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The Lasting Effects of Natural Disasters on Property Crime: Evidence from the 2010 Chilean Earthquake

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Abstract: Natural disasters cause human losses, destroy economic assets and are often followed by widespread looting and increases in altruistic behaviour; affecting ambiguously the long-term benefits and costs of crime. This study investigates whether the multiple consequences of natural disasters lead to lasting changes in property crime rates through assessing the effect on property crime dynamics of the 8.8 Richter Magnitude earthquake that struck Chile in February 2010. Using household data from victimization surveys and a difference in difference strategy, the analysis shows that exposure to a very strong earthquake intensity decreased by 1.1-2.2 percentage points the probability of home burglary the year of the earthquake. The effect remained stable over the 4 post-earthquake years studied. Similar effects of the earthquake are found for other property crimes including larceny and non-home burglary. The analysis of mechanisms reveals that the lasting drop in property crime rates in areas devastated by the earthquake seems to be linked to the positive effect of the earthquake on the strength of community life and on the adoption of community-based strategies to prevent crime in these municipalities.

JEL classification: K42, Q54

Key words: natural disasters, crime, informal guardianship

1 Motivation

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 crime (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 crime could lead to lasting effects on crime rates if the personal cost of committing crime 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 in the long-term the opportunity cost of crime. On the other hand, natural disasters may also strengthen community links (Dynes and Quarantelli, 1980; Bailey, 2009), facilitating the adoption of community-based crime prevention strategies and increasing the cost of committing crime. With mixed effects on the benefits and costs of crime, the 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 victimization survey conducted every year in 101 urban municipalities in Chile.

The results of the study reveal that exposure to a *very strong* earthquake intensity decreased the incidence of home burglary the year of the earthquake 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 when other sources of crime data and other types of property crime 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 samples and earthquake intensity thresholds to define treatment and control municipalities.

I examine different mechanisms for lower property crime in earthquake affected areas. The results show 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 the social capital at the community level boosted the adoption of community-based measures to prevent crime, increasing the cost of crime in earthquake affected areas. Alternative mechanisms such as an increase in the number of policemen 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 permanent adoption of 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 crime with long-term term consequences.

This study is primarily related with the body of literature that investigates the effect of natural disasters on the incidence of crime. Indeed, 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 crime. In this context, the contribution of the study is twofold. First, unlike previous studies that examine the evolution of crime rates over a maximum post-disaster period of 12 months, this study explores the impact of natural disasters on property crime over a longer period of time (4 post-disaster years). Second, this is the first study that investigates empirically the mechanisms driving the effects of natural disasters on property crime, providing empirical evidence that supports the different hypotheses of the informal guardianship theory and showing the key role that social capital at the community level can play in the reduction of property crime.

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 and section 8 expands the analysis to other types of property crime using an alternative source of crime data. 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.

The first stream of authors hypothesises 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 characterized 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 disorganization* theory developed in Shaw and McKay (1942). These two mechanisms can be embedded in traditional economics of crime models that describe crime rates as a function of crime's costs and benefits (Ehrlich, 1973; Becker, 1968): Through causing a temporary or permanent obstruction of law enforcement, generating power cuts and forcing some households to leave their dwellings, natural disasters decrease the cost of committing crime, leading to larger crime rates. The third path through which natural disaster may affect property crime is the labour market. If employment represents the opportunity cost of crime, the lasting negative effect of natural disasters on labour outcomes documented in Belasen and Polachek (2008) could boost the incidence of crime.

The second stream of the 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 and increasing the level of informal guardianship (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 crime costs, the rise in the provision of informal guardianship in affected communities compensates the reduced capacity of formal institutions to provide capable guardianship, increasing the probability of apprehension and the cost of committing crime in these communities.

The two streams propose different channels through which natural disasters can affect the costs and benefits of crime 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 and highlighting that the effect of natural disasters on property crime is an empirical question.

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 known to the police crime data, 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 et al. (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 lack methodological rigour. For example, only two of the studies discussed (Roy, 2010; Zahran et al., 2009) use a counterfactual approach to account for potential confounding factors 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 known to 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

[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).

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 organizations 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 summarizes the main losses at the regional level for the six 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). 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 in urban areas of these regions, particularly in Biobio[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 (Ormeño, 2010). Some of these episodes were documented by the media and involved hundreds of looters[4].

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 the police 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 and communities organizing 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 areas close to it (27% in treatment municipalities).

[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

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 of 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 earthquakey or the tsunami.

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 victimization 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 reported to or unmasked 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 Concepción where many individuals work and live in a different municipality. Second, the difference between some types of property crimes such as larcenies, burglaries or distraction theft is in many cases fuzzy. In consequence, some households might be unable to report reliably some specific types of crime to the enumerator. For these two reasons, I restrict the analysis conducted using the ENUSC database to home burglary; an offence that is unlikely to be confounded with other crimes by the households interviewed or the enumerator and for which the exact location is known.

Section 8 tests the robustness of the results and expands the analysis to other types of property crime including motor-vehicle theft, non-home burglary, larceny and robbery using 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 known to the police in each of the 345 Chilean municipalities by type of crime[7] and (b) the number of individuals apprehended

[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

by the police in every municipality.

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 build 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].

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

[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.

$$I_{MMI} = 1.3844M_w - 3.7355log_{10}(DistHC) - 0.0006DistHC + 3.8461 \tag{5.1}$$

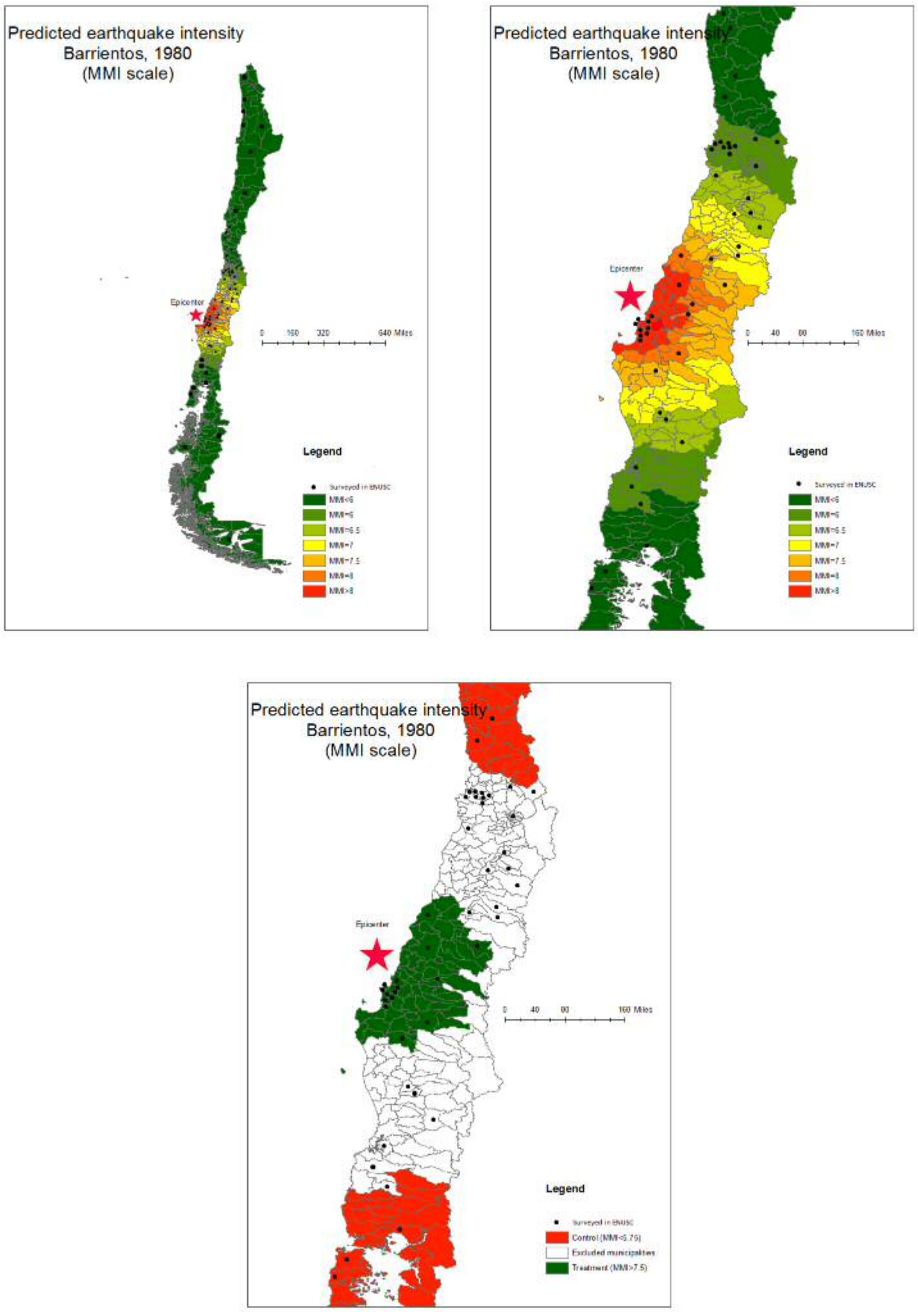
[9]The interpretation of the values in the Mercalli and MSK scales is reported in appendix A.

[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:

$$I_{MSK} = 43.11 - 18.96log_{10}(DistAs) + 0.0294DistAs \tag{5.2}$$

8 and 9 in appendix B.

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≤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
SPD 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
CASEN data (2009 and 2011; munip. level)														
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	79	0.035	0.03***	324	0.046	648	0.039
Unemployment rate	16	0.126	19	0.087	0.04***	61	0.121	79	0.085	0.04***	324	0.104	648	0.093
Income polariz. (75% vs 25%)	16	8.313	19	7.487	0.83	61	7.175	79	7.529	-0.35	324	7.270	648	7.585
Income polariz. (90% vs 10%)	16	21.037	19	18.708	2.33	61	17.782	79	18.703	-0.92	324	18.225	648	18.696
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
Rate pop 13-25 attending educ	16	0.634	19	0.574	0.06***	61	0.583	89	0.577	0.01	334	0.576	658	0.579
Other admin data (2007-2013; munip. level)														
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
Distance (km) to nearest city (250,000 inhab)	48	47	57	211	-164**	183	69	300	298	-230***	1,035	133	2,415	133
% 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
Mothers assoc. per 100 inhab.	41	0.050	51	0.024	0.03	160	0.072	277	0.061	0.01	949	0.055	2,240	0.055
Elderly assoc. per 100 inhab.	42	0.065	51	0.050	0.02	162	0.100	277	0.092	0.01	953	0.090	2,248	0.099
Sport clubs per 100 inhab.	42	0.119	51	0.146	-0.03	162	0.168	277	0.270	-0.10***	953	0.203	2,248	0.205
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

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 ENUSC survey 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.

An advantage of using predicted intensity as a measure of whether a municipality is affected by the earthquake is that while this only depends on the distance to the hypocentre, the extent of human losses, economic damages or even observed earthquake intensity (which is affected by the topography of the location) at the municipality level could arguably be affected by pre-disaster factors that may influence crime costs and benefits.

Table 2 summarizes 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 study. 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. The table reports the mean values for the variables used in the analysis both using only the before-earthquake periods and all periods available.

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 known to the police crime before the earthquake in treatment municipalities included in the ENUSC database was, overall, not significantly different from the incidence in control municipalities. However, some significant 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, the incidence of home burglary 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

[11] See table 11.

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 was 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, the number of policemen per capita before the earthquake in treatment municipalities was significantly lower. Finally, the strength of social life and the income inequality did not seem to differ before the earthquake in treatment and control municipalities.

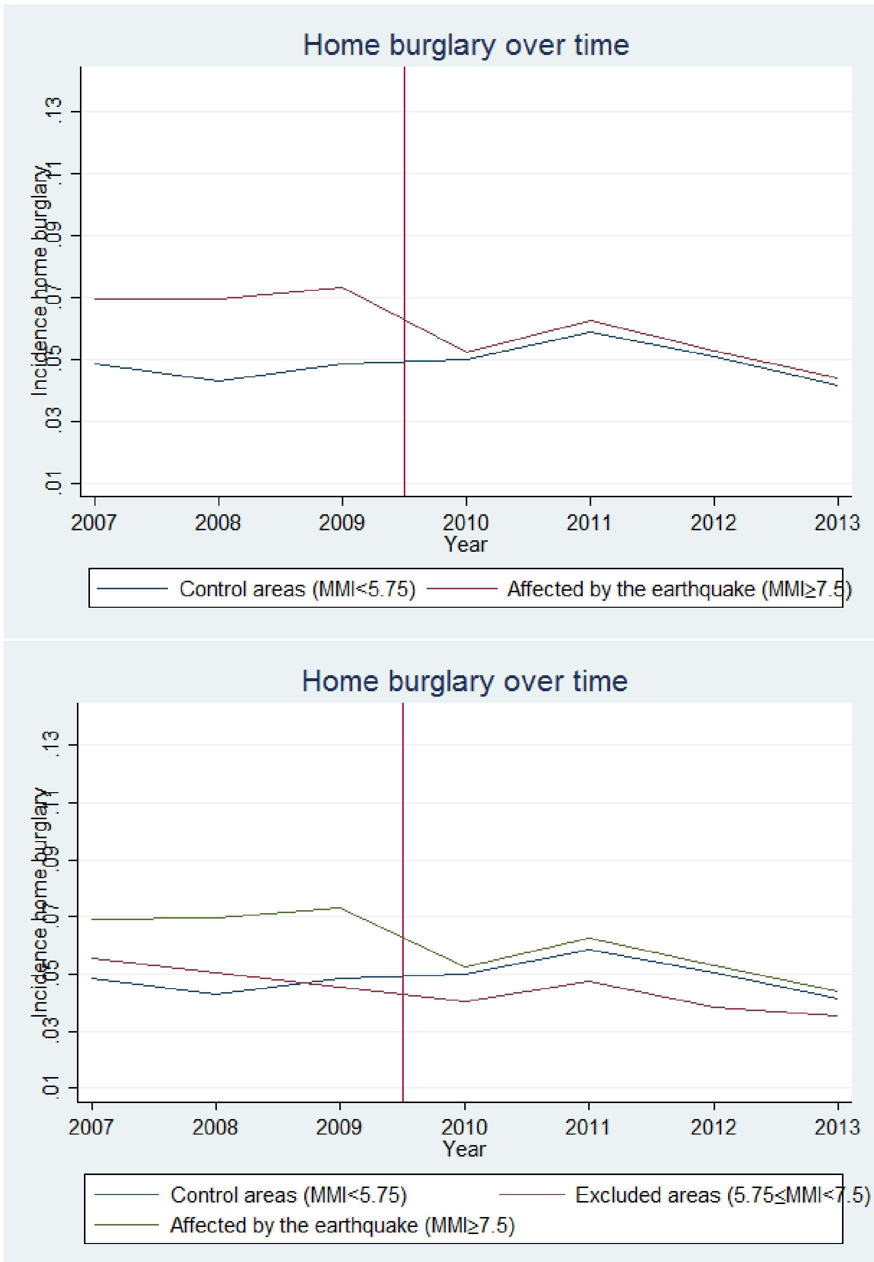
6 Empirical Strategy

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 almost 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 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 in absence of the earthquake, crime rates in control and treatment areas 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. On the other hand, figure 2 also suggests that before the 2010 earthquake, the incidence of home burglary in those intermediate municipalities excluded from the analysis was following a different trend over time. The lack of pre-earthquake parallel trends in these municipalities is also confirmed empirically[12], implying that the effect of the earthquake on crime rates in these intermediate municipalities cannot be reliably estimated using a difference in difference strategy.

Figure 2: Incidence of home burglary over time



[12]To test this hypothesis, I estimate a leads and lags model and test the joint significance of the lead variables. The F-test is significant at the 10% confidence level.

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 and omitting from the sample the households living in intermediate municipalities. Following Autor (2003), I first estimate a leads and lags model:

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

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, α_m is a vector of municipality dummies, and $(Year \times Earthquake)_{mt}$ 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:

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

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 period of interest (2010-2013) relative to municipalities not directly affected by the earthquake. Following the recommendation of Angrist and Pischke (2008) for difference in difference estimations with several pre- and post-treatment periods, I clustered the standard errors at the municipality level.

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.

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. The results of these analyses are also displayed graphically in figure 11 in appendix D.

One of the advantages of the leads and lags approach is that it provides a direct test for the 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. 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, depending on the intensity threshold used to define control and treatment municipalities. Furthermore, the effect of the earthquake remained stable during the 4 post-earthquake years studied, confirming the persistence of this effect over this period. Although the exact magnitude and level of significance for the year-effect estimates vary with the definition of the treatment and control groups, the coefficients are consistently negative and the pooled effect over the period of interest is statistically significant at the 5% in all the specifications, highlighting that the results are robust to the use of different predicted intensity thresholds to define treatment and control municipalities and to the use of the method developed by Astroza et al. (2010) to predict earthquake intensities.

A more detailed look at how the magnitude of the effect varies when different thresholds 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 column 1 are larger in absolute value than those reported in column 2. 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 and 2 are larger than those in columns 4 and 5. These results suggest that the higher the earthquake intensity exposed to, the larger the effect on home burglary. Furthermore, they also cast doubts on whether municipalities in the limit between control and intermediate areas could have been somehow affected by the earthquake and suggest that the use of longer distances from the hypocentre to define control municipalities could be more convenient.

The results reported in columns 1-8 of table 8 in appendix 10 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 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. Finally, as expected, the inclusion of households living in intermediate municipalities as a separate group in the regression hardly changes the magnitude of the estimates for the treatment group. Indeed, although the lack of parallel trends requires to take with caution the estimates for the intermediate municipalities, the smaller but negative and statistically significant coefficient for this group relative to control municipalities suggests the possibility that the earthquake may have also decreased the prevalence of property crime in intermediate municipalities.

Figure 3: Effect of the earthquake on home burglary over time

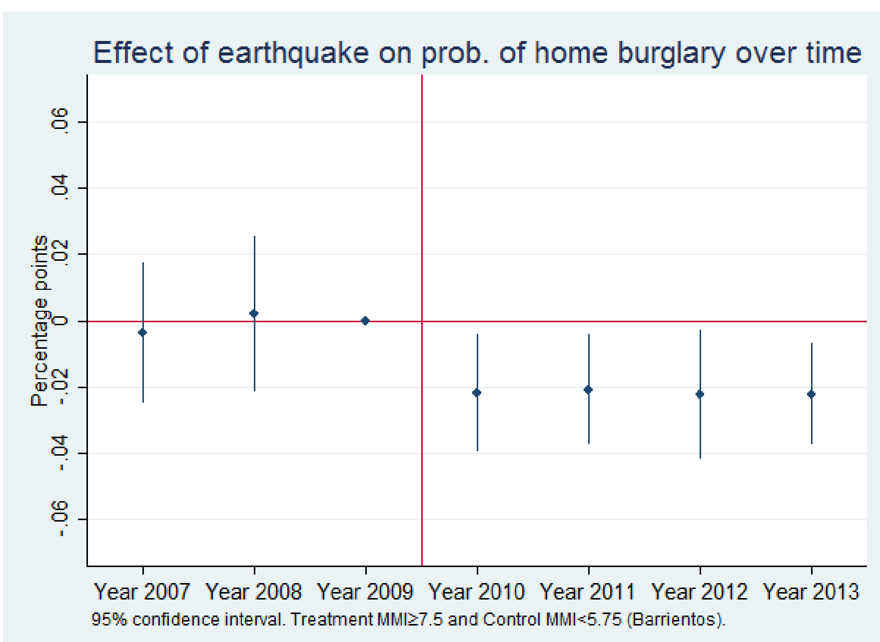


Table 3: Effects of the earthquake on home burglary (ENUSC data): Leads and lags analysis and pooled effects for the period 2007-2013

	(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:Leads and Lags						
Lead var. (Parallel trends)						
Earthquake × Year 2007	-0.004	0.001	-0.001	0.000	0.004	-0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Earthquake × Year 2008	0.002	0.004	0.002	0.001	0.004	-0.003
	(0.011)	(0.011)	(0.009)	(0.011)	(0.010)	(0.009)
Lag var. (Year-based effects)						
Earthquake × Year 2010	-0.022**	-0.016	-0.018**	-0.016**	-0.011	-0.016**
	(0.009)	(0.010)	(0.009)	(0.008)	(0.009)	(0.007)
Earthquake × Year 2011	-0.021**	-0.016*	-0.018*	-0.013	-0.008	-0.016**
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Earthquake × Year 2012	-0.022**	-0.017*	-0.017	-0.018**	-0.013	-0.012
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Earthquake × Year 2013	-0.022***	-0.016*	-0.019**	-0.017**	-0.011	-0.019**
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Specif. B:Pooled effect						
Earthquake × Post	-0.021***	-0.018***	-0.018***	-0.017***	-0.013**	-0.018***
	(0.005)	(0.005)	(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 leads and lags 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 clustered at the municipality level.***p<0.01;**p<0.05;*p<0.1.

Finally, although the direct effect of the earthquake 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.

8 Additional Analysis: Known to the Police Crime Data

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, expanding also the analysis to other types of property crime. 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.

8.1 The Effect of the Earthquake on Known to the Police Property Crime

Using the SPD database, I estimate equations 8.1 and 8.2 using the yearly incidence of home burglary, non-home burglary, larcenies, motor-vehicle theft and robbery per 1,000 inhabitants as dependent variables:

$$Crime_{mt} = \alpha_m + \sum_{\tau=-q}^{-1} \beta_\tau (Year \times Earthquake)_{mt} + \sum_{\tau=0}^{r} \beta_\tau (Year \times Earthquake)_{m\tau} + Year_t + \mu_{mt} \quad (8.1)$$

$$Crime_{mt} = \alpha_m + \beta (Year \times Earthquake)_{mt} + \gamma X_m + Year_t + u_{mt} \quad (8.2)$$

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 equations 8.1 and 8.2 are similar to equations 6.2 and 6.1 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 equations 8.1 and 8.2 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, utilizing 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[13] is incorporated.

The results of the analyses using these two samples are reported in table 4. Overall, the estimates are consistent with those obtained in the main analysis conducted in section 7. The coefficients reported in columns 1 and 2 suggest that earthquake decreased significantly home burglary the year of the earthquake. The effect remained significant 4 years after the earthquake although the magnitude of the effect was smaller. The estimates displayed in columns 3 and 4 show that the earthquake reduced the incidence of larceny the year of the earthquake and the magnitude of this effect remained relatively stable and statistically significant over all the period studied. The coefficients for the lag variables that measure the effects of the earthquake on non-home burglary are reported in columns 5 and 6. They are consistently negative although only statistically significant for the first post-earthquake year. Note however that the pooled effect of the earthquake on non-home burglary over the period of interest is negative and statistically significant at the 1%. The results reported in columns 7 and 8 reveal that unlike for the previous types of crime, the earthquake did not seem to affect the incidence of motor-vehicle theft. The results for the incidence of robbery are more ambiguous. While none of the coefficients for the lag variables reported in columns 9 and 10 is statistically significant at the 10%, the pooled effect of the earthquake on robbery over the period of interest is negative and statistically significant in the sample that only includes the period 2007-13 and negative but statistically indistinguishable from 0 at conventional confidence levels when the full period 2003-2013 is analysed.

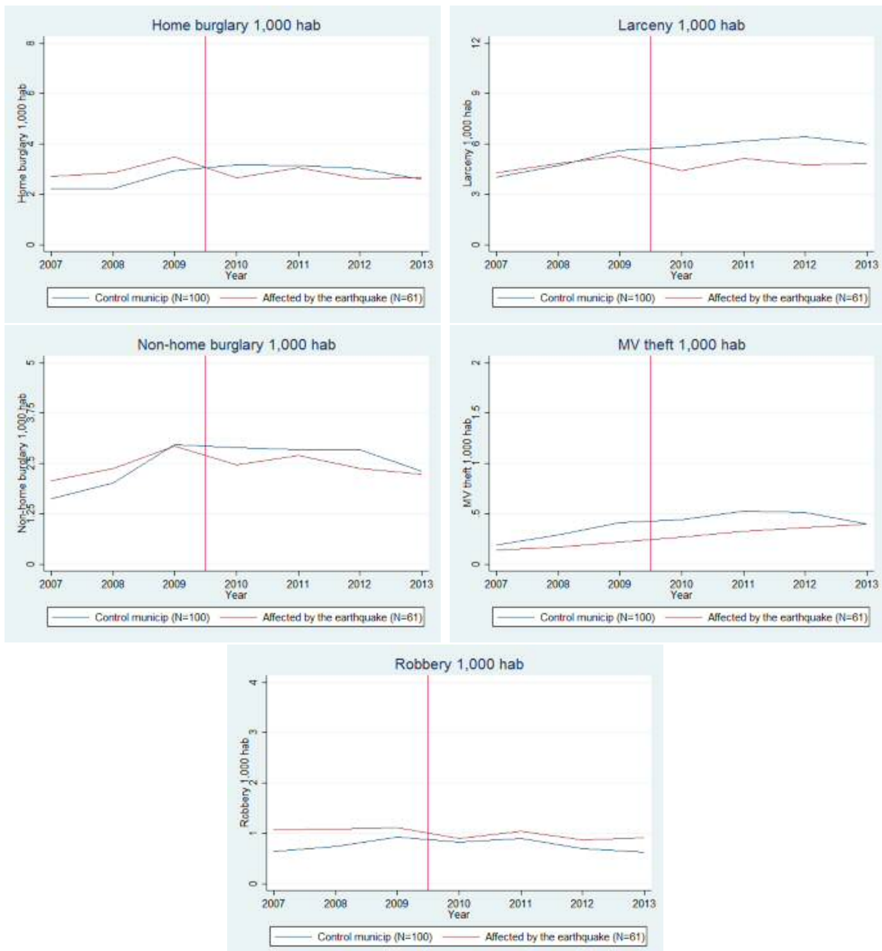
The results of the F-test for the lead variables suggest that although figures 4 and 5 reveal some differences in the pre-earthquake evolution of the known to the police incidence of home burglary, non-home burglary, larceny and motor-vehicle theft in treatment and control municipalities, these differences are not statistically significant in any of the two time periods used in the analysis. On the other hand, the results of this test show that the pre-earthquake evolution over time of the incidence of robbery is significantly different in treatment and control municipalities, casting doubts on the estimates provided in columns 9 and 10 of table 4.

One potential concern when interpreting the coefficients reported in table 4 is that unlike the ENUSC database, the SPD database only includes those offences reported to or unmasked by the police. Therefore, the SPD database misses those crimes that were neither reported to nor unmasked by the police. The reporting error in police records may generate two problems. First, a substantial share of crimes unknown to the police would lead to large standard errors. Second, if

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

the share of crimes that is unknown 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 4 might be explained by an effect of the earthquake on the share of crimes that is reported to or unmasked by the police rather than by an effect of the earthquake on *true* crime rates.

Figure 4: Incidence of crime over time (SPD data 2007-2013)

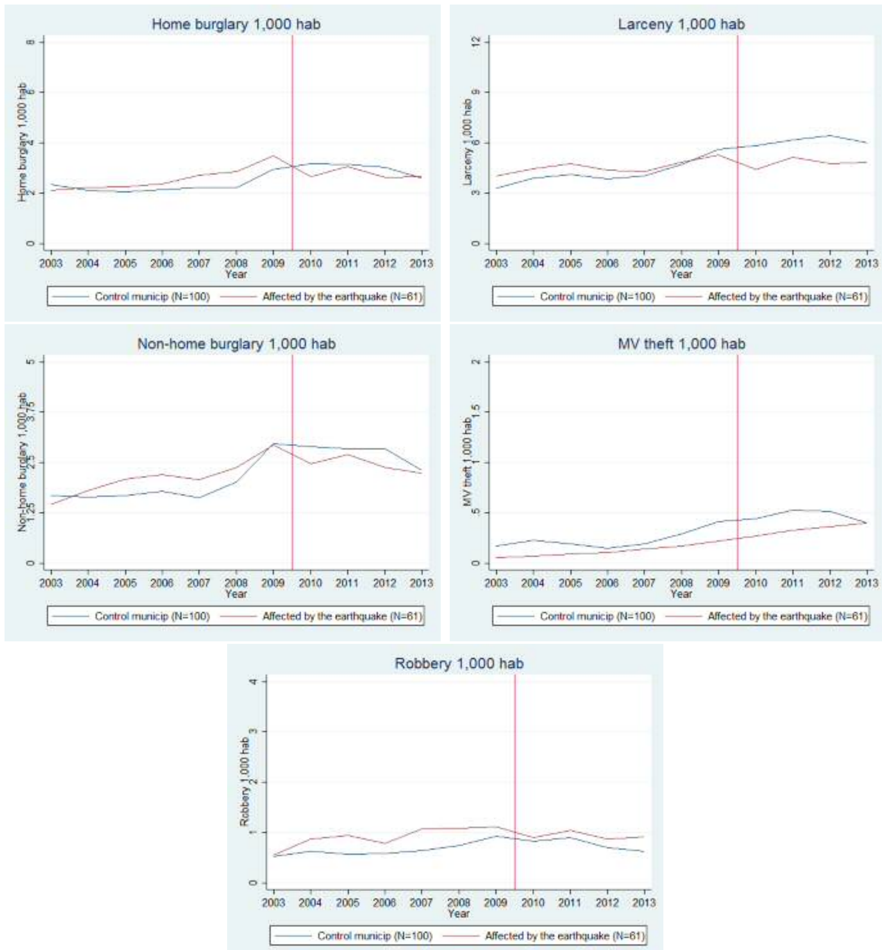


I explore this hypothesis using information available in the ENUSC survey on whether households report crimes to the police and estimating a difference in difference model in which the dependent variable is the share of larcenies, motor-vehicle theft, robbery and home burglary that is reported to the police. The results of this analysis, conducted at the regional level, are reported in table 11 in appendix C[14]. Both the regression analysis and the visual inspection of figure 10 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

[14]The analysis is conducted at the regional level because the ENUSC survey does not provide the location at the municipality level for most of the offences (larceny, motor-vehicle theft and robbery) that are used to construct the dependent variable.

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 4.

Figure 5: Incidence of crime over time (SPD data 2003-2013)



Overall, the results presented in this section are consistent with the findings of the analysis conducted in section 7 and show that the earthquake led to a lasting reduction in the incidence of home burglary. 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 et al. (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.

Table 4: Effects of earthquake exposure on property crime (2007-2013): SPD 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
Specif. A: Leads and lags										
Lag var. (Year-based effects)										
Earthquake × Year 2010	-1.080***	-1.080***	-1.113***	-1.113***	-0.387*	-0.387*	0.020	0.020	-0.115	-0.115
	(0.222)	(0.229)	(0.255)	(0.262)	(0.225)	(0.231)	(0.045)	(0.046)	(0.091)	(0.093)
Earthquake × Year 2011	-0.625**	-0.625**	-0.698**	-0.698**	-0.099	-0.099	-0.003	-0.003	-0.033	-0.033
	(0.259)	(0.267)	(0.320)	(0.329)	(0.276)	(0.284)	(0.081)	(0.084)	(0.086)	(0.089)
Earthquake × Year 2012	-0.955***	-0.955***	-1.359***	-1.359***	-0.423	-0.423	0.041	0.041	-0.014	-0.014
	(0.295)	(0.304)	(0.439)	(0.452)	(0.299)	(0.308)	(0.079)	(0.081)	(0.081)	(0.084)
Earthquake × Year 2013	-0.478*	-0.478*	-0.828**	-0.828**	-0.031	-0.031	0.188***	0.188***	0.093	0.093
	(0.283)	(0.291)	(0.359)	(0.370)	(0.274)	(0.282)	(0.060)	(0.062)	(0.077)	(0.079)
Specif. B: Pooled effect										
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	3.640	3.640	5.161	5.161	3.052	3.052	0.246	0.246	1.105	1.105
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										
$H_0 : \beta_{\tau=-q} = ... = \beta_{\tau=-1} = 0$	1.707	0.340	1.521	1.938	1.741	1.606	1.571	1.941	2.721**	3.641**

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. Specification A corresponds to the leads and lags model (equation 8.1). 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 8.2). 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 municipality is affected by the earthquake and whether the observation corresponds to a year after the earthquake. 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 in 2009. Standard errors clustered at the municipality level.***p<0.01;**p<0.05;*p<0.1.

8.2 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 two weeks 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 are the change in the incidence of crime between either the month of the earthquake (February 2010) or the first month after the earthquake (March 2010) and the last month before the earthquake (January 2010). The regression includes as control variables the population of the municipality and the incidence of crime in the last month before the earthquake.

The results of these analyses are reported in table 5. They suggest that property crime did not increase sharply in the aftermath of the earthquake. Rather, the known to the police incidence of home burglary, robbery and larceny 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 after 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 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 5 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 known to 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 crime, 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 5: Impact estimates (OLS): Short-term effects of the earthquake on different types of property crimes and on individuals apprehended (SPD data)

	Δ Home burglary (per 1,000 inhab)	Δ Larceny (per 1,000 inhab)	Δ Non-home burglary (per 1,000 inhab)	Δ Motor-vehicle thefts (per 1,000 inhab)	Δ Robbery (per 1,000 inhab)	Δ Apprehended (per 1,000 inhab)
Sample A:March 2010 - Jan 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 - Jan 2010						
Earthquake municip.	-0.083	-0.126*	-0.101	-0.009	0.012	0.067
	(0.054)	(0.065)	(0.088)	(0.009)	(0.017)	(0.074)
Observations	161	161	161	161	161	161
Av. rate Jan 2010 (Treat mun)	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 $\Delta Y = \beta_0 + \beta_1 Earthquake + \beta_2 Y + \mu$ where the dependent variable ΔY is the difference in crime rates/individuals apprehended between March 2010 (the month after the earthquake) and January 2010 (the last month before the earthquake) in sample A and the difference in crime rates/individuals apprehended between February 2010 (the month of the earthquake) and January 2010 in sample B. Y 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 benefits and costs of 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, increasing the provision of informal guardianship in damaged communities and therefore the costs of crime. The theory concludes that the rises in the levels of informal guardianship offset 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-based measures to prevent crime. The results of this analysis are displayed in table 6 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 10 of table 8 in appendix 10 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[15]. 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 coefficients reported in columns 9-11 of table 6 suggest that, overall, the earthquake increased the number of community-based organizations. 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 organized behaviour in communities affected by the earthquake during the days that followed the natural disaster (Grandón et al., 2014; Larranaga and Herrera, 2010b).

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

[15] Column 10 of table 8 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, organizing 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.

Table 6: Effects of the earthquake on social capital and the adoption of individual and community-based measures to prevent crime

Adoption of crime prevention measures	(1) Share number with neigh. (0/1)	(2) Community vigilance (0/1)	(3) Coord. with local author. (0/1)	(4) Community hires private vigil. (0/1)	(5) Dog (0/1)	(6) Bars in windows or doors (0/1)	(7) Safety lock (0/1)	(8) Alarm (0/1)
Pooled effects								
Earthquake × Post	0.061*	0.062**	-0.026	0.009	-0.001	-0.048	-0.064	0.050**
	(0.031)	(0.026)	(0.059)	(0.015)	(0.026)	(0.038)	(0.054)	(0.022)
Pre-earthq. trends								
F-test: Lead variables								
$H_0 : \beta_{\tau=-q} = ... = \beta_{\tau=-1} = 0$	1.794	1.498	1.495	0.326	1.778	1.475	0.960	6.917***
Observations	67,546	67,546	67,546	67,546	67,546	67,546	67,546	67,546
Dep var. (treatment areas)	0.243	0.098	0.323	0.061	0.405	0.454	0.268	0.065

Social capital: Community assoc.	(9) Mothers assoc. (per 100 inhab)	(10) Elderly assoc. (per 100 inhab)	(11) Sport clubs (per 100 inhab)
Pooled effects			
Earthquake × Post	0.016*	0.005	0.024*
	(0.008)	(0.005)	(0.013)
Pre-earthq. trends (F-test)			
F-test: Lead variables			
$H_0 : \beta_{\tau=-q} = ... = \beta_{\tau=-1} = 0$	2.308	0.085	0.063
Observations	1,033	1,037	1,037
Dep var. (treatment areas)	0.065	0.095	0.233

Note: Columns 1-8 estimate at the household level the effect of the earthquake on the adoption of different individual and community-based measured to prevent crime using the pooled effect difference in difference model (equation 6.2). Columns 9-11 estimate at the municipality level the effect of the earthquake on social capital variables using the pooled effect difference in difference model (equation 8.2) and the sample of municipalities for which this information is available. Social capital variables are number of associations per 100 inhabitants, using the population of the municipality in 2009. The models used in these regressions measure the average effect of the earthquake over the post-earthquake period of interest. The effect of interest is yielded 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 leads and lags 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 in 2009. Standard errors clustered at the municipality level. ***p<0.01;**p<0.05,*p<0.1.

in communities affected by the earthquake. 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[16], it is very likely that the extensive media coverage of the looting events and the power cuts increased the perception of crime in communities affected by the earthquake 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) organized collectively to overcome the damage caused by the earthquake and the provision of security was the main reported reason for collective organization in Biobio and the second (after the provision of water and food) in Maule. Also, Grandón et al. (2014) provide qualitative evidence from the city of Concepción that neighbours cooperated to provide informal guardianship and protect their communities from looting during the week that followed the earthquake.

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 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 8 in appendix 10 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.

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, population, poverty rate, extreme poverty rate, unemployment, rate of men 15-29 years old, two measures of income polarization, enrolment

[16]This analysis, conducted using the ENUSC data, is not reported in the paper but it is available upon request.

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[17]. The dependent variable in these regressions is the change in the variable of interest between the first year for which data are available after the earthquake (e.g. 2010 for administrative data and 2011 for variables constructed using the CASEN survey) and the last year before the earthquake (2009 for all variables). 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 7 and suggest that proximity to the hypocentre decreased the population of the municipality and increased its unemployment level, 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. Interestingly, table 10 in appendix 10 remarks that, with the exception of extreme poverty, the earthquake did not affect in the short-term any of the variables analysed in the excluded intermediate municipalities. This result is somehow expected because low earthquake intensities are unlikely to damage constructions other than the poorest dwellings that might be more vulnerable.

The results reported in table 7 suggest therefore that the lasting drop in property crime rates was not caused by an increase in the presence of policemen or by reconstruction programmes 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 8 in appendix 10 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 the larger looting events, did not generate any differential effect on the incidence of property crime across municipalities affected by the earthquake. This result dismisses the hypothesis that through temporarily increasing the cost of 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 in the municipalities affected by the earthquake.

Another mechanism for lower property crime rates after natural disasters is a reduction in the benefits of crime. Through destroying economic assets and expanding poverty, the earthquake may

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

Table 7: The effects of the earthquake on other sociodemographic and economic variables

	Δ Ln Munic. p/c budget	Δ Ln population	Δ Ln Polic. 100M inhab	Δ Poverty rate	Δ Extreme pov. rate	Δ Unemp. rate	Δ Polariz (75%vs25%)	Δ Polariz. (90%vs10%)	Δ Rate men 15-29	Δ Attending educ. (13-25)
Earthquake municip.	-0.004	-0.005**	0.029	0.027**	0.015***	0.019**	-0.459	-0.080	-0.001	0.014
	(0.014)	(0.002)	(0.023)	(0.011)	(0.004)	(0.008)	(0.409)	(1.761)	(0.004)	(0.016)
Observations	157	161	161	140	140	140	140	140	140	140
R-squared	0.005	0.064	0.047	0.158	0.507	0.175	0.433	0.426	0.226	0.275

Note: The table reports the short-term effects of the earthquake on different factors that have been identified in the literature as potential causes of crime. The model estimated is $\Delta Y_i = \beta_0 + \beta_1 Earthquake_i + \beta_2 Y2009_i + \beta_3 LnPopulat2009_i + \mu$ where the dependent variable (ΔY) is the change in the variable of interest between the closest available point after the earthquake and the closest available point before 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, income polarization, age composition and education enrolment, and 2010 for population and 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, 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.

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 et al., 2012).

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 programmes that may reduce crime in the short- and long-term. In table 7 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. However, it is also possible that many of these large investments conducted in damaged areas were not funded by the municipality but directly by the central government. Unfortunately, I do not have the necessary information to test this hypothesis and therefore, I cannot reject the possibility that the decrease in crime was partially explained by a redistribution of public investments and infrastructure towards the areas affected by the earthquake. Nonetheless, we know that if it existed, this effect did not operate through reducing unemployment.

10 Conclusions

This study exploits across space variation in exposure to an 8.8 Richter magnitude earthquake in Chile to provide the first evidence on the lasting effects of natural disasters on property crime. For this purpose, property crime data from household victimization 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 the year of the earthquake. Furthermore, the effect remained constant over the 4 post-earthquake years studied. The results are robust to the use of different sources of data, types of property crime, samples and alternative definitions of treatment and control municipalities. 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. An important driver of this effect was 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 cooperation 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 highlights the role played by social capital and cooperation at the community level in reducing crime, a question that has not been empirically investigated so far. 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, crime displacement, an increase in the perceived risk of crime, lasting effects of the curfew and army deployment and an increase in employment due to the reconstruction programmes are tested and ruled out in the light of the results. However, natural disasters are complex phenomena with numerous consequences and therefore, I cannot dismiss the possibility that the lasting drop in the prevalence of property crime after the earthquake was also channelled through other mechanisms not examined in this study.

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sectionRobustness Checks: Using All Observations and Heterogeneity of Effects

Table 8: Effects of the 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***	-0.021***	-0.021***	-0.019***	-0.023**	-0.023**	-0.023**	-0.026**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)	(0.011)
Intermediate areas × Post		-0.014***	-0.015***			-0.011	-0.010	
		(0.004)	(0.005)			(0.009)	(0.010)	
Pre-earthq. trends								
F-test: Lead variables								
$H_0 : \beta_{\tau=-q} = ... = \beta_{\tau=-1} = 0$	0.238	0.242	0.241	0.174	1.554	1.583	1.572	1.094
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	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	MMI<5.75	MMI<5.75	MMI<5.75	MMI<5.75
Intermediate areas	Excluded	5.75≤MMI<7.5	5.75≤MMI<7.5 Santiago excluded	Excluded	Excluded	5.75≤MMI<7.5	5.75≤MMI<7.5 Santiago excluded	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)	(0.006)	
Earthquake × Post		-0.024***
(Munic δ CBS=1)		(0.005)
Earthquake × Post		-0.011***
(Munic δ CBS=0)		(0.004)
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 effects of the earthquake on home burglary over the period of interest (equation 6.2) using different samples and specifications. 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 leads and lags 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 ENUSC data. Standard errors clustered at the municipality level.***p<0.01;**p<0.05,*p<0.1.

Table 9: Impact estimates (OLS): Short-term effects of the earthquake on different types of property crimes and on individuals apprehended (SPD data)

	Δ Home burglary (per 1,000 inhab)	Δ Larceny (per 1,000 inhab)	Δ Non-home burglary (per 1,000 inhab)	Δ Motor-vehicle thefts (per 1,000 inhab)	Δ Robbery (per 1,000 inhab)	Δ Apprehended (per 1,000 inhab)
Sample A:March 2010 - Jan 2010						
Earthquake municip.	-0.104***	-0.194***	0.042	-0.003	-0.021	-0.151**
	(0.028)	(0.051)	(0.050)	(0.007)	(0.013)	(0.067)
Intermediate municip.	-0.054*	-0.094*	-0.033	-0.007	0.050**	-0.089
	(0.029)	(0.052)	(0.027)	(0.008)	(0.022)	(0.065)
Sample B:Feb 2010 - Jan 2010						
Earthquake municip.	-0.074	-0.072	-0.068	-0.016*	0.031	0.074
	(0.047)	(0.055)	(0.066)	(0.009)	(0.022)	(0.074)
Intermediate municip.	-0.054	0.016	-0.043	-0.013	0.088***	0.034
	(0.043)	(0.053)	(0.047)	(0.010)	(0.031)	(0.065)
Observations	345	345	345	345	345	345
Av. rate Jan 2010 (Treat mun)	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 $\Delta Y = \beta_0 + \beta_1 Earthquake + \beta_2 Y + \mu$ where the dependent variable ΔY is the difference in crime rates/individuals apprehended between March 2010 (the first month after the earthquake) and January 2010 (the last month before the earthquake) in sample A and the difference in crime rates/individuals apprehended between February 2010 (the month of the earthquake) and January 2010 in sample B. Y measures the crime rate/number of people apprehended in January 2010. Municipalities exposed to a predicted $5.75 \leq MMI < 7.5$ are included in the sample as a separate treatment group (intermediate exposure). Robust standard errors in parentheses.***p<0.01;**p<0.05;*p<0.1.

Table 10: The effects of the earthquake on other sociodemographic and economic variables

	Δ Ln Munic. p/c budget	Δ Ln population	Δ Ln Polic. 100M inhab	Δ Poverty rate	Δ Extreme pov. rate	Δ Unemp. rate	Δ Polariz (75%vs25%)	Δ Polariz. (90%vs10%)	Δ Rate men 15-29	Δ Attending educ. (13-25)
Earthquake municip.	-0.006	-0.005*	0.023	0.021**	0.014***	0.017**	-0.427	-0.143	-0.002	0.016
	(0.014)	(0.002)	(0.023)	(0.010)	(0.005)	(0.008)	(0.419)	(1.734)	(0.004)	(0.016)
Intermediate municip.	-0.001	-0.001	0.017	0.001	0.008**	0.005	-0.082	-0.107	-0.003	0.015
	(0.014)	(0.002)	(0.021)	(0.006)	(0.003)	(0.005)	(0.401)	(1.281)	(0.003)	(0.013)
Observations	340	345	345	324	324	324	324	324	324	324
R-squared	0.012	0.045	0.020	0.151	0.473	0.169	0.202	0.429	0.217	0.346

Note: The table reports the short-term effects of the earthquake on different factors that have been identified in the literature as potential causes of crime. The model estimated is $\Delta Y_i = \beta_0 + \beta_1 Earthquake_i + \beta_2 Y2009_i + \beta_3 LnPopulat2009_i + \mu$ where the dependent variable (ΔY) is the change in the variable of interest between the closest available point after the earthquake and the closest available point before 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, income polarization, age composition and education enrolment, and 2010 for population and 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. Municipalities exposed to a predicted earthquake intensity $5.75 \leq MMI < 7.5$ are included as a separate treatment group (intermediate municipalities). 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, 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: Incidence of crime over time (SPD data 2007-2013)

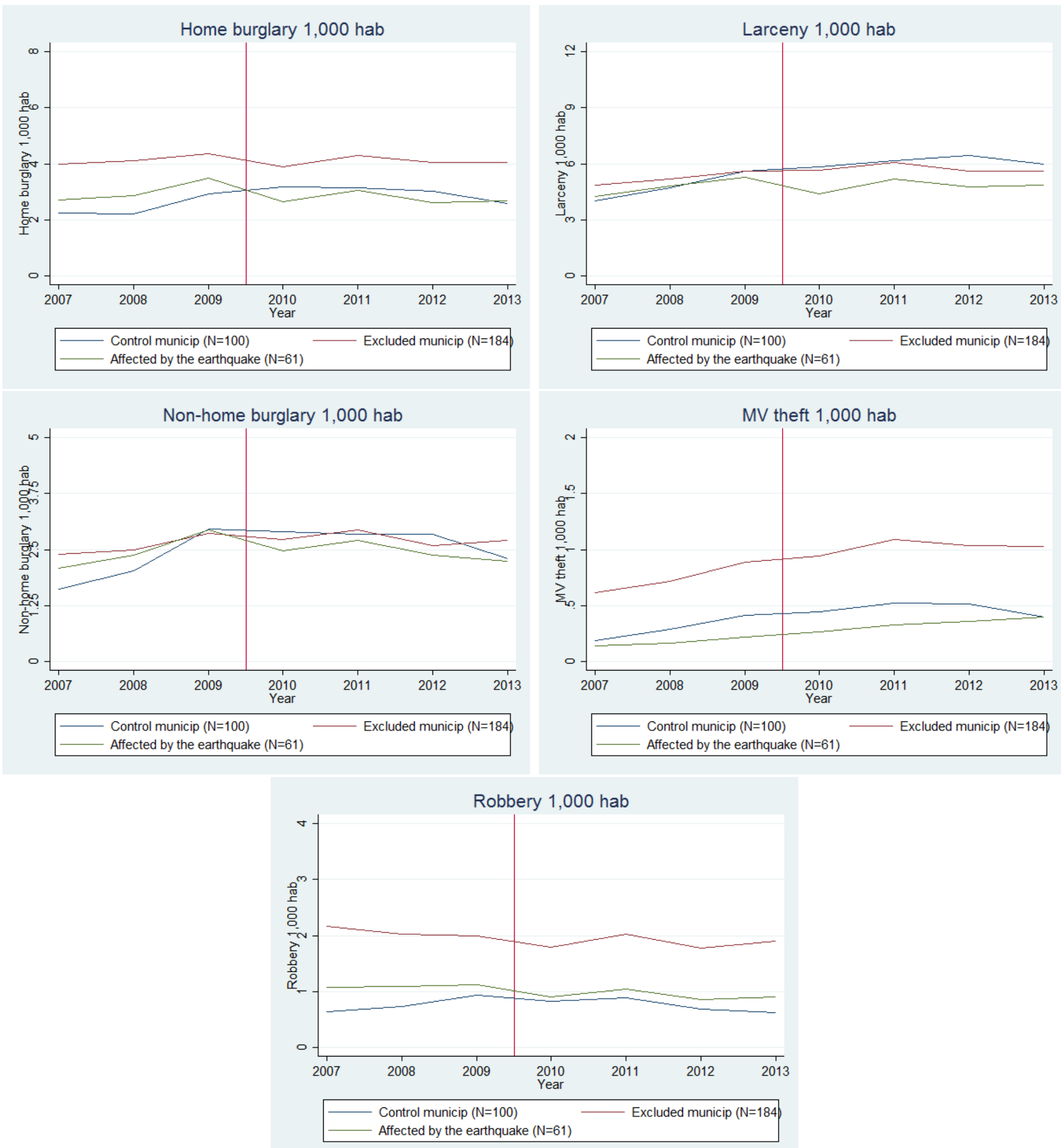
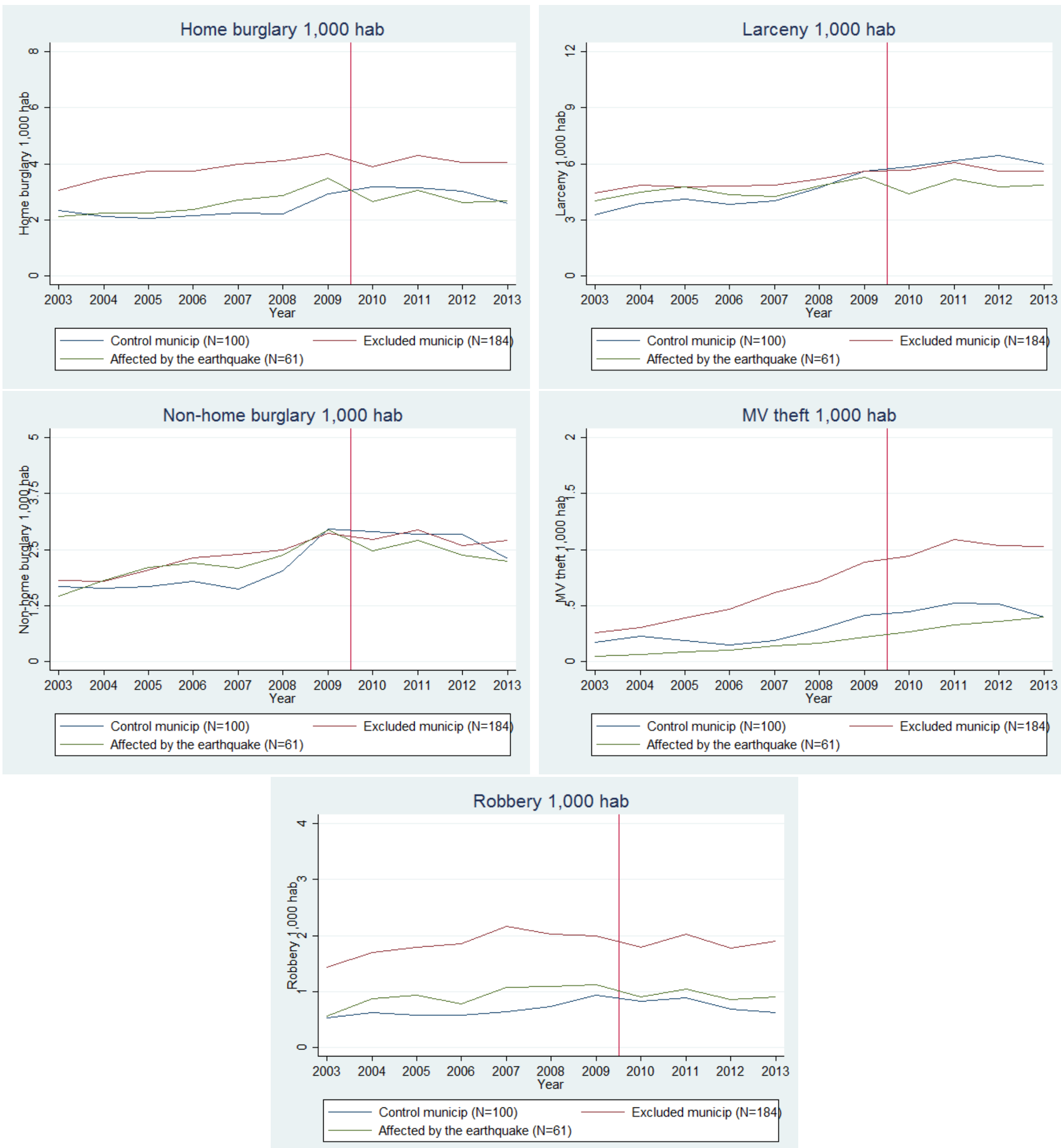


Figure 7: Incidence of crime over time (SPD data 2003-2013)



A 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 IX (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, monuments 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 an 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 chimneys 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

B Maps: Treatment, Control and Excluded Municipalities under the Use of Different Distance Thresholds

Figure 8: Treatment and Control areas

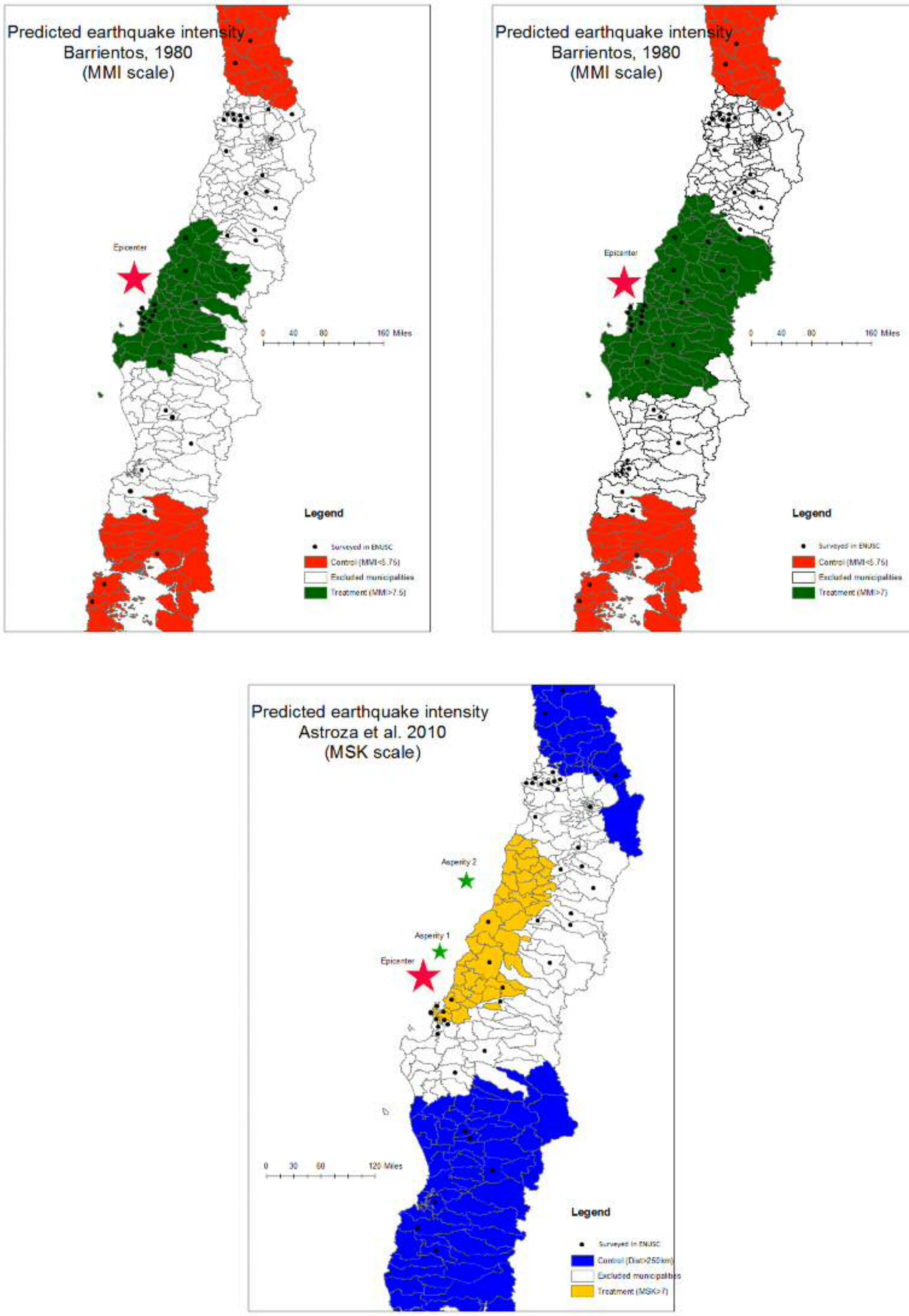
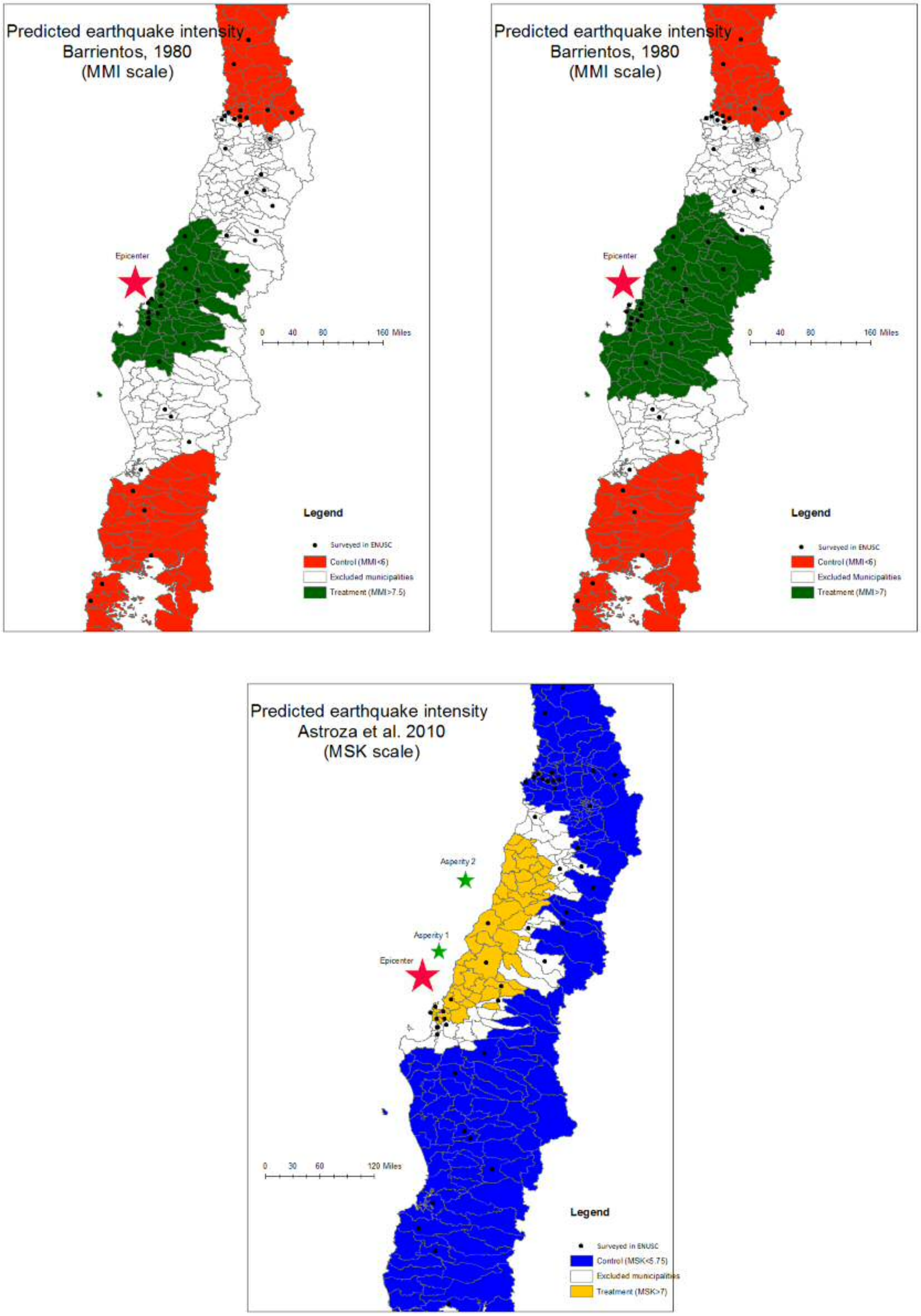


Figure 9: Treatment and Control areas



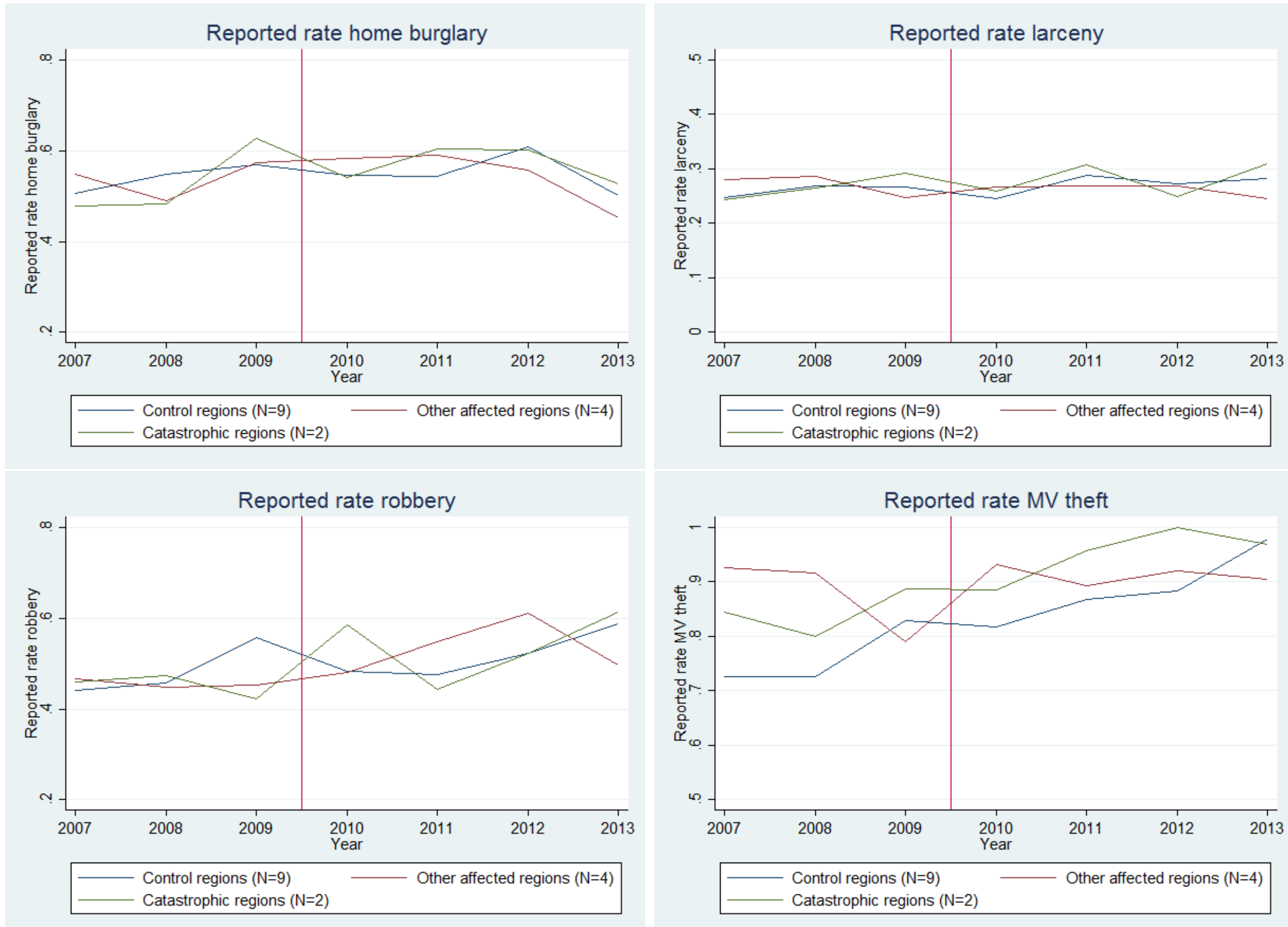
C Reporting Rate for Different Types of Crime (ENUSC Data): Analysis at the Regional Level

Table 11: Effect of the earthquake on the probability of reporting a crime to the police and mean reporting rates (regional level analysis)

	Share crime reported to the police
POST × Catastrophic regions	0.021
	(0.020)
POST × Other affected regions	-0.014
	(0.019)
Type of crime fixed effect	Yes
N Observations	412
$R2$	0.688
Type of crime	**Share reported to the police**
Home burglary	0.546
Larceny	0.268
Motor vehicle theft	0.862
Robbery	0.504

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

Figure 10: Evolution of reporting rate by type of crime (ENUSC data)



D Additional Graphs

Figure 11: Effects of the earthquake on home burglary over time (ENUSC data): Different thresholds used to construct treatment and control municipalities