16 Munic.)		Control (19 Munic.)		Diff	Treatment (61 Munic.)		Control (100 Munic.)		Diff	Before earth.		All periods	
	N	Mean	N	Mean	Treat-Cont	N	Mean	N	Mean	Treat-Cont	N	Mean	N	Mean
ENUSC data (2007-2013; housh. level)														
Home burglary (0/1)	12,314	0.071	15,809	0.047	0.02***						74,162	0.053	177,889	0.048
Dog (0/1)	12,314	0.399	15,812	0.410	-0.01						74,168	0.406	177,900	0.411
Bars windows/doors (0/1)	12,314	0.470	15,812	0.442	0.03						74,168	0.540	177,900	0.549
Safety lock (0/1)	12,314	0.311	15,812	0.235	0.08**						74,168	0.289	177,900	0.343
Alarm (0/1)	12,314	0.073	15,812	0.060	0.01						74,168	0.097	177,900	0.113
Share number with neigh (0/1)	12,314	0.265	15,812	0.225	0.04*						74,168	0.256	177,900	0.290
Comm. vigilance (0/1)	12,314	0.125	15,812	0.077	0.05***						74,168	0.123	177,900	0.150
Coord. with author. (0/1)	12,314	0.360	15,812	0.294	0.07**						74,168	0.296	177,900	0.319
Comm. hires priv. vig. (0/1)	12,314	0.070	15,812	0.055	0.01						74,168	0.094	177,900	0.107
Admin crime data (2007-2013; munip. level)														
Robbery 1,000 inhab	48	2.579	57	2.038	0.54	183	1.094	300	0.771	0.32*	1,035	1.516	2,415	1.442
MV theft 1,000 inhab	48	0.454	57	0.918	-0.46*	183	0.179	300	0.298	-0.12*	1,035	0.513	2,415	0.645
Larceny 1,000 inhab	48	6.021	57	6.542	-0.52	183	4.801	300	4.787	0.01	1,035	5.024	2,415	5.398
Non-home burglary 1,000 inhab	48	2.580	57	2.309	0.27	183	2.464	300	2.204	0.26	1,035	2.452	2,415	2.583
Home burglary 1,000 inhab	48	4.653	57	4.176	0.48	183	3.019	300	2.466	0.55*	1,035	3.466	2,415	3.499
Other data														
Poverty rate	16	0.225	19	0.144	0.08***	61	0.230	89	0.126	0.10***	334	0.170	658	0.165
Extreme poverty rate	16	0.058	19	0.035	0.02*	61	0.060	89	0.036	0.02***	334	0.046	658	0.039
Unemployment rate	16	0.126	19	0.087	0.04***	61	0.121	89	0.082	0.04***	334	0.102	658	0.092
Unemp. rate (blue collar)	16	0.123	19	0.080	0.04***	61	0.110	89	0.074	0.04***	334	0.090	658	0.080
Income polariz. (75% vs 25%)	16	8.259	19	7.408	0.85	61	7.066	89	7.685	-0.62*	334	7.275	658	7.175
Income polariz. (90% vs 10%)	16	20.809	19	18.382	2.43	61	17.341	89	19.505	-2.16	334	18.289	658	17.179
Rate men between 15-29	16	0.126	19	0.122	0.00	61	0.117	89	0.111	0.01*	334	0.116	658	0.116
Attending educ (13-25)	16	0.634	19	0.574	0.06***	61	0.583	89	0.577	0.01	334	0.576	658	0.579
Population (inhabs)	48	100,398	57	118,884	-18,486	183	38,475	300	30,733	7,742	1,035	48,589	2,415	49,520
% rural population	48	0.112	57	0.112	0.00	183	0.363	300	0.477	-0.11**	1,035	0.380	2,415	0.378
Policemen per 100,000 inhab	48	214.667	57	193.754	20.91	183	178.295	300	668.927	-490.63***	1,035	318.910	2,415	328.984
Municipality budget per capita (2008-2013)	31	71.593	38	82.204	-10.61*	120	107.891	195	318.545	-210.65***	680	174.172	2,057	216.105
Share aid over municipality budget (2011-2013)	48	0.017	57	0.000	0.02**	183	0.031	298	0.002	0.03***			1,031	0.014
Participate assoc. (0/1)	25,240	0.292	29,798	0.282	0.01	78,798	0.323	97,354	0.348	-0.02*	411,084	0.305	757,957	0.281

Note: Different data sources provide information for different periods of time. Control municipalities are those with a predicted MMI < 5.75 and treatment municipalities are those with a predicted MMI ≥ 7.5, calculated following Barrientos [1980]. ENUSC and CASEN surveys were not applied in all the municipalities. Descriptive statistics are provided for three different groups: (1) treatment and control municipalities included in the survey ENUSC for the years before the earthquake, (2) all treatment and control municipalities for the years before the earthquake and (3) all Chilean municipalities (treatment, control and intermediate) and periods available in each data source. The values for the variable *share of reconstruction aid over municipality budget* are only reported for the years after the earthquake. Blue collar unemployment is defined as unemployment among adults without secondary education.

The descriptive statistics for the first two samples show that before the earthquake, treatment and control municipalities were different in terms of some socioeconomic outcomes. For example, the table reveals that before the earthquake, treatment municipalities were significantly poorer, had higher rates of unemployment and lower per-capita public budgets than control municipalities. These differences between treatment and control municipalities are relevant in both the first sample (including only the municipalities surveyed in the ENUSC database, mainly urban areas) and in the second sample (that includes all treatment and control municipalities).

The pre-earthquake incidence of home burglary calculated using the ENUSC data was approximately 2.4 percentage points larger in treatment municipalities: while the probability of suffering a home burglary during the last 12 months was 4.7% in control municipalities, the 7.1% of the households living in treatment municipalities experienced a home burglary during the same period. The difference is significant at the 1%. On the other hand, the data from police records suggest that the incidence of recorded crime before the earthquake in treatment municipalities included in the ENUSC database was, overall, not systematically different from the incidence in control municipalities. However, some differences arise between treatment and control municipalities when the sample is not restricted to those municipalities included in the ENUSC database, confirming a significantly higher incidence of home burglary and robbery and a lower incidence of motor-vehicle theft in treatment municipalities before the earthquake. An interesting pattern that emerges from the comparison between crime data from the ENUSC survey and from police records is that although the exact comparison is not possible because offences definitions and the recording of crime victimisation do not match across data sources, the incidence of home burglary and other crimes in police records seems much lower than in the ENUSC data. The difference could be partially explained by the fact that approximately the 50% of these offences are not reported to the police[11].

The information on the adoption of crime prevention measures collected in the ENUSC survey shows that, overall, individuals in treatment municipalities were more likely to adopt individual and community-based crime prevention measures before the earthquake. On the other hand, the number of policemen per capita and the participation rates in local associations were not significantly different before the earthquake in treatment and control municipalities included in the ENUSC survey although when all treatment and control municipalities are considered, both rates were significantly lower in treatment municipalities. Finally, the level of income inequality did not seem to differ before the earthquake in treatment and control municipalities.

6 - Empirical Strategy

Earthquakes are natural disasters which its occurrence cannot be anticipated. However, some places are more likely to be affected by strong earthquakes. For example, areas lying in the interaction of two or more tectonic plates are more likely to suffer earthquakes of high intensity. This is indeed the case for Chile, a country with an important part of its entire surface lying in the border of the South-American, Nazca and Antarctic plates. Since 1900, Chile suffered 14 earthquakes of Richter magnitude equal or larger than 8 with epicentre in every Chilean region with

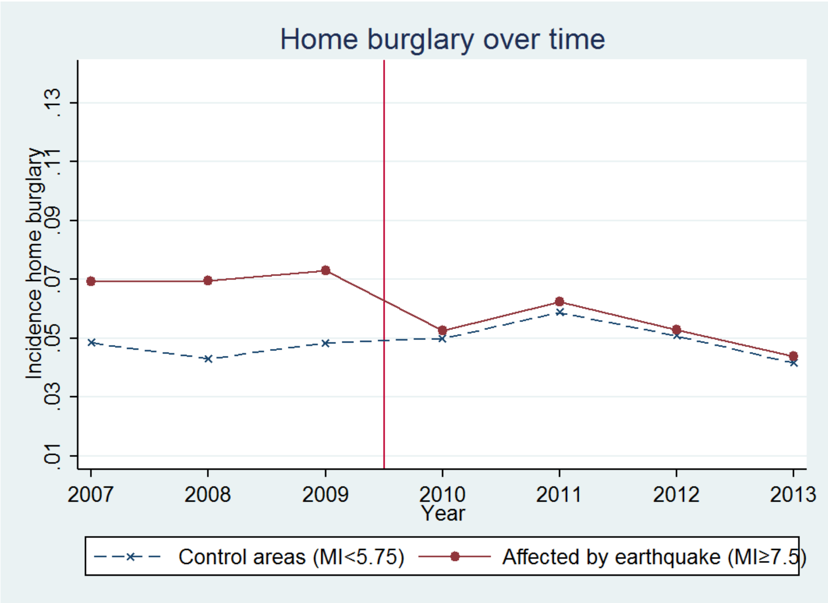
[11] See table A4.

the exception of the southern regions of Magallanes and Aysen. However, although the exact location of an earthquake cannot be considered random not even within Chile, the timing of its occurrence can be assumed so [Cavallo et al., 2010].

The exogenous nature of the timing in which an earthquake occurred and the impossibility to anticipate it set an ideal scenario for the use of a difference in difference strategy exploiting across- municipality and over-time variation in exposure to the earthquake for the identification of the lasting effects of exposure to the earthquake on property crime. Relying on comparing treatment and control units before and after exposure to a treatment, the difference in difference approach has been used in seminal papers to address a large variety of crucial research questions such as the effect of minimum wage on employment [Card and Krueger, 1994], the effect of school term length on student performance [Pischke, 2007] or the effect of employment protection on firms' outsourcing [Autor, 2003].

The results presented in table 2 suggest that treatment and control municipalities were different in terms of some socioeconomic characteristics and of the incidence of crime before the earthquake. However, the validity of the difference in difference approach in our setting does not rely on the comparability of treatment and control groups before the earthquake but on the assumption that

Figure 2: Incidence of home burglary over time (ENUSC)



in absence of the earthquake, crime rates in areas more and less exposed to the earthquake would have followed the same trajectory over time. This identifying condition can be partially tested through assessing whether before the earthquake, property crime rates in areas close and far away from the epicentre followed the same trend over time. If the evolution over time of crime rates was similar in treatment and control municipalities before the earthquake, it would be reasonable to assume that if the earthquake had not occurred, areas next to and far from the hypocentre would have followed the same crime trend over time during all the period studied. Figure 2 plots the evolution over time for the period 2007-2013 of the incidence of home burglary by level of exposure to the earthquake. A visual inspection of the latter figure suggests that although the levels are different, the evolution of the incidence of home burglary over time before the earthquake was the same in the areas next to the hypocentre that are defined as treatment municipalities and in the areas far from the hypocentre that are defined as control municipalities. Figure A1 in the appendix shows, overall, similar patterns for other types of property crime. In the next section, the study tests formally the existence of pre-earthquake parallel trends across Chilean municipalities in terms of home burglary and other property crime offences.

For the identification of the effect of the earthquake on property crime dynamics, I estimate two models using the ENUSC database formed of seven repeated cross sections of households. In the initial analysis, I remove from the sample the households living in intermediate municipalities. Following Autor [2003], I first estimate a leads and lags model:

$$Burglary_{imt} = \propto_m + \sum_{\tau=-q}^{-1} \beta_\tau \ (Year_t \times Earthquake_m)_{m\tau} + \sum_{\tau=0}^{r} \beta_\tau \ (Year_t \times Earthquake_m)_{m\tau} + Year_t + \mu_{imt} \tag{6.1}$$

Where $Burglary_{imt}$ is a dummy variable equal to 1 if household i in municipality m and in year t has suffered a home burglary in the last 12 months and 0 otherwise. $Year$ is a vector of year dummy variables, $\propto_m$ is a vector of municipality dummies, and $(Year \times Earthquake)_{m\tau}$ is a vector of variables constructed as the interaction of the dummy variable $Earthquake_m$ that is equal to 1 if the municipality m was exposed to a predicted $MMI \geq 7.5$ and 0 otherwise, with each year dummy. These interaction variables are known in the literature as the lead and lag variables. In our specification, the lead variables are the interaction between year and earthquake exposure for the years before the earthquake (from period $\tau = q$ to period $\tau = -1$). The lag variables are the interaction between year and earthquake exposure for the years after the earthquake (from period $\tau = 0$ to period $\tau = r$). The coefficients of the lead and lag variables yield the differential variation in the home burglary rate in treatment and control municipalities in the year of interest relative to 2009, the last year before the earthquake and the omitted category in the regression specification. The coefficients of the lead and lag variables estimated in equation 6.1 pursue a double objective. First, the estimated coefficients for the lead variables provide an empirical test for the parallel trends condition. If these coefficients are small and statistically indistinguishable from 0, the home burglary rate in treatment and control municipalities was arguably following the same trend before the earthquake. Second, if the coefficients for the lead variables are statistically indistinguishable from 0, the coefficients for the lag variables yield the effect of the earthquake on the incidence of burglary over time, providing information on the dynamics and persistence of this effect.

Second, I also estimate the following regression:

$$Burglary_{imt} = \propto_m + \beta(Earthquake \times POST)_{mt} + Year_t + u_{imt} \tag{6.2}$$

Where $(Earthquake \times POST)_{mt}$ is an interaction term of the variable $Earthquake$ that indicates whether municipality m was exposed to a predicted $MMI \geq 7.5$ and the variable $POST$, that is equal to 1 for those periods after the earthquake. The parameter β yields the pooled effect of exposure to the earthquake on the incidence of home burglary over the post-earthquake period of interest (2010-2013) relative to municipalities not directly affected by the earthquake. Because exposure to the earthquake was defined at the municipality level and the number of municipalities in treatment and control areas is limited (35 in the base specification), I follow Cameron, Gelbach, and Miller [2008] and cluster standard errors at the municipality level using the wild bootstrapped procedure described in the paper. Furthermore, in order to examine whether the clustered standard errors could be affected by the existence of spatial dependence, I also estimate the main regressions using the spatial HAC standard errors described in Conley [1999] and Conley [2010] as a robustness check. The results of this spatial adjustment, reported in table A1 in the appendix, show that this correction procedure yields overall slightly less conservative standard errors and does not affect relevantly the conclusions of the study.

We then estimate equations 6.1 and 6.2 using the whole sample of Chilean municipalities in the data and the continuous measure of exposure to the earthquake as the treatment variable in the analysis. In these regressions, rather than a dichotomous variable indicating whether the municipality is exposed, $Earthquake_m$ indicates the predicted Modified Mercalli Intensity of the earthquake in municipality m rounded at the 0.5 points. The parameter β yields the effect on crime of exposure to one additional point in the Modified Mercalli scale of earthquake intensity. Finally, the paper expands the analysis to other types of property crime through estimating regressions 1 and 2 using the dichotomous and continuous measures of exposure to the treatment and larceny, robbery and motor-vehicle theft as dependent variables.

Although the earthquake plausibly caused negligible direct economic damage in control municipalities, it is not possible to rule out the possibility that the earthquake affected *indirectly* economic outcomes in these municipalities. For example, the central government might have allocated some investments planned for municipalities not directly affected by the earthquake to the reconstruction of the most devastated municipalities. I discuss in section 7 the existence of *indirect* effects of the earthquake in control municipalities and the extent to which these *indirect* effects could affect the estimates reported in this study.

The identification strategy presented in this section does not assume that the crime in Chile during the period studied was only affected by the earthquake. Indeed, many other circumstances and programs could have affected crime in Chile during the years studied. For example, *Plan Cuadrante de Seguridad Preventiva* was launched in 1998 in Santiago and from 2002, sequentially expanded over the urban municipalities of the country. The program reorganised police resources within municipalities. Similarly, the program *Barrio en Paz* (Neighbourhood in peace), implemented in selected neighbours from 2010, increased the participation of majors in security policies. However, these programs do not focus in either treatment or control municipalities and in order to confound the impact of the earthquake, their effects should be systematically different in earthquake affected and unaffected areas and only operate after the disaster. Indeed, as it will be discussed later in the study, the increase in the number of policemen following the earthquake was not different in treatment and control municipalities. In this line, the exact timing of the effect of the earthquake on crime and the smooth change in crime rates in unaffected municipalities after the disaster provides suggestive evidence that the estimated effects are not driven by other circumstances or programs affecting crime rates in Chile.

7 - Results

Table 3 presents the main results of the study. Column 1 reports the estimates for equations 6.1 and 6.2 when the treatment group is defined as those households living in municipalities exposed to a predicted $MMI \geq 7.5$; and the control group is defined as those households living in municipalities exposed to a predicted $MMI < 5.75$. As described in the previous section, those households living in municipalities exposed to an intensity $5.75 \leq MMI < 7.5$ are excluded from the regression. The results of the leads and lags analysis reported in column 1 are also displayed graphically in figure 3. Columns 2-6 report the estimates for equations 6.1 and 6.2 when alternative earthquake intensity thresholds and the alternative method developed by Astroza et al. [2010] to predict earthquake intensities are used to define treatment and control municipalities. Finally, the results of the leads and lags analysis using all the municipalities in the data and the continuous measure of exposure to the earthquake are presented in figure 4.

Table 3: Effects of earthquake on home burglary: Leads and Lags Analysis and Pooled Effects for the period 2007-2013

	(1) Home burglary (0/1)	(2) Home burglary (0/1)	(3) Home burglary (0/1)	(4) Home burglary (0/1)	(5) Home burglary (0/1)	(6) Home burglary (0/1)
Specif. A:Lead and Lag						
Lead var. (Parallel trends)						
Earthquake × Year 2007	-0.004	0.001	-0.001	0.000	0.004	-0.011
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.011)
Earthquake × Year 2008	0.002	0.004	0.002	0.001	0.004	-0.003
	(0.011)	(0.011)	(0.011)	(0.013)	(0.011)	(0.013)
Lag var. (Year-based effects)						
Earthquake × Year 2010	-0.022**	-0.016	-0.018**	-0.016**	-0.011	-0.016**
	(0.010)	(0.010)	(0.009)	(0.008)	(0.009)	(0.008)
Earthquake × Year 2011	-0.021**	-0.016*	-0.018*	-0.013	-0.008	-0.016*
	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)	(0.009)
Earthquake × Year 2012	-0.022**	-0.017*	-0.017	-0.018*	-0.013	-0.012
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Earthquake × Year 2013	-0.022**	-0.016*	-0.019*	-0.017**	-0.011	-0.019*
	(0.009)	(0.008)	(0.010)	(0.008)	(0.008)	(0.010)
Specif. B:Pooled effect						
Earthquake × Post	-0.021***	-0.018***	-0.018***	-0.017***	-0.013**	-0.012*
	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)
Observations	67,540	70,814	68,878	81,276	84,550	159,259
Sh. burglary (treatment areas)	0.071	0.067	0.065	0.071	0.067	0.065
Treatment areas						
MMI/MSK	≥ 7.5	≥ 7	≥ 7	≥ 7.5	≥ 7	≥ 7
Km hypocentre/asperity	≤180	≤239	≤124	≤180	≤239	≤124
Control areas						
MMI/MSK	< 5.75	< 5.75	< 4.9	< 6	< 6	< 5.75
Km to hypocentre/asperity	>473	>473	>250	>415	>415	>170
Intensity prediction method	Barrientos MMI/hypocentre	Barrientos MMI/hypocentre	Astroza MSK/asperity	Barrientos MMI/hypocentre	Barrientos MMI/hypocentre	Astroza MSK/asperity

Note: The table reports the estimates at the household level for the effect of the earthquake on home burglary over time using the ENUSC database and different predicted intensity thresholds to define treatment and control municipalities and methods to predict earthquake intensity. Specification A corresponds to the lead and lag model (equation 6.1). It yields the year-based effect of the earthquake during the period of interest. Specification B corresponds to the pooled effect difference in difference model (equation 6. 2). It measures the average effect of the earthquake over the post-earthquake period of interest. Lead and lag variables are not included in specification B and the effect of interest is captured by an interaction between the dummy variables that capture whether the household lives in a municipality affected by the earthquake and whether the household is interviewed after the earthquake. The mean of the dependent variable is provided for the treatment areas before the earthquake. Standard errors are clustered and wild-bootstrapped at the municipality level.***p<0.01;**p<0.05;*p<0.1.

Figure 3: Effect of the earthquake on home burglary over time: Treatment vs Control (ENUSC data)

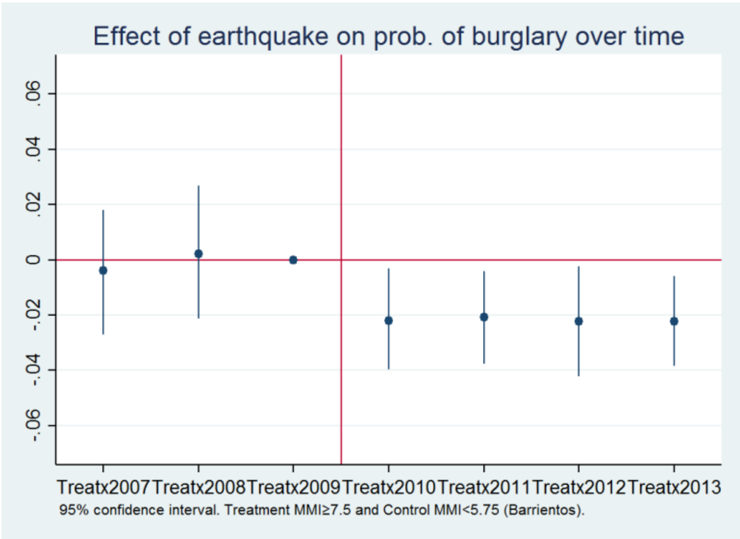
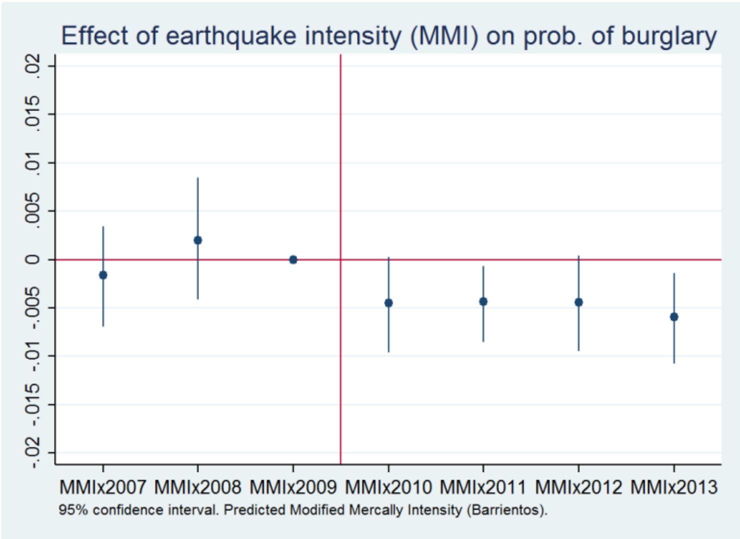


Figure 4: Effect of the earthquake on home burglary over time: MMI as a continuous measure of exposure to the earthquake (ENUSC data)



One of the advantages of the leads and lags approach is that it provides a direct test for the pre-earthquake parallel trends condition in difference in difference models with more than one pre-treatment period. This condition would be satisfied if the coefficients that measure the year-specific effects of the earthquake on crime the years before the earthquake (the leads) are small and not statistically significant.

The estimates for the lag variables reported in table 3 show that for every threshold used to define treatment and control groups, the coefficients for the effect of the earthquake for the years before its occurrence are very small and largely insignificant. More generally, the coefficients of the lead variables reported in figure 4 reveal that the evolution of home burglary over time before the earthquake was unrelated with the continuous measure of exposure to the earthquake. On the other hand, the table shows that the coefficients that measure the effect of the earthquake on home burglary (the lag variables) are negative, large and statistically significant at conventional confidence levels in the majority of the specifications. Overall, the results suggest that the earthquake decreased significantly the incidence of home burglary the year of the earthquake in areas close to the hypocentre relative to those areas far away from it. The magnitude of this effect on the probability of experiencing a home burglary during the last 12 months ranges between 1.1 and 2.1 percentage points (equivalent to a 15%-30% reduction in the prevalence of home burglary relative to the last pre-earthquake period in treatment municipalities), depending on the intensity threshold used to define control and treatment municipalities. Figure 4 shows that an increase of one point in the MMI scale of earthquake intensity reduces the prevalence of home burglary by 0.005 percentage points. Furthermore, the effect of the earthquake remained stable during the 4 post-earthquake years studied, confirming the persistence of the effect over the period examined. Although the exact magnitude and level of significance for the year-effect estimates vary with the definition of the variable measuring exposure to the earthquake, the coefficients are consistently negative and the pooled effect over the period of interest is statistically significant at the 10% in all the specifications, highlighting that the results are robust to the use of different predicted intensity thresholds to define treatment and control municipalities, to the use of the method developed by Astroza et al. [2010] to predict earthquake intensities and to the use of a continuous measure of exposure to the earthquake.

A more detailed look at how the magnitude of the effect varies when different thresholds to define treatment and control groups are used suggests that the smaller (larger) the distance to earthquake hypocentre (predicted intensity) threshold used to define the treatment group, the larger and more significant the effect of the earthquake is. In this sense, for example, the estimates in columns 1 and 4 are larger in absolute value than those reported in column 2 and 5. Similarly, the larger (smaller) the distance (predicted intensity) threshold used to define the control group, the larger and more significant the effect of the earthquake is. The latter is illustrated by the fact that estimates in columns 1, 2 and 3 are larger than those in columns 4, 5 and 6. Although these differences are not statistically different from each other, they might indicate a linear relation between the degree of exposure to the earthquake and the magnitude of the effect and highlight that smaller levels of exposure to the earthquake (MMI=6) may also have an effect on property crime.

The results reported in columns 1-8 of table A2 in appendix A confirm that the main findings are robust to the inclusion of municipality time trends in the regressions. Furthermore, the estimates provided in columns 4 and 8 in the same table show that the effect of the earthquake on home burglary is also robust to the exclusion of households living in municipalities that were affected by the tsunami, suggesting that the impact of the earthquake is not confounded by the effects of the tsunami in some earthquake affected municipalities.

Although the direct effect of the earthquake on home burglary in control municipalities was likely negligible, I cannot rule out the existence of indirect effects of the earthquake, ultimately affecting crime in these municipalities. For example, the central government might have allocated some investments planned for municipalities not directly affected by the earthquake to the reconstruction of the most devastated municipalities, potentially affecting crime in control municipalities. If the effect of the earthquake in control municipalities had the same direction (although smaller in magnitude) than in treatment municipalities, the effect of the earthquake on property crime estimated in this section should be interpreted as a lower bound for the true effect. On the other hand, if the effect of the earthquake in control municipalities had the opposite direction than the effect in treatment municipalities, the coefficients estimated in this study would overestimate the true effect. Although I cannot reject any of the last two hypotheses, figure 2 shows a sharp break in the crime trends in treatment municipalities the year of the earthquake and a smooth trend in control municipalities the same year, suggesting that if any, the indirect effect of the earthquake on crime in control municipalities would be small.

Table 4 reports the analysis examining the effect of earthquake exposure on the prevalence of larcenies, motor-vehicle theft and robberies using the ENUSC data. The results suggest that exposure to a $MMI \geq 7.5$ reduces the prevalence of larceny by 2.8 percentage points and the probability of robbery by 1.5 percentage points. On the other hand, the analysis reveals no effect of the earthquake on motor-vehicle theft. The estimates using the continuous measure of exposure to the earthquake and all the municipalities in the data are reported in table A3 in the appendix. The table shows results consistent with those obtained when using the dichotomous definition of exposure to the earthquake presented in table 4.

Table 4: Effect of earthquake exposure on different offences (2007-2013): ENUSC data

	(1) Larceny (0/1)	(2) Motor-vehicle theft (0/1)	(3) Robbery (0/1)
Specif. A:Lead and Lag			
Lead var. (Parallel trends)			
Earthquake × Year 2007	0.002	0.008	0.013*
	(0.013)	(0.008)	(0.007)
Earthquake × Year 2008	-0.003	0.001	-0.005
	(0.012)	(0.004)	(0.006)
Lag var. (Year-based effects)			
Earthquake × Year 2010	-0.007	-0.001	-0.012
	(0.015)	(0.004)	(0.008)
Earthquake × Year 2011	-0.037**	-0.002	-0.014*
	(0.016)	(0.006)	(0.008)
Earthquake × Year 2012	-0.035***	-0.000	-0.011
	(0.011)	(0.008)	(0.007)
Earthquake × Year 2013	-0.037***	0.002	-0.014*
	(0.013)	(0.004)	(0.008)
Specif. B:Pooled effect			
Earthquake × Post	-0.028***	-0.003	-0.015***
	(0.010)	(0.005)	(0.005)
Mean dep. var treatment	0.102	0.014	0.058
Observations	67,536	27,347	67,540

Note: The table reports the estimates at the household level for the effect of the earthquake on larceny, robbery and motor-vehicle theft. Specification A corresponds to the lead and lag model (equation 6.1). It yields the year-based effect of the earthquake during the period of interest. Specification B corresponds to the pooled effect difference in difference model (equation 6.2). It measures the average effect of the earthquake over the post-earthquake period of interest. Lead and lag variables are not included in specification B and the effect of interest is captured by an interaction between the dummy variables that capture whether the household lives in a municipality affected by the earthquake and whether the household is interviewed after the earthquake. The mean of the dependent variable is provided for the treatment areas before the earthquake. Standard errors are clustered and wild-bootstrapped at the municipality level.***p<0.01;**p<0.05;*p<0.1.

At this point it is worth to mention that the ENUSC survey only reports the municipality where the crime victim lives but not the location where the crime took place. Thus, although the results for these property crimes reinforce the main argument that exposure to the earthquake reduces property crime and dismiss the possibility of crime displacement from home burglary to other property crime, the results for these crimes are only presented as complementary analysis and the precise magnitudes of the coefficients should be interpreted with caution.

8 - Additional analysis: Crime recorded by the police

This section uses the SPD database that includes yearly and monthly crime and apprehension data from police records to conduct the following analyses. First, I check the robustness of the results presented in section 7 to the use of a different data source and a longer pre-earthquake period. Second, I examine whether the social chaos and the episodes of looting that occurred in the aftermath of the earthquake were accompanied by sharp increases in the incidence of property crimes reported to the police. Third, I test whether within 30 days from the earthquake and in a context of looting, army deployment and the enactment of a curfew, the number of individuals apprehended by the police raised in treatment municipalities.

The effect of the earthquake on property crime recorded by the police

Using the SPD database, I estimate equation 8.1 using the yearly incidence of home burglary, non-home burglary, larcenies, motor-vehicle theft and robbery per 1,000 inhabitants as dependent variables:

$$Crime_{mt} = \propto_m + \beta(Earthquake \times POST)_{mt} + Year_t + u_{mt} \tag{8.1}$$

where $Crime_{mt}$ is the incidence per 1,000 inhabitants of each specific type of property crime in the municipality m in year t. The models are estimated using OLS and standard errors are clustered at the municipality level. Note that equation 8.1 is similar to equation 6.2 although this section uses crime data available at the municipality level and therefore, the regressions are estimated using municipalities as the unit of analysis.

The estimation of equation 8.1 for every type of crime is conducted using two different samples. The first of them includes the period 2007-2013, which covers the years included in the ENUSC data used in section 7. The analysis conducted with this first sample examines the robustness of the main results to the use of a different source of data, utilising the same time period employed in the main analysis. The second sample includes crime data for a wider pre-earthquake period, covering the years 2003-2013. The analysis of the latter sample yields information on whether the parallel trends condition still holds when a longer pre-earthquake period of time[12] is incorporated. The key identification condition for regression 8.1 is that the evolution of crime rates over time would have

[12]The first year for which the SPD database includes data for all the types of crime analysed is 2003.

been the same in treatment and control municipalities if the earthquake would have not taken place. Figure 5 displays graphically the evolution of the prevalence of crime across treatment and control municipalities for the period 2007-2013. Figure A2 in the appendix displays the same trends for the years 2003-2013. The existence of pre-earthquake parallel trends across treatment and control municipalities is empirically tested through estimating lead and lag models and then testing whether the coefficients of the lead variables (measuring the differential variation for the years before the earthquake relative to the last pre-earthquake year) are jointly statistically different from 0. Although the graphs could suggest some differential trends across treatment and control municipalities before the earthquake, these are statistically indistinguishable from 0 for home-burglary, non-home burglary and larceny in every specification.

The results of the analyses using the periods 2007-2013 and 2003-2013 are reported in table 5. Analysis A shows the results using a dichotomous definition of exposure to the earthquake and excluding intermediate municipalities, which are those exposed to a predicted $5.75 \leq MMI < 7.5$. In Analysis B, I report the results of the analysis using the continuous measure of municipality exposure to the earthquake (MMI) as treatment variable and include in the sample the 345 Chilean municipalities. The results across these two analyses are overall consistent, and resemble those obtained in the analysis of the ENUSC datasets. The coefficients reported in columns 1-6 suggest that the earthquake decreases significantly the prevalence of home and non-home burglary and larceny. On the other hand, the estimates measuring the effect of the earthquake on motor-vehicle theft in Analysis A are negative but small and statistically insignificant at conventional confidence levels. The lack of effect on motor-vehicle theft yielded by Analysis A is aligned with the results obtained in the previous section using the household victimisation survey, but contrasts with the significant negative effects detected in Analysis B. On the other hand, the result of the joint F-test for the lead coefficients in Analysis B suggests that the evolution of the prevalence of motor-vehicle theft before the earthquake was not orthogonal to the distance to the earthquake hypocentre, requiring to take with caution the results of Analysis B for motor-vehicle theft. Finally, the results for robbery also vary relevantly across specifications and samples. Consistent with the estimates obtained using ENUSC data, the results reported for Analysis A conducted for the period 2007-2013 show a negative and significant effect of exposure to the earthquake on robbery, although the results of the joint F-test for the lead variables suggest the parallel trends assumption might not hold in this specification. On the other hand, the estimate of the effect sinks and losses its statistical significance when the pre-earthquake period is expanded to 2003-2013. Analysis B also indicates no effect of the earthquake on the prevalence of robbery when the analysis is conducted using a continuous measure of exposure to the earthquake and all the Chilean municipalities in the sample.

Figure 5: Incidence of crime over time (Admin data 2007-2013)

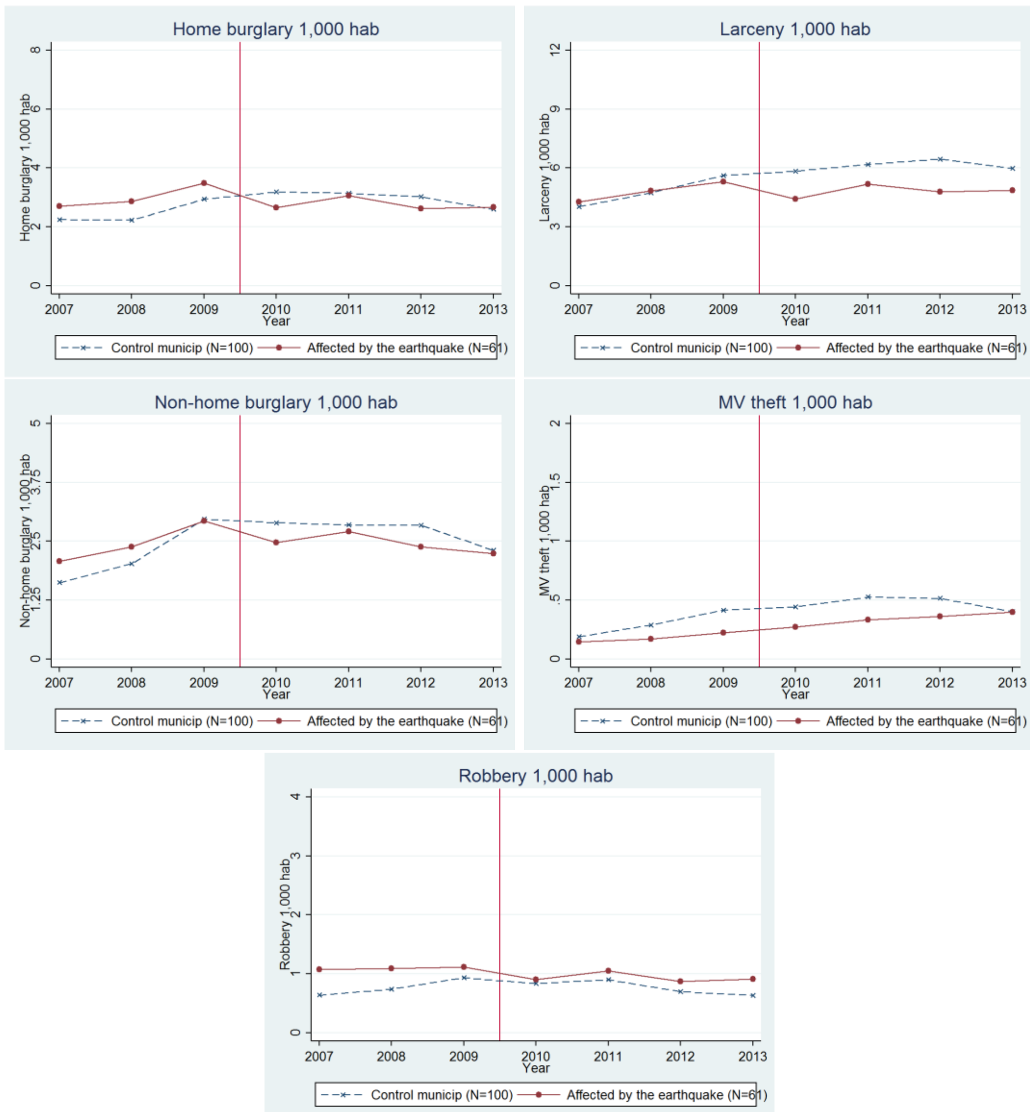


Table 5: Effect of earthquake exposure on property crime (2007-2013): Known to the police crime data

	(1) Home burglary 1,000 inhab	(2) Home burglary 1,000 inhab	(3) Larceny 1,000 inhab	(4) Larceny 1,000 inhab	(5) Non-home burgl. 1,000 inhab	(6) Non-home burgl. 1,000 inhab	(7) MV theft 1,000 inhab	(8) MV theft 1,000 inhab	(9) Robbery 1,000 inhab	(10) Robbery 1,000 inhab
Analysis A: Treatment vs Control										
Earthquake × Post	-0.508***	-0.786***	-1.669***	-1.327***	-0.491***	-0.529***	-0.017	-0.011	-0.096	-0.158**
	(0.174)	(0.185)	(0.288)	(0.293)	(0.157)	(0.166)	(0.074)	(0.060)	(0.067)	(0.077)
Mean dep. var treatment	2.576	3.019	4.579	4.801	2.139	2.464	0.122	0.179	0.921	1.094
Observations	1,769	1,127	1,767	1,127	1,769	1,127	1,769	1,127	1,767	1,127
Treatment municip.	61	61	61	61	61	61	61	61	61	61
Control municip.	100	100	100	100	100	100	100	100	100	100
Sample (Years)	2003-13	2007-13	2003-13	2007-13	2003-13	2007-13	2003-13	2007-13	2003-13	2007-13
Pre-earthq. trends										
F-test: lead variables										
$H_0 : \beta_{T=-q} = ... = \beta_{T=-1} = 0$	1.707	0.340	1.521	1.938	1.741	1.606	1.571	1.941	2.721**	3.641**
Analysis B: Continuous exposure										
MMI × Post	-0.163***	-0.234***	-0.586***	-0.505***	-0.151***	-0.160***	-0.085***	-0.043*	-0.032	-0.023
	(0.056)	(0.057)	(0.093)	(0.091)	(0.049)	(0.051)	(0.032)	(0.024)	(0.024)	(0.027)
Mean dep. var	3.140	3.466	4.670	5.024	2.132	2.452	0.367	0.513	1.344	1.516
Observations	3,791	2,415	3,787	2,415	3,791	2,415	3,791	2,415	3,787	2,415
N municip.	345	345	345	345	345	345	345	345	345	345
Sample (Years)	2003-13	2007-13	2003-13	2007-13	2003-13	2007-13	2003-13	2007-13	2003-13	2007-13
Pre-earthq. trends										
F-test: lead variables										
$H_0 : \beta_{T=-q} = ... = \beta_{T=-1} = 0$	0.788	0.174	1.162	1.169	1.054	0.375	2.780**	4.695***	1.720	0.500

Note: The table reports the estimates at the municipality level for the effect of the earthquake on different types of property crime using data from crime records. Estimates correspond to the pooled effect difference in difference model (equation 8.1). It measures the average effect of the earthquake over the post-earthquake period of interest using the treatment and control municipalities in Analysis A and the continuous measure of exposure to the earthquake and all the municipalities in Analysis B. The effect of interest is captured by an interaction between the dummy variables that capture whether the municipality is affected by the earthquake and whether the observation corresponds to a year after the earthquake in Analysis A and by an interaction between the continuous variable reporting earthquake exposure on MMI scale and whether the observation corresponds to a year after the earthquake in Analysis B. For each type of crime and specification, two samples are used. The first includes only the period 2007-2013, which is the period used in the analysis of the ENUSC data. The second sample includes the period 2003-2013, using all the pre-earthquake years for which the SPD data is available. A test for the common trends assumption is reported for every estimation. For this, I use an F-test to examine the joint significance of the lead variables. The mean of the dependent variable is provided for the treatment areas for the years before the earthquake in Analysis A and for Chilean municipalities for the years before the earthquake in Analysis B. Standard errors clustered at the municipality level.***p<0.01;**p<0.05;*p<0.1.

Together with whether the parallel trends condition holds for robbery and motor-vehicle theft across the different specification, one potential concern when interpreting the coefficients reported in table 5 is that unlike the ENUSC database, the SPD database only includes those offences recorded by the police. Therefore, the SPD database misses those crimes that were not recorded by the police. The reporting error in police records may generate two problems. First, a substantial share of crimes unrecorded by the police would lead to large standard errors. Second, if the share of crimes that is not reported to the police is affected by the earthquake, the models would yield biased estimates of the effect of the earthquake on true property crime rates. For example, at the limit, the results discussed in table 5 might be explained by an effect of the earthquake on the share of crimes that is recorded by the police rather than by an effect of the earthquake on true crime rates.

I explore this hypothesis using information available in the ENUSC survey on whether households report crimes to the police and estimating a difference in difference model in which the dependent variable is the share of larcenies, motor-vehicle theft, robbery and home burglary that is reported to the police. The results of this analysis, conducted at the regional level, are reported in table A4 in appendix A. The results of the regression suggest that the earthquake does not systematically affect the share of crime that is reported to the police. Nonetheless, and even if the earthquake does not affect the probability of reporting crime to the police, the fact that approximately 50% of the home burglaries and robberies and 75% of the larcenies are not reported to the police introduces measurement error in the dependent variable, leading to wider standard errors for the coefficients reported in table 5.

Despite these limitations, the results of this analysis are consistent with those obtained in section 7 and suggest a reduction in the prevalence of home burglary and other types of property crimes such as larcenies and non-home burglaries. Furthermore, the results on the different types of property crimes also exclude the possibility that rather than decreasing property crime, the earthquake simply displaced criminals from engaging in burglary to commit other types of property crime. The latter hypothesis, studied by Bell, Jaitman, and Machin [2014] in the context of the 2011 London riots, could be relevant if judges increased the severity of sentencing for criminals committing burglaries in areas affected by the earthquake or if criminals falsely perceived more severe sentencing for these crimes. Although the criminal law did not change following the earthquake, the social awareness and media coverage of the looting events may have induced judges in these areas, at least temporally, to increase the severity of sentencing for burglary. However, the fact that the reduction in crime rates seems to operate over different types of property crime precludes the hypothesis that the earthquake simply displaced crime from burglary to other types of property crime. Finally, the results presented in this section show that with the exception of robbery, expanding the pre-earthquake period from 2007-2009 to 2003-2009 does not change the results relevantly, neither compromise the testing of the parallel trends condition.

Crime and punishment in the aftermath of the earthquake

Some treatment municipalities experienced looting episodes, the enactment of a curfew and the deployment of the army during the month that followed the earthquake. Through incapacitating criminals or providing a first contact with crime for some looters, the deployment of the army, the curfew and the looting episodes could have affected the incidence of crime in treatment municipalities in a lasting way.

This subsection investigates crime and apprehension in the aftermath of the earthquake through estimating the effect of exposure to the earthquake on the incidence of different crimes and on the apprehension rate the month of the earthquake and one month after the earthquake using the monthly SPD data. The dependent variables in these regressions is the incidence of crime and the number of people apprehended either the month of the earthquake (February 2010) or the first month after the earthquake (March 2010). The regressions include as control variables the population of the municipality and the incidence of crime in the last month before the earthquake. The treatment variable is a dummy variable equal to 1 for those municipalities exposed to a predicted $MMI \geq 7.5$ and 0 for municipalities exposed to a predicted$MMI < 5.75$. Intermediate municipalities were excluded from the estimations.

The results of this analysis are provided in table 6. Table A5 in the appendix reports the results using predicted MMI rounded at the 0.5 points as a continuous measure of exposure to the earthquake and all the municipalities in the data. The estimates reported in these tables suggest that property crime did not increase sharply in the aftermath of the earthquake. Rather, the incidence of home burglary, robbery and larceny recorded by the police one month after the earthquake was significantly lower in earthquake affected municipalities. Although these results could be surprising, Grandón et al. [2014] suggest that the most prevalent type of property crime in the aftermath of the earthquake was group looting towards large supermarkets and shops that although involved many people, in terms of numbers of offences reported to the police might be small. Furthermore, the same study highlights that the looting of houses or small shops was an extremely rare event in the aftermath of the earthquake. In any case, the latter estimates should be interpreted with caution because crime data from police records aggregated at the monthly level might not be the most suitable for this analysis. First, the cost of reporting to the police an offence might be larger the days that followed the earthquake due to institutional collapse, potentially leading to an underestimation of the short-term effect of the earthquake on true crime rates. Second, the effect of the earthquake on crime might be restricted to a few days or hours after its occurrence and before the deployment of the army. However, the aggregation of the crime data at the monthly level may not be adequate to assess the very short-term effects of the earthquake.

The results reported in the last column in table 6 highlight that far from increasing, the number of individuals apprehended per 1,000 individuals decreased in the aftermath of the earthquake relative to control municipalities. These results dismiss the possibility that the contraction in property crime rates in earthquake affected municipalities is driven by a higher rate of incarceration in these municipalities as a consequence of the curfew and the deployment of the army.

One explanation for the reduction in incarceration rates and in the recorded by the police incidence of some types of property crimes in the aftermath of the earthquake could be the deterring effect of the army deployment and of the curfew. If so, through temporarily increasing the cost of participating in criminal activities, the presence of the army and the curfew may have persistent effects on the incidence of crime. This hypothesis is explored in section 9 as a potential mechanism for the lasting reduction in property crime after the earthquake.

Table 6: Impact estimates (OLS): Short-term effect of earthquake on different types of property crimes (crime data from policy records) and on individuals apprehended

	Home burglary (per 1,000 inhab)	Larceny (per 1,000 inhab)	Non-home burglary (per 1,000 inhab)	Motor-vehicle thefts (per 1,000 inhab)	Robbery (per 1,000 inhab)	Apprehended (per 1,000 inhab)
Sample A:March 2010						
Earthquake municip.	-0.098***	-0.211***	0.039	-0.004	-0.026**	-0.155**
	(0.028)	(0.052)	(0.051)	(0.006)	(0.012)	(0.066)
Sample B:Feb 2010						
Earthquake municip.	-0.060*	-0.129***	-0.043	-0.013	-0.003	0.055
	(0.034)	(0.047)	(0.041)	(0.008)	(0.015)	(0.062)
Observations	161	161	161	161	161	161
Av. rate Jan 2010	0.328	0.527	0.215	0.057	0.138	0.542

Note: The regressions estimated use monthly data from police records (SPD database) and OLS methods to estimate at the municipality level the short term effects of the earthquake on property crime and on individuals apprehended. The equation estimated is $Y = \beta_0 + \beta_1 Earthquake + \beta_2 Y_{jan2010} + \mu$ where the dependent variable Y is the crime rates/number of individuals apprehended in March 2010 (the month after the earthquake) in sample A and in February 2010 (the month of the earthquake) in sample B. $Y_{jan2010}$ measures the crime rate/number of people apprehended in January 2010. Municipalities exposed to a predicted $5.75 \leq MMI < 7.5$ are excluded from the analysis. Robust standard errors in parentheses. ***p<0.01;**p<0.05;*p<0.1.

9 - Analysis of mechanisms

Natural disasters are complex phenomena that may influence the prevalence of property crime through many channels. This section discusses the relevance of some of the most evident ones. However, it is beyond the scope of the study to comprehensively examine every individual path through which the earthquake could have reduced the incidence of property crime over the post-earthquake period studied.

The lasting reduction in property crime after the earthquake is consistent with the predictions of the informal guardianship theory. The latter argues that natural disasters are generally followed by altruistic behaviours that strengthen community links and co-operation among neighbours. The positive effect of natural disasters on social capital might be particularly large in Chile due to the community-oriented management of the provision of the emergency aid. In this line, Calo-Blanco et al. [2017] provide empirical evidence on the positive effects of earthquakes on social capital in Chile. The informal guardian theory concludes that the rise in the levels of social capital facilitates co-operation and boosted the provision of informal guardianship in these communities, offsetting the potential perverse effects of disasters on crime caused by their negative impact on other crime determinants such as the capacity of the police to enforce the law.

In order to test the informal guardianship channel, I estimate equation 6.2 at the household level using as dependent variables the information collected in the ENUSC survey on adoption of different household- and community-level measures to prevent crime. The results of this analysis are displayed in table 7 and show that the earthquake boosted the provision of informal guardianship by households, mainly through the adoption of community-based measures such as creating community alarms or sharing telephone numbers with neighbours. Furthermore, the estimates reported in column 9 of table A2 in appendix A suggest that the drop in the incidence of home burglary was more than twice among households living in municipalities affected by the earthquake that increased the provision of community-based strategies to prevent crime than among households living in earthquake affected municipalities that did not increase it, although the effects are not statistically different from each other at conventional significance levels[13]. Although the rise in the incidence of community-based measures to prevent crime among treatment municipalities was probably not random and therefore the results of this analysis should not be interpreted as causal, the estimates point to this mechanism as an important path through which the earthquake may have decreased crime. Also in line with the informal guardianship theory, the estimates reported in column 1 of table 7 shows that the earthquake increased the participation in associations of the civil society such as sports club, parental associations or

[13] Column 10 of table A2 reports the estimation using two separate treatment groups. The first treatment arm includes those municipalities affected by the earthquake that increased the provision of community-based strategies to prevent crime after the earthquake. A municipality is considered to have increased the provision of community- based strategies to prevent crime when the average number of community-based measures to prevent crime (including sharing telephone numbers with neighbours, organising community vigilance, coordinating with local authorities for the provision of security and hiring private vigilance) adopted in post-earthquake years in the municipality is higher than in pre-earthquake years. The second treatment group includes those municipalities affected by the earthquake that did not increase the provision of community-based strategies to prevent crime after the earthquake.

community councils[14]. This finding is consistent with a positive effect of the earthquake on the strength of community life. Finally, qualitative studies analysing social dynamics in the aftermath of the earthquake remark the widespread prevalence of pro-social, altruistic and organised behaviour in communities affected by the earthquake during the days that followed the natural disaster [Grandón et al., 2014, Larranaga and Herrera, 2010b], which could have been the result of the interaction between neighbours dynamics that followed the earthquake.

However, the rise in the adoption of community-based crime prevention measures and the provision of informal guardianship could be also driven by an increase in the perceived risk of crime in communities affected by the earthquake, boosting the demand for crime prevention measures. If so, the rise in the provision of informal guardianship and the drop in crime could have happened even in the absence of any effect of the earthquake on social capital. Although 10 months after the earthquake the perception of crime was not significantly different in earthquake affected and unaffected areas[15], it is likely that the extensive media coverage of the looting events and the power cuts increased the perception of crime in earthquake affected communities even when the looting of houses and small business was very rare in the aftermath of the earthquake.

In line with this argument, Larranaga and Herrera [2010a] remark that in the regions of Biobio and Maule, the two regions most affected by the earthquake, the 37% and the 22% of the population affected by the earthquake (93% of its population) organised collectively to overcome the damage caused by the earthquake and the provision of security was the main reported reason for collective organisation in Biobio and the second (after the provision of water and food) in Maule. Also, there is qualitative evidence showing that in the city of Concepción, neighbours cooperated to provide informal guardianship and protect their communities from looting during the week that followed the earthquake [Grandón et al., 2014].

[14] This analysis is conducted using the information on individual participation in associations of the civil society reported in the CASEN survey rounds 2003, 2009, 2011 and 2013. The round 2006 of the CASEN survey is not used because no information is provided in that round on participation in associations.
[15] The results of this analysis, conducted using the ENUSC data, is not reported in the paper but it is available upon request.

Table 7: Effect of earthquake on social capital and adoption of individual and community measures to prevent crime

	(1) Participate association (0/1)	(2) Share number with neigh. (0/1)	(3) Community vigilance (0/1)	(4) Coord. with local author. (0/1)	(5) Community hires private vigil. (0/1)	(6) Dog (0/1)	(7) Bars in windows or doors (0/1)	(8) Safety lock (0/1)	(9) Alarm (0/1)
Pooled effects									
Earthquake × Post	0.031**	0.061*	0.062**	-0.026	0.009	-0.001	-0.048	-0.064	0.050**
	(0.014)	(0.034)	(0.027)	(0.062)	(0.016)	(0.028)	(0.038)	(0.057)	(0.023)
Pre-earthq. trends									
F-test: Lead variables									
$H0 : \beta_{T=-q} = ... = \beta_{T=-1} = 0$	0.000	1.479	2.110	1.326	2.264	1.576	0.043	0.169	2.676
Observations	351,116	67,546	67,546	67,546	67,546	67,546	67,546	67,546	67,546
Dep var. (treatment areas)	0.323	0.265	0.125	0.360	0.070	0.399	0.470	0.311	0.073

Note: Column 1 estimates at the individual level the effect of the earthquake on participation in associations of the civil society such as sport clubs, neighbourhood associations, women's group, etc. using rounds 2003, 2009, 2009 and 2011 of the CASEN survey. The round 2006 of the CASEN survey is ommitted because it does not include information on participation in organizations. Columns 2-9 estimate at the household level the effect of the earthquake on the adoption of different individual and community-based measured to prevent crime. The effects in all columns are estimated using the pooled effect difference in difference model (equation 2). The effect of interest is captured by an interaction between the dummy variables that capture whether the municipality is affected by the earthquake and whether the year is after the earthquake. A test for the common trends assumption is reported for every estimation. For this test, I estimate a lead and lag model and use an F-test to examine the joint significance of the lead variables. The mean of the dependent variable is provided for the treatment areas before the earthquake. Standard errors clustered at the municipality level. ***p<0.01;**p<0.05,*p<0.1.

To explore whether the lasting drop in the incidence of crime in earthquake affected areas was simply driven by an increment in the perceived risk of crime in these municipalities with lasting consequences in terms of adoption of crime prevention measures, I examine whether the effect of the earthquake was significantly different in those treatment municipalities that experienced looting events in the aftermath of the earthquake. For this, I divide the municipalities affected by the earthquake in two separate groups. The first group includes those municipalities affected by the earthquake that experienced looting in the aftermath of the earthquake. The second group includes those municipalities affected by the earthquake that did not. Arguably, the perception of risk of crime in the aftermath of the earthquake was higher among the first treatment group of municipalities. The results are presented in column 9 of table A2 in appendix A and show that the magnitude of the effect of the earthquake in areas close to the hypocentre that experienced looting and that did not experience it relative to control municipalities was very similar and the difference between these two magnitudes is statistically indistinguishable from 0 at conventional confidence levels. The latter results suggest that although in the first instance the rise in the perceived risk of crime in earthquake affected areas could have driven the adoption of crime-prevention measures, the rise in the perceived risk of crime in the aftermath of the earthquake cannot explain the observed persistent reduction in the incidence of property crime after the earthquake. Nonetheless, the eruption of looting across some of the municipalities affected by the earthquake could have not been random even among municipalities exposed to the same earthquake intensity and therefore, the results of this analysis should only be interpreted as suggestive. Plausibly more convincing to rule out the increase in risk hypothesis is the lack of any effect of the earthquake on the adoption of individual-based measures to prevent crime such as the probability of owning a dog or having bars in windows or doors reported in table 7.

In order to investigate the relevance of some of the alternative mechanisms, I first assess at the municipality level the short-term effects of exposure to the earthquake on different socioeconomic outcomes that the literature has linked to crime. I estimate the short-term effects of the earthquake on the number of policemen per 100,000 inhabitants, poverty rate, extreme poverty rate, unemployment, blue collar unemployment, rate of men 15-29 years old, two measures of income polarisation, enrolment in education for individuals 13-25 and municipality budget at the municipality level. All of these factors have been discussed in the literature as potential causes of crime[16]. The dependent variable in these regressions is the variable of interest the first year for which data are available after the earthquake (2010 for administrative data and 2011 for variables constructed using the CASEN survey). The regressions include as control variables the population of the municipality in the year 2009 and the level of the variable of interest in the year 2009.

The estimates are reported in table 8 and suggest that proximity to the hypocentre increased its unemployment levels, poverty and extreme poverty rate. On the other hand, the analysis shows negligible and statistically insignificant effects of earthquake exposure on inequality, number of policemen, budget of the municipality, education enrolment and the rate of men 15-29 years old.

[16] The evidence on the relevance of most of these factors as drivers of property crime is reviewed in Soares [2004].

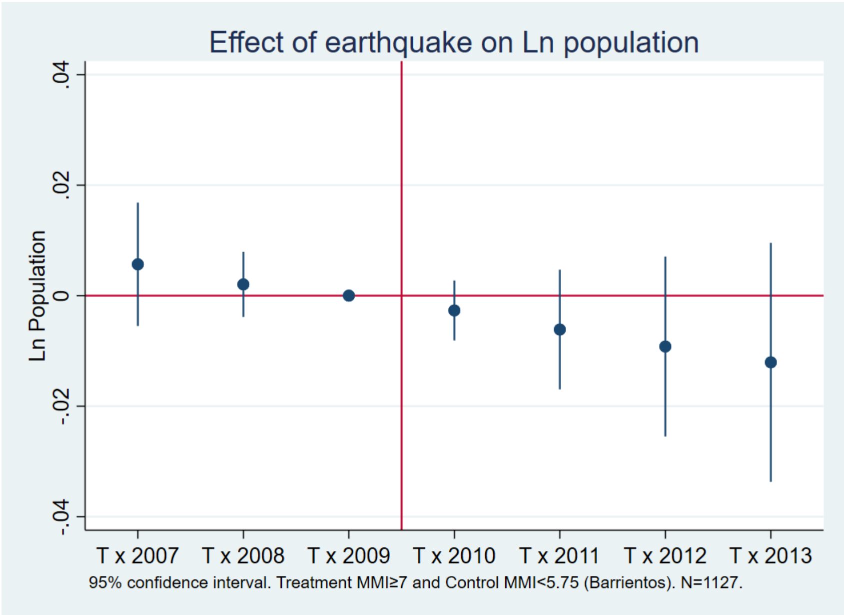
The results reported in table 8 suggest therefore that the lasting drop in property crime rates was not caused by an increase in the presence of policemen or by reconstruction programs in catastrophic areas reducing unemployment, which has been assessed as a key determinant of crime [Chalfin and Mccrary, 2015]. Another mechanism that may have contributed to the reduction in the incidence of property crime observed in earthquake affected areas would be a larger incarceration rate in these municipalities. To cope with looting in the aftermath of the earthquake, the Chilean government declared a curfew and deployed the army in the areas affected by riots. If these institutional efforts led to larger apprehension and incarceration rates, the incidence of crime in earthquake affected municipalities could have dropped as a consequence. However, in the previous section, I show that the earthquake did not increase apprehension rates in the aftermath of the earthquake. Consistently, the results reported in column 9 of table A2 in appendix A show that the effect of the earthquake on the incidence of home burglary was not significantly different in treatment municipalities that experienced looting episodes and in those that did not. These two results suggest that the drop in property crime rates in earthquake affected areas was not driven by higher incarceration rates in the aftermath of the earthquake. Furthermore, the lack of a differential effect in municipalities that experienced looting events also indicates that the presence of the army and the curfew, that affected mainly those municipalities that experienced looting events, is unlikely to explain by itself the drop in the incidence of property crime in municipalities affected by the earthquake. In other words, this result seems to dismiss the hypothesis that through temporarily increasing the cost of committing crime and keeping out of crime some individuals, the curfew and the deployment of the army could have driven the lasting reduction in the incidence of property crime.

Table 8: The effect of the earthquake on other sociodemographic and economic variables

	Ln Munic. p/c budget	Ln Polic. 100M inhab	Poverty rate	Extreme pov. rate	Unemp. rate	Unemp. rate (blue collar)	Polariz (75%vs25%)	Polariz. (90%vs10%)	Rate men 15-29	Attending educ. (13-25)
Earthquake municip.	-0.004	0.029	0.027**	0.015***	0.019**	0.021**	-0.529	-0.624	-0.001	0.014
	(0.014)	(0.023)	(0.011)	(0.004)	(0.008)	(0.010)	(0.350)	(1.639)	(0.004)	(0.016)
Observations	157	161	140	140	140	140	140	140	140	140
R-squared	0.005	0.047	0.158	0.507	0.175	0.219	0.386	0.387	0.226	0.275

Note: The table reports the short-term effect of the earthquake on different factors that have been identified in the literature as potential causes of crime. The model estimated is $Y_i = \beta_0 + \beta_1 Earthquake_i + \beta_2 Y\,2009_i + \beta_3 LnPopulat2009_i + \mu$ where the dependent variable (Y) is the variable of interest in the closest available point after the earthquake. Because the data on the budget is at the start of the year, the first relevant post-earthquake year is 2011 for this variable. The first post-earthquake year for which information is available is 2011 for poverty, unemployment, unemployment among adults without secondary education, income polarization, age composition and education enrolment, and 2010 for policemen. The last pre-earthquake year is 2009 for all the variables. The regressions include as control variables the Ln of population ($LnPopulat2009$) and the variable of interest ($Y2009$) in 2009. The estimation is conducted at the municipality level using OLS and excluding from the estimation the municipalities exposed to a predicted earthquake intensity $5.75 \leq MMI < 7.5$. The difference in the number of observations across the different regressions is explained by the fact that the survey used to construct the poverty, unemployment, unemployment among adults without secondary education, polarization, demography and education variables is not implemented in all the Chilean municipalities and the municipality budget data does not include information for all the municipalities. Robust standard errors in parentheses. ***p<0.01;**p<0.05,*p<0.1.

Figure 6: Effect of the earthquake on population (Admin data 2007-2013)



One hypothesis that could contribute to explain the estimates for the effect of the earthquake on crime is the potential displacement of population following the earthquake, eventually affecting crime rates in treatment and control municipalities. The link between population density and crime has been previously established in the literature (see for example Soares [2004]). Furthermore, some studies show that catastrophes leading to big population displacements could foster crime in destination municipalities. For example, Varano et al. [2010] show that following hurricane Katrina, the prevalence of some types of crime raised substantially in the cities of Houston and Phoenix, two of the main destinations of the population displaced from New Orleans. I examine this hypothesis through assessing the effect of the earthquake on population dynamics during the period 2007-2013. The results from leads and lags regressions are reported in figure 6. Although the coefficients indicating the effect of the earthquake on population are consistently negative, they are also small and none of them is statistically significant at conventional confidence levels. The population in municipalities exposed to $MMI \geq 7.5$ decreased by less than 1% the year of the earthquake. Although the data on population during the period of interest is based on yearly predictions from the Chilean National Institute of Statistics[17], the lack of large migration movements the year of the earthquake is consistent with internal migration patterns observed in the survey CASEN 2011 [Herrada, 2018]. The magnitude of the coefficients reported in figure 6, which are statistically indistinguishable from 0, pales when compared with the population displacement following other disasters such as the Katrina hurricane in New Orleans, where approximately half of the 400,000 people displaced after the earthquake had not returned to the city one year after the disaster [Sastry and Gregory, 2014]. One potential hypothesis to explain the small migration effect following the earthquake was that the reallocation of the population affected by the earthquake within the same municipality seemed to be a specific target of the reconstruction plan [MIDESO, 2018]. Overall, the results dismiss the hypothesis that the observed

[17] Detailed information on the methods used for population predictions is available on INE [2018]

coefficients are driven by a positive effect of displaced population on crime rates in control areas or more generally, by large changes in population density affecting the supply of crime or the demand of protection from crime in treatment or control municipalities.

Another mechanism for lower property crime rates after natural disasters is a reduction in the expected benefits of committing crime. Through destroying economic assets and expanding poverty, the earthquake may have decreased the economic returns to some property crimes. In other words, through increasing poverty and destroying assets, the earthquake may have decreased the expected benefit of larceny, robbery or home burglary. Although this argument seems intuitive, theoretical models of economics of crime predict an ambiguous effect of poverty on property crime: Although poverty decreases the economic returns to property crime, it also reduces its opportunity costs. Indeed, the existing empirical evidence shows that different economic shocks increasing poverty in India, Mozambique and Russia have boosted property crime rather than decreasing it [Fafchamps and Minten, 2006, Iyer and Topalova, 2014, Ivaschenko, Nivorozhkin, and Nivorozhkin, 2012].

In order to test further this hypothesis I use the CASEN surveys and examine how the earth- quake affected ownership of assets. Relying on data from a survey implemented 3 months after the earthquake, table A6 in the appendix shows that 17% of the households living in treatment municipalities lost their TV and 5% of them lost a computer. However, the results of a difference in difference analysis for assets for which information is reported in the survey suggest that any potential effect of the earthquake on assets ownership was vanished by 2011 when the first complete post-earthquake CASEN survey was implemented. The regressions were estimated using rounds 2009 and 2011 of the CASEN survey and the analysis was conducted at the municipality level. The dependent variable in these regressions is the share of ownership in the municipality of each asset in the 2011 round of the CASEN survey. The regressions include as control variables the population of the municipality in the year 2009 and the share of ownership of the asset of interest in the municipality in 2009. The results of the analysis are reported in table 9 and show that among all the assets analysed, the earthquake only had a small negative effect, statistically significant at 10%, on the percentage of households that own a landline telephone by 2011. In contrast with the persistence of the effect of the earthquake on home burglary during the whole post-earthquake period studied (2010-2013), the lack of a relevant effect of the earthquake on ownership of assets such as computers suggests that the role of the stealable assets destruction mechanism as a driver of the persistent drop in crime rates during the post-earthquake period studied was probably limited.

Table 9: The effect of the earthquake on household ownership of different assets

	Sh. Washing-machine	Sh. Fridge	Sh. Heater	Sh. landline telephone	Sh. Paid TV	Sh. Computer
Earthquake municip.	0.016	0.010	0.015	-0.020*	-0.012	-0.003
	(0.018)	(0.011)	(0.019)	(0.011)	(0.017)	(0.014)
Observations	140	140	140	140	140	140
R-squared	0.159	0.195	0.026	0.060	0.030	0.082

Note: The table reports the effect of the earthquake on different assets using the closest CASEN survey before and after the earthquake. The model estimated is $Y_i = \beta_0 + \beta_1 Earthquake_i + \beta_2 Y\,2009_{\,i} + \beta_3 LnP\ opulat2009_i + \mu$ where the dependent variable (Y) is the variable of interest in the 2011 CASEN survey. The regressions include as control variables the Ln of population ($LnPopulat2009$) and the variable of interest ($Y2009$) in 2009. The estimation is conducted at the municipality level using OLS. Robust standard errors in parentheses.***p<0.01;**p<0.05,*p<0.1.

An alternative hypothesis that would help to explain why areas affected by the earthquake experienced strong decreases in crime rates is larger public investments in programs that may reduce crime in the short- and long-term. In table 8 I show that despite the existence of specific transfers from the central government to the municipalities affected by the earthquake (accounting in average for approximately the 3% of the budget of treatment municipalities), exposure to the earthquake did not increase the total municipality budget per inhabitant. Consistent with the rise of unemployment found in earthquake affected municipalities, these results suggest that municipalities exposed to the earthquake did not have more resources than control municipalities to implement large public investments programs that could have dropped lastingly property crime.

10 - Conclusions

This study exploits across space variation in exposure to an 8.8 Richter magnitude earthquake in Chile to provide evidence on the lasting effects of natural disasters on property crime. For this purpose, property crime data from household victimisation surveys and from police records are analysed using a difference in difference strategy. The estimates show that exposure to a very strong earthquake intensity decreased significantly the incidence of home burglary and other types of property crime such as larcenies or non-home burglary. The results are robust to the use of different sources of data, samples and alternative definitions of exposure to the earthquake. Although I cannot rule out the possibility that these results are affected by indirect effects of the earthquake in control municipalities, the sharp break in the crime trend in treatment municipalities the year of the earthquake and the smooth trend in control municipalities the same year suggest that if existent, such an indirect effect would be small and could not explain entirely the results.

The study also explores some of the mechanisms through which the earthquake may have reduced property crime in the medium and long-term. The analysis of mechanisms suggests that an important driver could have been the lasting boost in the adoption of community-based measures to prevent crime in earthquake affected areas. More broadly, the results are consistent with the stream of the literature that argues that natural disasters increase the level of co-operation within neighbourhoods and the strength of community life leading to larger levels informal guardianship in affected communities and increasing the cost of committing crime after catastrophic events. Furthermore, the evidence points to the role played by social capital and cooperation at the community level in reducing crime. Although the link between broader measures of social capital and crime have been rigorously investigated before in Buonanno, Montolio, and Vanin [2009] and Akcomak and Ter Weel [2012] for Italy and the Netherlands with mixed results, the role of social capital at the neighbourhood level and the provision of informal guardianship on crime has not been empirically investigated so far. In this sense, the results of the study call for more research investigating to what extent reducing cooperation costs among neighbours and fostering the involvement of communities in the provision of security, particularly in areas where the capacity of the state to enforce the law is limited, could be an effective strategy to address crime.

Alternative mechanisms to explain the lasting drop in the incidence of property crime after the earthquake such as an increase in the number of policemen in areas affected by the earthquake, higher incarceration rates, an increase in the perceived risk of crime, a reduction in the expected benefits of committing crime due to the destruction of assets, large population displacements affecting crime in control or treatment groups, lasting effects of the curfew and army deployment and an increase in employment due to the reconstruction programs are tested and ruled out in the light of the results.

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Appendix A: Additional tables and figures

Figure A1: Incidence of property crime over time for different types of crimes (ENUSC)

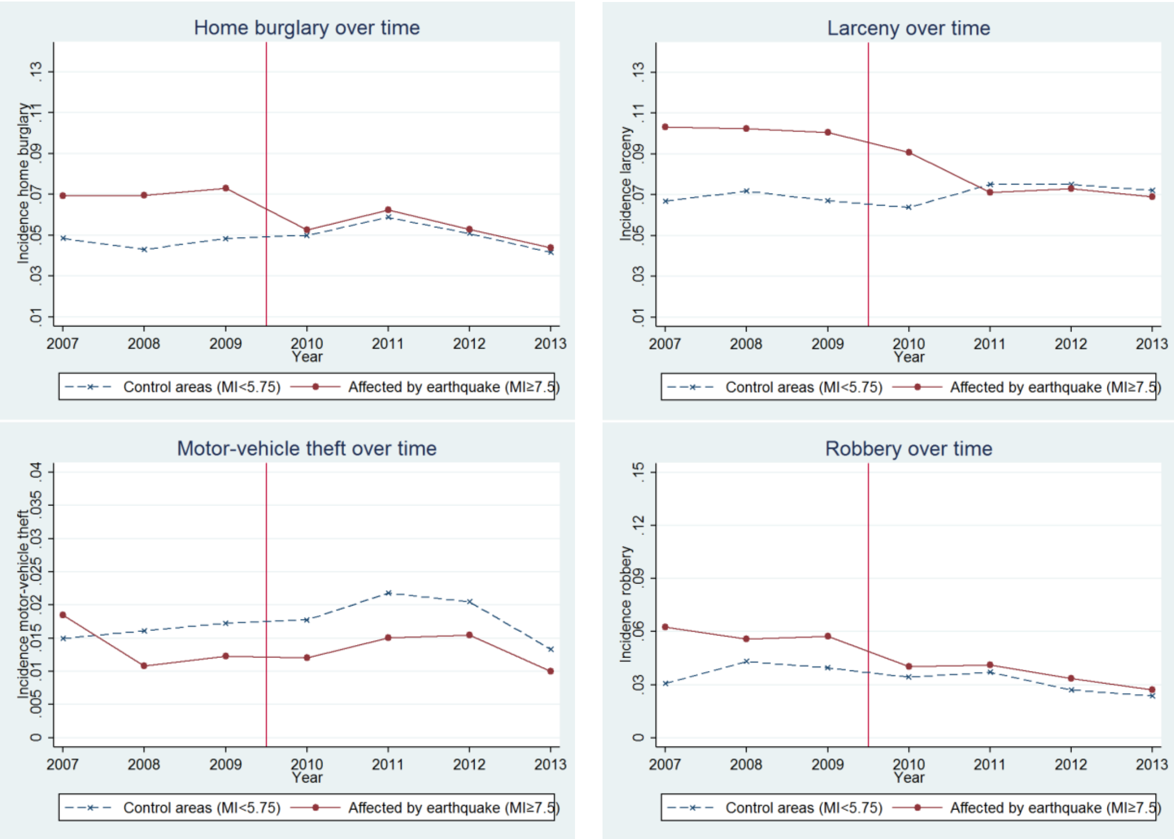

Table A1: Effect of earthquake on home burglary: Leads and lags analysis and pooled effects for the period 2007-2013 (Spatial HAC standard errors)

	(1) Home burglary (0/1)	(2) Home burglary (0/1)	(3) Home burglary (0/1)	(4) Home burglary (0/1)	(5) Home burglary (0/1)	(6) Home burglary (0/1)	(7) Home burglary (0/1)
Specif. A:Lead and Lag							
Lead var. (Parallel trends)							
Earthquake × Year 2007	-0.004	0.001	-0.001	0.000	0.004	-0.011	-0.002
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.002)
Earthquake × Year 2008	0.002	0.004	0.002	0.001	0.004	-0.003	0.002
	(0.009)	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.002)
Lag var. (Year-based effects)							
Earthquake × Year 2010	-0.022**	-0.016*	-0.018**	-0.016**	-0.011	-0.016**	-0.005**
	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)	(0.002)
Earthquake × Year 2011	-0.021***	-0.016***	-0.018***	-0.013*	-0.008	-0.016***	-0.004***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.001)
Earthquake × Year 2012	-0.022***	-0.017**	-0.017**	-0.018**	-0.013**	-0.012**	-0.004**
	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)	(0.002)
Earthquake × Year 2013	-0.022***	-0.016***	-0.019***	-0.017***	-0.011*	-0.019***	-0.006***
	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.001)
Specif. B:Pooled effect							
Earthquake × Post	-0.021***	-0.018***	-0.018***	-0.017***	-0.013***	-0.012***	-0.005***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)
Observations	67,540	70,814	68,878	81,276	84,550	159,259	177,889
Sh. burglary (treatment areas)	0.071	0.067	0.065	0.071	0.067	0.065	0.053
Explantory variable:	Dichotomous	Dichotomous	Dichotomous	Dichotomous	Dichotomous	Dichotomous	Continuous (MMI)
Treatment areas							All
MMI/MSK	≥ 7.5	≥ 7	≥ 7	≥ 7.5	≥ 7	≥ 7	munic.
Km hypocentre/asperity	≤ 180	≤ 239	≤ 124	≤ 180	≤ 239	≤ 124	used
Control areas							
MMI/MSK	< 5.75	< 5.75	< 4.9	< 6	< 6	< 5.75	
Km to hypocentre/asperity	> 473	> 473	> 250	> 415	> 415	> 170	
Intensity prediction method	Barrientos MMI/hypocentre	Barrientos MMI/hypocentre	Astroza MSK/asperity	Barrientos MMI/hypocentre	Barrientos MMI/hypocentre	Astroza MSK/asperity	Barrientos MMI/hypocentre

Note: The table reports the estimates at the household level for the effect of the earthquake on home burglary over time using the ENUSC database and different predicted intensity thresholds to define treatment and control municipalities, different methods to predict earthquake intensity and a continuous measure of exposure to the earthquake (in column 9). Specification A corresponds to the lead and lag model (equation 1). It yields the year-based effect of the earthquake during the period of interest. Specification B corresponds to the pooled effect difference in difference model (equation 2). It measures the average effect of the earthquake over the post-earthquake period of interest. Lead and lag variables are not included in specification B. In column 1-8 the treatment variable $Earthquake \times Post$ is an interaction between the dummy variables that capture whether the household lives in a municipality affected by the earthquake and whether the household is interviewed after the earthquake. In column 9 the treatment variable $Earthquake \times Post$ is an interaction between a continuous measure indicating the earthquake intensity measured in MMI scale and whether the household is interviewed after the earthquake. The mean of the dependent variable is provided for the treatment areas before the earthquake. Standard errors are corrected for spatial dependency using the procedure described in Conley et al. (2008) and a cut-off of 300km.***p<0.01;**p<0.05;*p<0.1.

Table A2: Effect of earthquake on home burglary: Different samples, municipality time trends and heterogeneity of effects

Different samples

	(1) Home burglary (0/1)	(2) Home burglary (0/1)	(3) Home burglary (0/1)	(4) Home burglary (0/1)	(5) Home burglary (0/1)	(6) Home burglary (0/1)	(7) Home burglary (0/1)	(8) Home burglary (0/1)
Pooled effects								
Earthquake × Post	-0.021***			-0.019***	-0.023**			-0.026**
	(0.005)			(0.006)	(0.011)			(0.012)
MMI × Post		-0.005***	-0.006***			-0.005**	-0.005*	
		(0.002)	(0.002)			(0.002)	(0.003)	
Pre-earthq. trends								
F-test: Lead variables								
$H_0 : \beta_{T=-q} = \ldots = \beta_{T=-1} = 0$	0.446	2.461	0.674	0.003	2.068	4.756	1.621	0.597
Municip. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municip. time trends	No	No	No	No	Yes	Yes	Yes	Yes
Observations	67,540	177,889	111,622	57,100	67,540	177,889	111,622	57,100
Treatment areas	MMI≥ 7.5			MMI≥ 7.5	MMI≥ 7.5			MMI≥ 7.5
Control areas	MMI<5.75			MMI<5.75	MMI<5.75			MMI<5.75
Continuous treatment variable	No	Yes	Yes	No	No	Yes	Yes	No
Santiago			Santiago excluded				Santiago excluded	
Tsunami affected municip	Included	Included	Included	Excluded	Included	Included	Included	Excluded

Heterog. of effects

	(9) Home burglary (0/1)	(10) Home burglary (0/1)
Pooled effects		
Earthquake × Post	-0.023***	
(Munic with looting)	(0.005)	
Earthquake × Post	-0.019***	
(Munic without looting)	(0.007)	
Earthquake × Post		-0.024***
(Munic δ CBS=1)		(0.006)
Earthquake × Post		-0.011**
(Munic δ CBS=0)		(0.005)
Observations	67,540	67,540
Treatment areas	MMI≥ 7.5	MMI≥ 7.5
Control areas	MMI<5.75	MMI<5.75

Note: Columns 1-8 examine the pooled effect of the earthquake on home burglary over the period of interest (equation 2) using different samples and specifications. In columns 2, 3, 6 and 7 the explanatory variable of interest is the predicted Modified Mercalli Intensity to which the municipality is exposed. In columns 1, 4, 5 and 8 the explanatory variable of interest is a dummy variable equal to 1 for treated municipalities. The effect of interest is yielded by an interaction between the explanatory variables that capture exposure to the earthquake and a dummy variable equal to 1 for years after the earthquake. A test for the common trends assumption is reported for every estimation. For this test, I estimate a lead and lag model and use an F-test to examine the joint significance of the lead variables. Columns 9-10 estimate the pooled effect of the earthquake using the same control group and splitting the treatment municipalities in two different groups: Those treatment municipalities that experienced looting (column 9) or an increase in the provision of community-based crime prevention measures (column 10) and those that did not. All the regressions are estimated at the household level using the ENUSC data. Wild bootstrapped clustered at the municipality level standard errors.***p<0.01;**p<0.05,*p<0.1

Table A3: Effect of earthquake exposure on different offences (2007-2013): ENUSC data and continuous measure of exposure to the earthquake (MMI)

	(1) Larceny (0/1)	(2) Motor-vehicle theft (0/1)	(3) Robbery (0/1)
Specif. A:Lead and Lag			
Lead var. (Parallel trends)			
MMI × Year 2007	-0.003	0.001	-0.002
	(0.004)	(0.002)	(0.002)
MMI × Year 2008	-0.004	-0.000	-0.003*
	(0.003)	(0.002)	(0.002)
Lag var. (Year-based effects)			
MMI × Year 2010	-0.006	-0.001	-0.004*
	(0.005)	(0.002)	(0.002)
MMI × Year 2011	-0.015***	-0.000	-0.005**
	(0.005)	(0.002)	(0.003)
MMI × Year 2012	-0.012***	0.000	-0.004
	(0.004)	(0.002)	(0.003)
MMI × Year 2013	-0.015***	0.001	-0.006**
	(0.003)	(0.001)	(0.003)
Specif. B:Pooled effect			
MMI × Post	-0.010***	-0.000	-0.003**
	(0.002)	(0.001)	(0.002)
Mean dep. var	0.089	0.017	0.059
Observations	177,870	71,942	177,878

Note: The table reports the estimates at the household level for the effect of the earthquake on larceny, robbery and motor-vehicle theft. Specification A corresponds to the lead and lag model (equation 1). It yields the year-based effect of increasing in one predicted MMI the exposure to the earthquake during the period of interest. Specification B corresponds to the pooled effect difference in difference model (equation 2). It measures the average effect of the earthquake over the post- earthquake period of interest. Lead and lag variables are not included in specification B and the effect of interest is captured by an interaction between a continuous variable measuring the predicted MMI of the municipality where the household lives and a dummy variable indicating whether the household is interviewed after the earthquake. The mean of the dependent variable is provided for all Chilean municipalities. Standard errors are clustered and wild-bootstrapped at the municipality level.***p<0.01;**p<0.05;*p<0.1

Figure A2: Incidence of crime over time (Admin data 2003-2013)

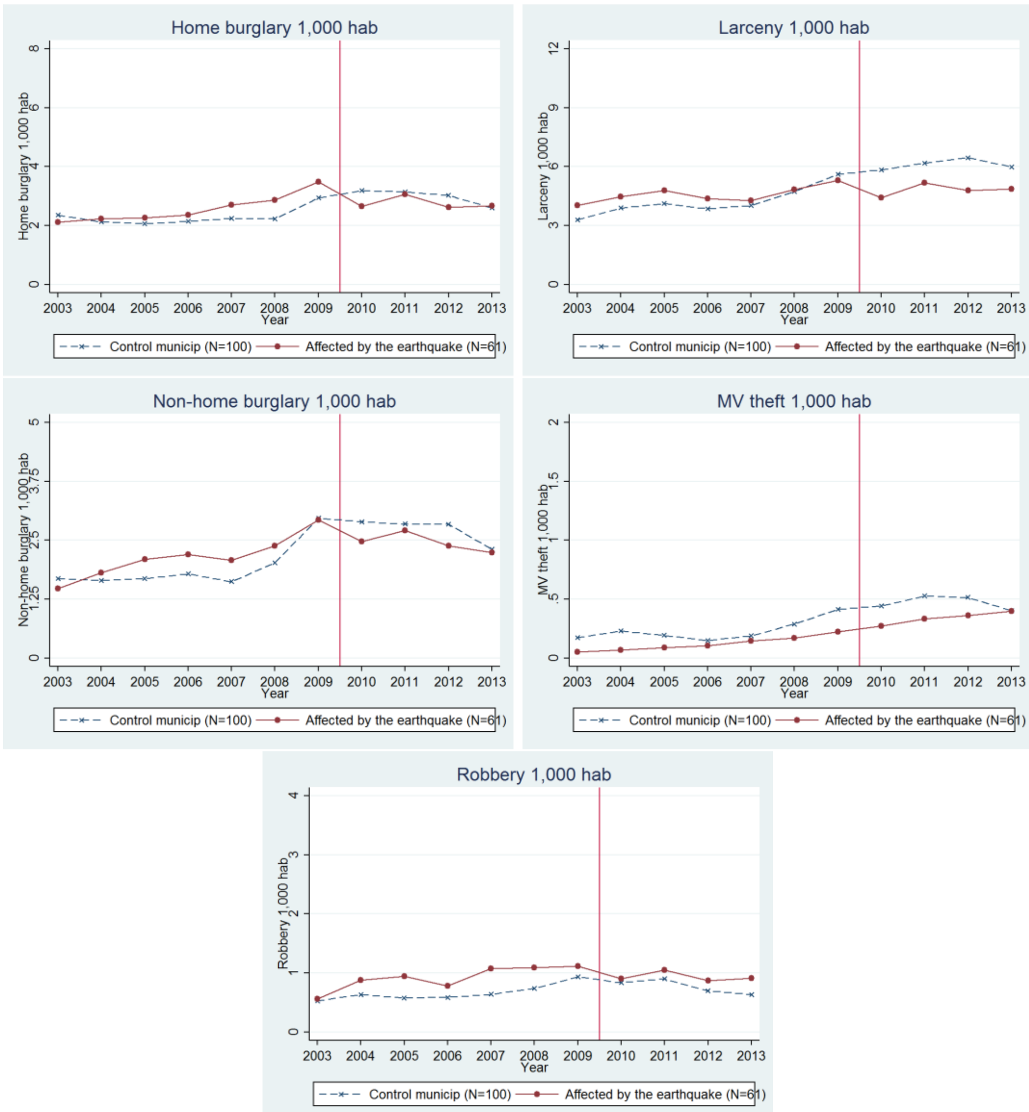

Table A4: Effect of earthquake on probability of reporting a crime to the police and mean reporting rates (regional level analysis)

	Share crime reported to the police
POST × Catastrophic regions	0.035
	(0.028)
POST × Other affected regions	-0.011 (
	0.023)
Type of crime fixed effect	Yes
N Observations	412
R2	0.644

Type of crime	Share reported to the police
Home burglary	0.551
Larceny	0.268
Motor vehicle theft	0.869
Robbery	0.509

Note: The control regions are Tarapaca, Antofagasta, Arica y Parinacota, Coquimbo, Atacama, Los Rios, Los Lagos, Aysen, Magallanes. Information on reported crime for the regions of Los Rios and Arica y Parinacota for the years 2007 and 2008 is not available. Catastrophic regions include the regions of Maule and Biobio and other affected regions include the regions of Santiago, Valparaiso, Araucania and Libertador O'Higgins. The regressions also include a dummy variable that is equal to 1 for the years after the earthquake and a vector of exposure to the earthquake fixed effects (catastrophic, other affected regions and control). The dependent variable in the regression is the share of crime reported to the police in each region and for each type of property crime (larceny, motor-vehicle theft, robbery and home burglary). Robust standard errors in parentheses.***p<0.01;**p<0.05;*p<0.1

Table A5: Impact estimates (OLS): Short-term effect of earthquake on different types of property crimes (crime data from police records) and on individuals apprehended using continuous exposure to the internet

	Home burglary (per 1,000 inhab)	Larceny (per 1,000 inhab)	Non-home burglary (per 1,000 inhab)	Motor-vehicle thefts (per 1,000 inhab)	Robbery (per 1,000 inhab)	Apprehended (per 1,000 inhab)
Sample A:March 2010						
MMI	-0.043***	-0.067***	0.016	-0.001	-0.021***	-0.066***
	(0.009)	(0.015)	(0.018)	(0.002)	(0.004)	(0.020)
Sample B:Feb 2010						
MMI	-0.021*	-0.021	-0.008	-0.004	-0.011**	0.017
	(0.011)	(0.014)	(0.011)	(0.003)	(0.005)	(0.022)
Observations	345	345	345	345	345	345
Av. rate Jan 2010	0.328	0.527	0.215	0.057	0.138	0.542

Note: The regressions estimated use monthly data from police records (SPD database) and OLS methods to estimate at the municipality level the short term effects of the earthquake on property crime and on individuals apprehended. The equation estimated is $Y = \beta_0 + \beta_1 Earthquake + \beta_2 Y_{jan2010} + \mu$ where the dependent variable Y is the crime rates/individuals apprehended in March 2010 (the month after the earthquake) in sample A or in February 2010 (the month of the earthquake) in sample B. $Y_{jan2010}$ measures the crime rate/number of people apprehended in January 2010. The treatment variable measures earthquake exposure using the MMI scale rounded at the 0.5 points. No municipalities are excluded from the analysis. Robust standard errors in parentheses.***p<0.01;**p<0.05;*p<0.1.

Figure A3: Effect of the earthquake on population (Admin data 2007-2013). Continuous measure of exposure to the earthquake)

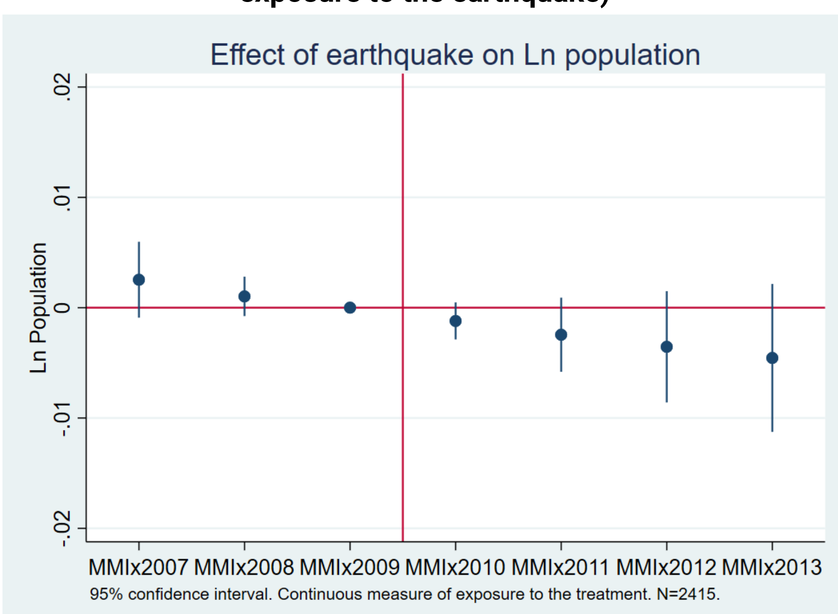

Table A6: Assets destroyed during earthquake (post-Earthquake CASEN survey, May 2010): Municipalities exposed to MMI > 7.5

	(1) Share of households lost asset
Washing machine	0.068
Fridge	0.074
Heater	0.042
Computer	0.058
TV	0.173
Music equipment	0.094
DVD	0.076

Note: The table reports the share of households living in treatment municipalities that lost any of the following assets during the earthquake. Data is obtained from the Post-earthquake CASEN survey that interviewed approximately 22,000 households that were interviewed in the 2009 CASEN survey and by that time, were living in treatment municipalities.

Appendix B: Earthquake intensity scales

Modified Mercalli intensity (MMI) scale measures the destruction capacity of an earthquake rather than the current destruction that it generates. Given a Richter magnitude, the Modified Mercalli scale in a place depends on the distance to the hypocentre and on the topography of the place. The interpretation of some of the values of the Modified Mercalli scale relevant for this study is reported below.

- MMI XI (Violent): Damage considerable in specially designed structures; well-designed frame structures thrown out of plumb. Damage great in substantial buildings, with partial collapse. Buildings shifted off foundations.

- MMI VIII (Severe): Damage slight in specially designed structures; considerable damage in ordinary substantial buildings with partial collapse. Damage great in poorly built structures. Fall of chimneys, factory stacks, columns, monument walls. Heavy furniture overturned.

- MMI VII (Very strong): Damage negligible in buildings of good design and construction; slight to moderate in well-built ordinary structures; considerable damage in poorly built or badly designed structures; some chimneys broken.

- MMI VI (Strong): Felt by all, many frightened. Some heavy furniture moved; a few instances of fallen plaster. Damage slight.

- MMI V (Moderate): Felt by nearly everyone; many awakened. Some dishes, windows broken. Unstable objects overturned. Pendulum clocks may stop.

Medvedev-Sponheuer-Karnik (MSK) scale measures the severity of ground shaking on the basis of observed effects in an area affected by an earthquake. Given a Richter magnitude, the MSK scale in a place depends on the distance to the hypocentre and on the topography of the place. The interpretation of some of the values of the MSK scale relevant for this study is reported below.

- MSK IX Destructive: General panic. People may be forcibly thrown to the ground. Waves are seen on soft ground. Substandard structures collapse. Substantial damage to well-constructed structures. Underground pipelines ruptured. Ground fracturing, widespread landslides.

- MSK VIII Damaging: Many people find it difficult to stand, even outdoors. Furniture may be overturned. Waves may be seen on very soft ground. Older structures partially collapse or sustain considerable damage. Large cracks and fissures opening up, rockfalls.

- MSK VII Very strong: Most people are frightened and try to run outdoors. Furniture is shifted and may be overturned. Objects fall from shelves. Water splashes from containers. Serious damage to older buildings, masonry chimney collapse. Small landslides.

- MSK VI Strong: Felt by most indoors and by many outdoors. A few persons lose their balance. Many people are frightened and run outdoors. Small objects may fall and furniture may be shifted. Dishes and glassware may break. Farm animals may be frightened. Visible damage to masonry structures, cracks in plaster. Isolated cracks on the ground.

- MSK V Fairly strong: Felt indoors by most, outdoors by few. A few people are frightened and run outdoors. Many sleeping people awake. Observers feel a strong shaking or rocking of the whole building, room or furniture. Hanging objects swing considerably. China and glasses clatter together. Doors and windows swing open or shut. In a few cases window panes break. Liquids oscillate and may spill from fully filled containers. Animals indoors may become uneasy. Slight damage to a few poorly constructed buildings.

Appendix C: Maps: Treatment, control and excluded municipalities under the use of different distance thresholds

Figure C1: Treatment and control areas

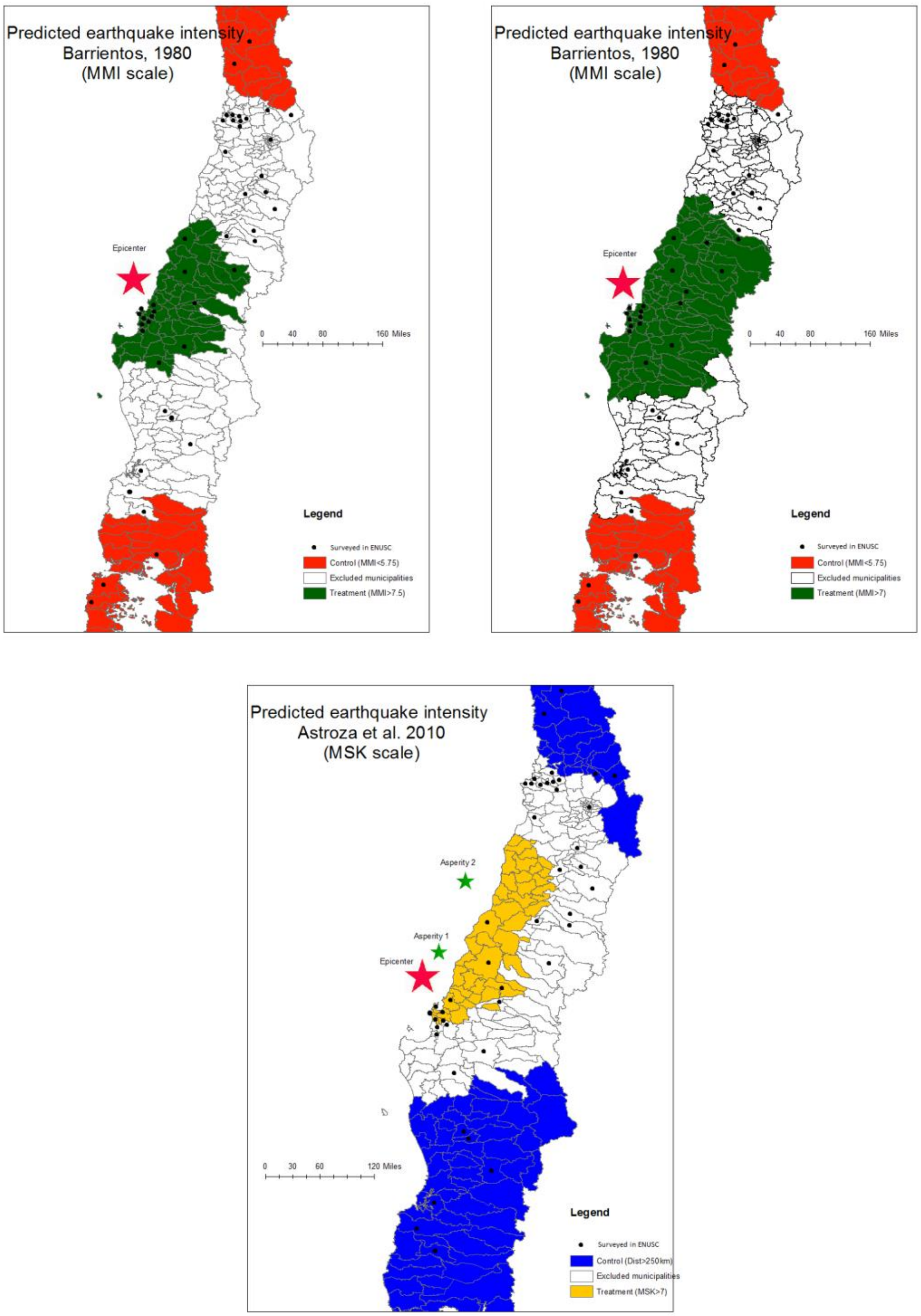

Figure C2: Treatment and control areas