What Is the Causal Effect of Poverty on Property Crime? Evidence from Chile

Jorge García Hombrados*

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Abstract

In February 27th 2010, an earthquake Richter magnitude 8.8 affects the south of Chile leading to increases in poverty rates in municipalities of the south and the center of Chile. This study exploits the variation in the exposure of Chilean municipalities to this exogenous income shock combining instrumental variables and spatial panel econometric models to investigate the causal effect of poverty on property crime at the municipality level in Chile. Preliminary results show that once endogeneity and spatial dependence are accounted for, poverty has a strong and significant effect on property crime, measured as incidence of car thefts. A 10 percentage points increase in poverty incidence increases in 54 the number of car thefts per 100,000 inhabitants. Furthermore, the study shows that the incidence of property crime of a municipality is not only affected by its poverty level but also by the level of poverty in neighbour municipalities. The significance of the effect of poverty on property crime is robust to alternative specifications, econometric models and to other robustness checks.

*University of Sussex

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1 Introduction

Crime is an act or omission which constitutes an offence and is punishable by law[1]. Thus, the acts that constitute crime differ across countries and time along with the law. Nonetheless, in practical terms, the acts that constitute crime are largely common across cultures and time (Miller, 2009). Different studies show that crime imposed large costs on society burdening development. For example, Daniele and Marani (2008) and Levantis and Azmat (2000) find evidence of a negative effect of crime on productivity and Bartel (1974) shows that crime decreases entrepreneur activity. Also, crime may cause over-investment in crime protection mechanisms (Clotfelter, 1977) and may lead to sub-optimal migration decisions (Cullen and Levitt, 1999). More generally, Morrison et al. (2005); Powdthavee (2005); Kumar (2013); Mehlum et al. (2005) and Walberg et al. (1998) present evidence of strong negative effects of property and violent crime on human development and human well-being in different settings. The evidence also suggests that the negative effects of crime might be larger for poor people (Fafchamps and Moser, 2003), particularly in low- and middle-income countries (Soares and Naritomi, 2010). The large social and private costs of crime reveal the importance of understanding the determinants of crime for policy making. This is indeed a priority in the policy agenda of many low- and middle-income countries, particularly in Latin America, the world's region with highest crime rates (Soares and Naritomi, 2010).

Although many typologies has been developed, most of the literature divided crime in three main categories: crimes against persons, property and society (Miller (2009); FBI (2012)). Although the negative effects of all types of crime are well established in the literature, each of these types of crime may operate through a different mechanisms and may also differ in some of their causes. This study focuses on examining the determinants of crime against property or property crime, which are those crimes in which the object is to obtain money, property or some other benefit. Particularly, the paper assesses whether poverty is a relevant determinant of property crime.

Together with urbanization and inequality, poverty is commonly believed to be a key explanatory factor of property crime. However, the estimation of the causal effect of poverty on property crime is empirically complex for different reasons. First, the link between poverty and property crime might be affected by reverse causality. For example, poverty may boost property crime through decreasing the opportunity cost of legal activities. However, property crime may also foster poverty through discouraging business (Fafchamps and Minten, 2006). Second, the relation between property crime and poverty might be also driven by omitted factors affecting both crime and poverty. For example, Fafchamps and Minten (2006) remarks that individuals with high predisposition for crime are likely to lack some non-cognitive skills (e.g. discipline) that could reduce their employability, arguably affecting the likelihood of poverty. Third, Soares (2004) shows that most of the studies that assess the effect of poverty, income or inequality on crime use administrative data on crime. However, the existence of measurement error in the administrative data on crime due to lack of crime report to police is well established in the literature for most types of crime (Soares, 2004). If the magnitude of measurement error in administrative data on property crime is significantly correlated with poverty (e.g. the probability of reporting a property crime given its occurrence is larger in non-poor areas),

[1]This is the crime definition in the Oxford Dictionary

the use of administrative data on property crime would bias the estimation of the effect of poverty on property crime. Indeed, Soares (2004) provides strong evidence of a large negative correlation between reporting rates of crime and income at a country level calling for caution when using administrative data on crime to examine the link between crime and poverty. Finally, criminals' mobility between municipalities (Buonanno et al., 2009) and the interaction of agents such as copycatting or peer group effects across near spatial units (Anselin et al., 2000) may lead to a problem of spatial dependence. Spatial dependence would arise if the incidence of property crime in a municipality also depend on the incidence of property crime and the characteristics of neighbour municipalities. If not accounted for adequately, spatial dependence would render the estimate of the effect of poverty on property crime biased and inconsistent (Anselin et al., 2000). Any attempt to assess empirically the causal effect of poverty on property crime needs to address the potential existence of these problems.

This study uses instrumental variables, spatial panel models and a combined spatial two stage least squares estimator to overcome the methodological problems enumerated above and estimate the unbiased causal effect of poverty on property crime at the municipality level in Chile. The paper is structured as follows. Section 2 reviews the literature on the link between poverty and crime. The Chilean context is described in section 3. Section 4 introduces the theoretical framework used in the analysis. Section 5 discusses the identification strategy used to estimate the causal effect of poverty on property crime. The data is introduced in section 6. Section 7 discusses the validity of the instrumental variable and presents descriptive statistics and the results of the impact effects. Section 8 tests the robustness of the results to different hypothesis and alternative definitions of key variables. Section 9 discusses the policy implications of the results and concludes.

2 Literature Review

Assessing the determinants of total and property crime in developed and developing countries is at the top of the research agenda of academics of many disciplines. One of the main contributions from economist to the study of crime determinants is the introduction of cost-benefit analysis of participation in illegal activities. Ehrlich (1973) was the first study using this approach. The study by Ehrlich develops an empirical model of participation in illegal activities that sets the theoretical framework of most of current research on the assessment of crime determinants (Fafchamps and Minten, 2006).

Following the Ehrlich approach, most of the literature since the 70's has focused on examining three main property and total crime factors that are believed to affect substantially the costs and benefits of crime: urbanization, inequality, and poverty. Urbanization may affect all types of crime through making crime detection more difficult, and thus, through decreasing the cost of crime (Fafchamps and Minten, 2006). Most of the empirical studies show a strong and positive association between urbanization and crime (see Soares (2004)), at least in developed countries. However, there are some rigorous studies in low-income countries with opposed results. For example, using data from Madagascar, Fafchamps and Minten (2006) shows that isolation seems to increase homicide rates and some property crime such as crop theft. Although more evidence is needed, the results of Fafchamps and Minten (2006) may indicate that urbanization has a different effect on crime in developed and developing countries.

There are different paths through which inequality may have an effect on property crime. First, inequality might be capturing the differential returns to criminal activity. In other words, larger inequality may increase the relative returns to illegal activities (Demombynes and Ozler, 2005). Second, through increasing relative deprivation and frustration, inequality may positively affect all types of crime (Demombynes and Ozler, 2005). Overall, most of the empirical studies suggest the existence of a strong association between inequality and property and violent crime (e.g. Eberts and Sehwirian (1968); Tullock (1976); Jacobs (1981); Carroll and Jackson (1983); Fowles and Merva (1996); Fajnzylber et al. (2002); Lederman et al. (1998); Soares (2004))). However, the results are not homogeneous and there are also some studies which do not find any significant association or even suggest a negative association between total crime and inequality (e.g. Allen (1996); Williams (1984); Stack (1984); Patterson (1991)).

In opposition to inequality and urbanization, the cost-benefit framework develop by Ehrlich predicts an ambiguous effect of poverty incidence on property crime. On the one hand, enrollment in illegal activities could be a smoothing strategy for poor individuals with little facilities to enter in the labor market and thus, with higher relative returns to illegal activity. The latter would lead to a positive link between poverty and property crime (Fafchamps and Minten, 2006). Also, detection of criminals in poor areas is often more difficult, thus decreasing the costs of crime and fostering a positive relation between poverty and all types of crime (Freeman, 1996). Because they have lower returns to legal jobs, poor people may also have lower opportunity costs for time in prison and thus, lower expected costs for all types of crime (Eide et al., 2006). On the other hand, a higher risk-aversion among poor people may induce a negative relation between poverty and all types of crime (Ehrlich, 1973). Also, the commission of property crime in non-poor areas may arguably yield higher economic benefits than in poor areas although the investments in crime protection might be also larger in the former. Finally, economic fines associated to apprehension might discourage particularly poor people which may have more difficulties to comply with these fines, implying larger relative costs for poor people if apprehended. Several studies aim to shed light on this ambiguous link by empirically assessing the effect on property and violent crime of different measures of poverty such as income, poverty incidence or unemployment with mixed results.

Most of the studies assessing the link between poverty and crime at a sub-national level (e.g. county, city, etc) suggest that poverty has little effect on both violent and property crime (see Dréze and Khera (2000); Krueger and Pischke (1997); Doyle et al. (1999); Kelly (2000); Blau and Blau (1982); Jarell and Howsen (1990); Freeman (1996); Oreopoulos (2003); Ludwig et al. (2001) and Chiu and Madden (1998)). Because crime determinants might be different in developed and developing countries (Fafchamps and Minten, 2006), it is important to highlight that these studies are set in the USA or other high-income countries. Although increasingly available, the evidence on the causal effect of poverty on crime in low- and middle-income countries is still very small and the results are heterogeneous. Exploiting an unusual and unexpected sequence of political and social events leading to an unexpected poverty shock in Madagascar, Fafchamps and Minten (2006) find evidence of significant and positive effects of transitory poverty on some property crime such as crop thefts. On the other hand, the study failed to find any significant effect of transitory poverty on other property crime such as cattle theft or on other type of crime offences such as homicides. Clearer patterns of results are found in a recent study in India. Using district panel data from India and exploiting exogenous variation in district exposure to national trade reforms and rainfall shocks, Iyer and Topalova (2014) shows that poverty has a positive and significant effect on both property and violent crimes. In line with Iyer and Topalova (2014) results and using panel data for Russia, Ivaschenko et al. (2012) shows relevant and significant positive effect of poverty on property, economic and violent crime. On the other hand, Dréze and Khera (2000) -also using district data in India- does not find any relevant effect of poverty on homicides.

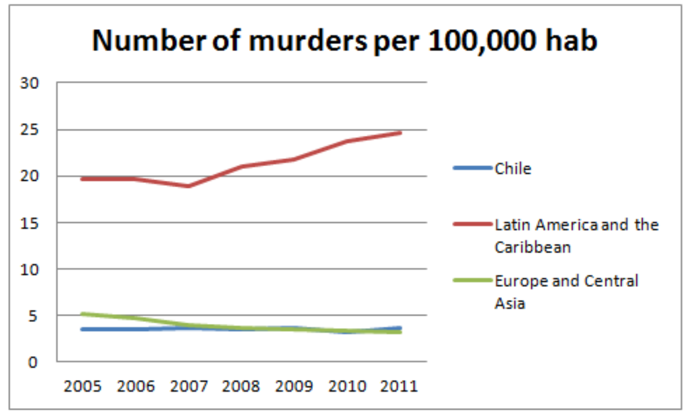
An alternative to assess the link between poverty and crime is through the use of country level analysis. Overall the results of these studies suggest that while income seems to have a positive effect on property crime (e.g. Wellford (1974); Wolf (1971); McDonald (1976); Stack (1984)), it seems to have a negative effect on violent crime (e.g. Krohn (1978); McDonald (1976); Wellford (1974)). However, Soares (2004) calls for caution when interpreting the results of these studies due to their use of cross-country administrative data on crime. The paper argues that particularly for property crime, the strong positive association between income and property crime at the country level might be driven by higher rates of crime report to police in richer countries rather than by true higher rates of crimes. Indeed, Soares (2004) provides strong evidence of a positive correlation between income and property crime reporting at an international level and shows that when the reporting error is accounted for, the effect of income on property crime is indeed negative.

To sum up, the literature suggest a small or negligible effect of poverty on property crime in developed countries. On the other hand and although not homogeneous and still scarce, the existing evidence points to a positive link between poverty and property crime in low- and middle-income countries. Furthermore, this positive link seems to be stronger in those studies with sound identification strategies (e.g. Iyer and Topalova (2014);Ivaschenko et al. (2012)).

In addition to the reporting error problem highlighted by Soares (2004), there are other methodological difficulties that complicate the estimation of the causal effect of poverty on property crime. First, the link between poverty and property crime might be affected by reverse causality. For example, poverty may boost property crime through decreasing the opportunity cost of legal activities. However, property crime may also foster poverty through discouraging business (Fafchamps and Minten, 2006). Second, the relation between property crime and poverty might be also driven by omitted factors affecting both crime and poverty. For example, Fafchamps and Minten (2006) remarks that individuals with high predisposition for crime are likely to lack some non-cognitive skills (e.g. discipline) that could reduce their employability, arguably affecting the likelihood of poverty. Third, criminals' mobility between municipalities (Buonanno et al., 2009) and the interaction of agents such as copycatting or peer group effects across near spatial units (Anselin et al., 2000) may lead to a problem of spatial dependence. Spatial dependence would arise if the incidence of property crime in a municipality also depend on the incidence of property crime and the characteristics of neighbour municipalities. If not accounted for adequately, spatial dependence would render the estimate of the effect of poverty on property crime biased and inconsistent (Anselin et al., 2000). All these methodological issues lead to a large skepticism and caveats in the literature on

Figure 1: Evolution of crime in Chile

Source: ENUSC survey



Source: World Bank Data

what it is known about the causal effect of poverty on crime (Bourguignon (2000); Fajnzylber et al. (2002)). To the best of our knowledge, this is the first sub-national study that aims to estimate the effect of poverty on property crime using an identification strategy to account for the described methodological problems in a low- and middle-income country.

3 The Context

Chile is a middle-income country with a GDP p/c of $USD 15,458 in 2012[2]. Since the end of Pinochet's dictatorship in the late 80's, Chile has experienced more than two decades of large improvements in almost all the development and democracy indicators leading to its admission in the OECD in January 2010. Nonetheless, Chilean society still faces key challenges including large rates of inequality and poverty incidence (Contreras, 2011). For example, the 14% of the Chileans live below the national poverty line [3] and Chile presents the highest Gini coefficient in the OECD. The fight against inequality and poverty is currently a hot topic in the Chilean political discussion and the flagship of the political coalition that win the national elections in March 2014 promising fiscal and educational reforms to address inequality and poverty.

The survey Public Opinion in Chile conducted annually by the Centro de Estudios Públicos (CEP) shows that crime is the first worry for most Chileans since 2008. This worry is particularly intense among the poor, which seems to be the group most affected by crime. Despite the worry of Chilean people about crime, Chile presents by far the lowest crime incidence among Latin American countries for almost all types of crime according to the World Bank data. For example, the crime rate in Brazil -a middle-income South American country with large GDP growth rates in the last decade- doubles the crime rate in Chile. Figure 1 presents the evolution of crime rates in Chile.

[2]World Bank data
[3]CASEN 2011

4 Theoretical framework

This section presents an individual utility maximization framework based on the seminal paper Ehrlich (1973) as the departing theoretical framework to assess the causal effect of poverty on property crime. In this utility maximization framework, individuals choice to allocate their given time to a combination of non-market activities c, illegal market activities or property crime i and legal market activities l. For simplicity, no entry costs are required in any of these activities. The returns to illegal market activities or property crime depends on two possible states of the world s, apprehension of the individual a and getting free with property crime n. If an individual engage into illegal market activities ($t_i > 0$), apprehension occurs with a probability p_i. In case of apprehension a, the returns to illegal market activities are $Q_i(t_i)$ minus a discounted pecuniary or equivalent fine $F_i(t_i)$. If the individuals get free with property crime, they do not receive any fine. In this state of the world n, which occurs with probability $(1 - p_i)$, the returns to illegal activities are $Q_i(t_i)$. The returns to legal market activities are denoted by Q_l and they are independent of the state of the world s.

Individuals are assumed to behave rationally and maximize the following utility function:

$$U_s = U(R_s, t_c, K(t_i)) \tag{4.1}$$

where U() is the indirect utility function of individuals, R_s denotes the asset production functions in each of the states s, t_c indicates the time dedicated to non-market activities and K is a direct function of t_i and represents the direct loss of utility associated to engaging in illegal market activities. Note that unlike $F(t_i)$, the reduction in utility linked to participation in illegal market K is associated to factors such as moral conscience and it is independent of whether or not the individual is apprehended. K is assumed to depend on t_i and to have a concave functional form.

The following two equations present the asset production function R_s in the different states of the world. Equation 4.2 shows the stock of assets in the state n (getting free with property crime), which occurs with a probability $(1 - p_i)$, and equation 4.3 shows the stock of assets in the state a (apprehension), which occurs with probability p_i. In both equations, Q' is the market value of the individual's assets.

$$R_n = Q' + Q_i(t_i) + Q_l(t_l) \tag{4.2}$$

$$R_a = Q' + Q_i(t_i) + Q_l(t_l) - F_i(t_i) \tag{4.3}$$

In this framework, the individuals decide the time they dedicate to illegal market activities, legal market activities and non-market activities through maximizing the expected utility presented in equation 4.4 with respect to t_c, t_i and t_l, subject to the asset production functions 4.3 and 4.2 and the time and non-negativity restrictions set in equations 4.5 and 4.6.

$$EU(R_s, t_c, K) = p_i U(R_a, t_c, K(t_i)) + (1 - p_i) U(R_n, t_c, K(t_i)) \tag{4.4}$$

$$t_0 = t_i + t_l + t_c \tag{4.5}$$

$$t_i \geq 0; t_l \geq 0; t_c \geq 0. \tag{4.6}$$

Kuhn-Tucker first order optimality conditions for the previous maximization problem are stated in the following equations:

$$\frac{\partial EU}{\partial t} - \lambda \leq 0$$

$$\left(\frac{\partial EU}{\partial t} - \lambda\right) t = 0 \tag{4.7}$$

$$t \geq 0$$

where t stands for the optimal values of each of t_i, t_l and t_c, and λ is the marginal utility of time spent in production of assets.

Given any value of t_c, the optimal allocation of time between legal and illegal market activities (l and i) in case of an anterior solution must satisfy the first order condition stated in the following equation:

$$-\frac{(\partial Q_i/\partial t_i) - (\partial Q_l/\partial t_l)}{(\partial Q_i/\partial t_i) - (\partial F_i/\partial t_i) - (\partial Q_l/\partial t_l)} = \frac{p_i U'(R_a)}{(1-p_i)U'(R_n)} \tag{4.8}$$

Equation 4.8 implies that an equilibrium involving some level of participation in illegal activities would require the relative marginal return to illegal activities $\partial Q_i/\partial t_i - \partial Q_l/\partial t_l$ to be positive. Furthermore, the utility of the relative marginal return to participation in illegal activities $U\left(\partial Q_i/\partial t_i - \partial Q_l/\partial t_l\right)$ should exceed utility of the marginal *moral* reduction in utility caused by participation in illegal activities $U(\partial K(t_i)/\partial t_i)$. Also, an equilibrium that involve some level of participation in legal activities would require the utility of the relative marginal return to illegal activities $U\left(\partial Q_i/\partial t_i - \partial Q_l/\partial t_l\right)$ to be smaller than the utility of the potential marginal fine plus the marginal *moral* reduction in utility caused by participation in illegal activities. Formally, the latter condition is expressed as follows: $U\left(\partial K(t_i)/\partial t_i + \partial F(t_i)/\partial t_i\right) > U\left(\partial Q_i/\partial t_i - \partial Q_l/\partial t_l\right)$.

Assuming that property crime rate in a given location is a direct function of the aggregation of the time participating in illegal activities of the e individuals living in the location $\sum_1^e t_i$, the framework predicts that the property crime rate depends on the marginal returns to legal market activities, the marginal returns to property crime, the probability of apprehension, the magnitude of the fine and the marginal *moral* reduction in utility caused by participation in illegal activities. Equation 4.9 formalises these relations:

$$Crime = C(\sum_1^e t_i) = \Phi(q_i, q_l, f, k, p_i) \tag{4.9}$$

where $Crime$ is the rate of property crime, q_i is the marginal return to property crime $\partial Q_i/\partial t_i$, q_l is the marginal return to legal market activities $\partial Q_l/\partial t_l$, f is the potential marginal fine associated to apprehension $F(t_i)/\partial t_i$, k is the marginal *moral* reduction in utility caused by participation in illegal activities $\partial \mathrm{K}(\mathrm{t}_i)/\partial t_i$ and p_i is the probability of apprehension.

The next step in the development of the theoretical framework is to determine how poverty relates with equation 4.9. First, poor people and poor areas arguably have lower marginal returns to legal market activities q_l than non-poor people and thus, relatively higher returns to property crime $q_i - q_l$. Second, detection of criminals in poor areas is often more difficult. In our framework, this implies lower p_i in poor areas. Third, lower q_l in poor areas would lead to lower opportunity costs for time in prison, implying that poor people may have lower f. Fourth, higher levels of risk aversion and more difficulties to cope with fines if apprehended may imply a higher f for poor people. Fifth, the commission of property crime in non-poor areas may arguably yield higher economic benefits than in poor areas implying higher q_i in non-poor areas. Additional factors could be also inserted in this framework. Population density, urbanization and number of policemen are strong determinants of p_i. Unemployment and education are arguably related with q_l. Social capital and urbanization are related with k and inequality is strongly related with the relative marginal return to illegal activities $q_i - q_l$.

The theoretical framework predicts unambiguously the direction of the effects of social capital, inequality, unemployment, education, population density and urbanization on property crime. On the other hand, the framework predicts an ambiguous effect of poverty on property crime. Whether the net effect of poverty on property crime is positive, negative or non-existent would depend on which mechanism dominates. While the first, second and third mechanisms described above would lead to a positive effect of poverty on property crime, the fourth and fifth mechanisms would lead to a negative effect of poverty on property crime. Thus, an empirical estimation is necessary to determine the sign and measure the effect of poverty on property crime and shed light on which mechanisms dominate.

Before dipping in the development of the identification strategy, it is worth to note that the utility maximization framework does not differentiate between individual's involvement in organised or non-organised crime. Because incentives are not different, the existence of organised crime does not invalidate the use of cost-benefit frameworks to assess the determinants of crime and similar theoretical frameworks have been used in seminal papers to understand determinants of both organised and non-organised crimes (e.g. Fafchamps and Minten (2006), Bourne (2011)). Nonetheless, organised crime presents some particularities that needs to be taken into account when investigating the link between poverty and crime. First, organised crime may restrict in the short run the incorporation of individual criminals to the same illegal activity (Fafchamps and Minten, 2006). Second, criminal organisations arguably have larger capacity to invest in crime success. The latter implies that criminal organisations may have better information and capacity to move to commit a crime. These particularities suggest that the existence of organised crime could lead (may be falsely) to a weaker relation between poverty and property crime rates, particularly if these are measured at small administrative levels. Thus, the existence of organised crime remarks the importance to account for the mobility of criminals to commit a crime in order to assess appropriately the link between poverty and any type of crime in a given administrative unit.

5 Identification strategy

The theoretical framework used in this study predicts an ambiguous effect of poverty on property crime and thus, an empirical estimation is needed to shed light on the direction of the net effect. In this section, the study presents the identification strategy used in the analysis to estimate the effect of poverty on property crime. The departing point of the analysis is the following equation:

$$Crime_{mt} = \alpha_1 Poverty_{mt} + \alpha_2 X_{mt} + \delta_m + v_{mt} \tag{5.1}$$

where $Crime_{mt}$ is the rate of property crime observed in municipality m at time t, $Poverty_{mt}$ is the incidence of poverty, X_{mt} is a vector of time-varying municipality controls including population, number of policemen, number of neighbourhood associations and percentage of rural population, δ_m captures municipality m time-invariant specific effects and v is the error term. The parameter β_1 would yield the effect of poverty on property crime. The parameters of equation 5.1 are estimated through a fixed-effects (FE) model and through a random-effects (RE) model. An alternative strategy to assess the effect of poverty on property crime is the use of a First-Difference (FD) model:

$$\Delta Crime_{mt} = \tau_1 \Delta Poverty_{mt} + \tau_2 \Delta X_{mt} + \Delta v_{mt} \tag{5.2}$$

in which the variables are differenced one period and the parameters are estimated through OLS. Whether the FE, RE or FD are more appropriate depend on whether δ_m is correlated with the explanatory variables and on the the serial correlation of the error term v_{mt} across time. If δ_m is correlated with $Poverty$ or X_{mt}, the RE model is not appropriate. On the other hand, the FE model requires the error term v_{mt} to be serially uncorrelated across time while the FD model requires v_{mt} to follow a random walk. The appropriateness of these models is explored in this study through the conduction of a Wooldridge test on serial correlation and a Robust Hausman test.

Nonetheless, the use of FD, FE and RE models presented above would be discouraged if the estimation presents a problem of spatial dependence. Criminals' mobility between municipalities (Buonanno et al., 2009) and the interaction of agents such as copycatting or peer group effects across near spatial units (Anselin et al., 2000) implies that the characteristics and property crime level of a municipality may affect the property crime levels of a neighbour municipality leading to correlation in the error term of these neighbour municipalities. The correlation in the error term of neighbour observations, commonly known as spatial dependence, renders the estimates biased and inconsistent if they are not adequately accounted for (Anselin et al., 2000). Overcoming this problem requires the use of spatial econometric models. The following equation presents a general specification of a spatial econometric model with panel data:

$$Crime_{mt} = \beta_1 Poverty_{mt} + \beta_2 X_{mt} + \beta_3 * W * Crime_{mt} + \beta_4 * D * Z_{mt} + \delta_m + v_{mt} \tag{5.3}$$

$$v_{mt} = \lambda * E * v_{mt} + u_{mt} \tag{5.4}$$

where u_{mt} is a normally distributed error term, W is the weighting spatial contiguity matrix based on one neighbour for the autoregressive component, D the weighting spatial contiguity matrix based on one neighbour for the spatially lagged independent variables, E the weighting spatial matrix based on one neighbour for the idiosyncratic error component and Z is a vector of variables including the whole set of independent variables ($Poverty$ and X).

There are three main spatial econometrics models, each of them addresses spatial dependence through a different empirical strategy. First, the Spatial Autoregressive (SAR) model formalizes the neighbour effects through including as a variable in the right hand side of the specification the values of the dependent variable in neighbour municipalities. The SAR specification is equivalent to equations 5.3 and 5.4 with $\lambda = \beta_4 = 0$

$$Crime_{mt} = \beta_1 Poverty_{mt} + \beta_2 X_{mt} + \beta_3 * W * Crime_{mt} + \delta_m + u_{mt} \tag{5.5}$$

Secondly, the Spatial Durbin (SMD) model formalizes the neighbour effects through including as additional variables in the right hand side of the specification the values of the dependent and independent variables in neighbour municipalities. The SMD specification is equivalent to equations 5.3 and 5.4 with $\lambda = 0$.

$$Crime_{mt} = \beta_1 Poverty_{mt} + \beta_2 X_{mt} + \beta_3 * W * Crime_{mt} + \beta_4 * D * Z_{mt} + \delta_m + u_{mt} \tag{5.6}$$

A third approach to deal with spatial dependence is through modeling the error term. This is the case of the Spatial Error Model presented below, which is equivalent to 5.3 and 5.4 with $\beta_3 = \beta_4 = 0$.

$$Crime_{mt} = \beta_1 Poverty_{mt} + \beta_2 X_{mt} + \delta_m + \lambda * E * v_{mt} + u_{mt} \tag{5.7}$$

This study estimates the effects of poverty on property crime through the three spatial panel models described above using maximum likelihood estimators. Then, in order to determine which of the spatial panel models fits better our data, the study follows the procedure described in Belotti et al. (2013)[4] to explore whether λ, β_4 and β_3 are individually or jointly equal to 0 and then, determine which model is more appropriate for estimating the effect of poverty on property crime in this study.

Nonetheless, two additional concerns may compromise the validity of spatial panel models to adequately assess the effect of poverty on property crime. First, it is commonly argued in the literature that not only poverty affects property crime but also that property crime might lead to poverty through for example discouraging business (Bartel, 1974) or lowering productivity (Daniele and Marani (2008). In presence of reverse causality between poverty and property crime, the non-spatial and spatial panel models presented above would yield a biased effect of poverty on property

[4]See also the authors post available at http://www.econometrics.it/?p=312&cpage=1#

crime. Second, the mentioned models would not yield the true causal effect of poverty on property crime if the relation between property crime and poverty is driven by a time-variant unobservable factor correlated with poverty and oroperty crime. An example of an unobservable variable driving the relation between property crime and poverty is presented in Fafchamps and Minten (2006). The paper highlights that individuals with high predisposition for crime are likely to lack some non-cognitive skills (e.g. discipline) that could reduce their employability, arguably affecting the likelihood of poverty.

To address the reverse causality and omitted variable problems in the spatial panel models, this study proposes the combination of an instrumental variable approach with a spatial panel model. The instrumental variable approach exploits the existence of a source of exogeneous variation in poverty to overcome the endogeneity of the poverty regressor. The instrumental variable proposed in this study is the variation in the exposure of municipalities to the exogenous shock on poverty caused by the earthquake occurred the 27th of February of 2010 in the South of Chile.

The proposed combined approach is a Spatial Two Stage Least Squares (S2SLS) estimator that allows for endogenous regressors and a spatial lag. This estimator is used in Anselin and Lozano-Gracia (2008) and Dall'erba and Gallo (2003). Currently, there is not any Stata command to do this. I am working on developing the Stata program. The results provided for this model in this draft are not accurate and some adjustments still need to be done to the program to report correctly the coefficients and the standard errors. The current version of the results is based on the incorrect procedure described in Buonanno 2009 In the first stage, the endogenous variable is regressed on the instrumental variable and on a set of control variables. In our case, poverty incidence is regressed on a set of municipality variables affecting poverty and on the instrumental variable; a set of exposure to earthquake dummies. Additionally, because the parameters of the spatial model will no longer be estimated through maximum likelihood, it is also necessary to instrument for the spatial lag of the dependent variable. This is implemented using the control variables and the spatial lag of the control variables as instruments for the spatial lag of property crime. Equations 5.8 and 5.9 present the specifications of the first stage equations:

$$Poverty_{mt} = \alpha + \gamma_1 EarthquakeIntensity_{mt} + \gamma_2 X_{mt} + \mu_{mt} \tag{5.8}$$

$$W * Crime_{mt} = \alpha + \psi_1 W * X_{mt} + \psi_2 X_{mt} + \mu_{mt} \tag{5.9}$$

where $EarthquakeIntensity_{mt}$ is a vector of dummy variables based on year and distance to epicenter aiming to measure earthquake intensity in a municipality at a given period, $W * Crime_{mt}$ is the spatial lag of the property crime and $W * X_{mt}$ are the spatial lag of the set of control variables X_{mt} presented earlier. Note that the years before the 2010 earthquake, all municipalities are assumed to have the same values for earthquake exposure regardless of their distance to the earthquake epicenter.

In the second stage of the SP2SLS procedure, property crime is regressed on the predicted values of poverty and on the predicted values of spatial lag of crime obtained in equations 5.8 and 5.9 and on the set of control variables using a FE Spatial Durbin specification, which is the model that demonstrates to better fit our data [5]. The specification of the second stage equation, is presented in equation 5.10:

$$Crime_{mt} = \omega_1 \widehat{Poverty}_{mt} + \omega_2 X_{mt} + \omega_3 * W * \widehat{Crime}_{mt} + \omega_4 * D * Z_{mt} + \delta_m + u_{mt} \quad (5.10)$$

where $\widehat{Poverty}_{mt}$ and $W * \widehat{Crime}_{mt}$ are the predicted values for poverty and spatial lag of property crime in equations 5.8 and 5.9. The effect of poverty on property crime is yield by the parameter ω_1.

The validity of a model involving the use of instrumental variables such as the S2SLS used in this study lies on two strong conditions: relevance and exogeneity of the instrument. The relevance assumption implies that the instrumental variable needs to be a strong and significant determinant of the endogenous variable. Particularly in small samples, failure to fulfill this condition -known in the literature as *the weak instrument problem*- would bias the instrumental variable estimation (Bound et al., 1995). In this study, the assumption implies that the variables measuring earthquake intensity are strong determinants of poverty. Besides, the relevance assumption can be tested empirically. A standard procedure to assess the fulfillment of the relevance condition is through conducting a joint F test for the instrumental variables in the first stage regression. If the value of the F-test is above 10 and the individual coefficients of the instrumental variables are significant at the 99%, the instruments are believed to be relevant (Staiger and Stock (1997); Wooldridge (2012)). The relevance assumption is formalized as follows:

$$corr(EarthquakeIntensity_{mt}, Poverty_{mt}) \neq 0 \quad (5.11)$$

The second validity condition is the exogeneity of the instrumental variable. The exogeneity condition requires the orthogonality of the instrumental variable to the error term in the second stage equation. In other words, the instrumental variable should only affect the main outcome variable through affecting the endogenous variable. Deaton (2009) discusses in detail the meaning of exogeneity. The paper argues that exogeneity requires not only that the instrumental variable is not affected by the outcome of interest, but also that the instrumental variable does not affect the outcome of interest directly or through a different mechanism other than through the endogenous variable. Unlike the relevance condition, the exogeneity condition cannot be tested empirically because an unbiased estimator of the error term is not available. Thus, fulfilling the exogeneity condition requires a convincing argument on why the instrument only affects the outcome of interest through affecting the endogenous variable. The exogeneity condition is formalized as follows:

$$corr(EarthquakeIntensity_{mt}, u_{mt}) = 0 \quad (5.12)$$

Section 7.1 discusses the exogeneity and relevance of the instrumental variable used in this study.

Finally, section 8 tests the robustness of the results to different hypothesis by re-estimating the effect of poverty on property crime using additional control variables, alternative definitions of

[5] please see discussion on appropriateness of different spatial panel model in the section Results

variables and excluding from the analysis municipalities that suffered a looting episode immediately after the 2010 earthquake.

6 The Data

6.1 Property Crime

The municipality data on property crime for the period 2007-2013 is obtained from the Subsecretaria de Prevención del Delito (SPD) in Chile. This institution, dependent from the Ministry of Government and Public Security, publishes municipality annual data on different types of offences including robbery, different types of theft, rape and homicides.[6].

It is important to note that the data published by the SPD includes the offences denounced by citizens to the police plus the offences that are denounced by the police (unmasked by the police while they are ongoing). Thus, if there are offences that are not reported to the police, crime incidence would be measured with error in this dataset.

Measurement error in property crime variables would bias the estimation of the effect of poverty on these variables if the probability of reporting a property crime to police is correlated with poverty (Fafchamps and Minten, 2006). The latter might arise if for example, in those municipalities with larger poverty incidence, the report of crime to the police is less likely. Using cross country data on crime and poverty, Soares (2004) shows that poverty is strongly correlated with report of crime at the national level.

Thus, it is important to check that the data and measures of property crime that are used in this study to assess the effect of poverty on property crime are not affected by a substantial measurement error correlated with poverty. In order to asses the validity of different measures of property crime in the SPD data, I first explore the extent of reporting to police of different property crimes available in the SPD data: car theft, car accessory theft, distraction theft, robbery and theft and a measure of total numbers of offences. The assessment of the extension of measurement error is conducted using available data from the Encuesta Nacional Urbana de Seguridad Ciudadana (ENUSC) for the period 2007-2013. The ENUSC is a victimization household survey representative at the municipality level that is conducted yearly by the Ministry of Government and Public Security in Chile in 101 municipalities.

Arguably, victimization surveys such as the ENUSC are not affected by imperfect crime report to police. Furthermore, ENUSC collects data also on whether each of the offences suffered by the household is reported to police. Table 1 presents the proportion of different crime measures including the number of car thefts, car accessory theft, distraction theft, aggravated robbery, theft and total number of offences that are reported to the police for the period 2007-2013. The results confirm that overall, less than 50% of the offences and thefts are reported to police. Nonetheless, an interesting exception emerge from the data: more than 90% of car thefts are reported to police. This result is in line with Buonanno et al. (2009), which find similar rates of reporting to police of car theft in Italy.

[6]The crime data are available at http://www.seguridadpublica.gov.cl/tasa$_{d}e_{d}enuncias_{y}{}_{d}etenciones.html$

The results presented in table 1 highlight the convenience of using car theft and discourage the use of the rest of property crime variables in the analysis. However, and although the measurement error in car theft seem to be small, it is also necessary to assess whether the latter, in addition to small, is uncorrelated with poverty. To assess this, the proportion of car thefts that are reported to police is regressed on poverty incidence. If poverty incidence has a significant effect on the proportion of car thefts that are reported to police, the administrative data on car theft might be affected by a reporting error that although small, is correlated with crime. The latter would bias the estimation of the effect of poverty on property crime. The approach used in this paper to assess the extension of the reporting error of car thefts and its correlation with poverty follows the strategy used in Soares (2004).

Table 2 presents the results of different specifications examining the link between poverty and proportion of car thefts reported to police in Chile. The table shows that the poverty coefficient is small in most of the specifications and statistically non-significant in all of them, meaning that at the municipality level, poverty levels do not seem to be correlated with probability of reporting a car theft. These results validate the use of SPD data on car theft as an adequate property crime variable to examine the effect of poverty incidence on property crime.

Table 1: Reported Rates of different Crimes in 101 Municipalities in Chile - Panel Data (2007-2013)

	N	Mean	Standard Deviation	Minimum	Maximum
Reported rates of total crime	702	0.36	0.09	0.12	0.72
Reported rates of car theft	702	0.93	0.21	0	1
Reported rates of car accessory theft	702	0.31	0.16	0	1
Reported rates of distraction theft	702	0.33	0.21	0	1
Reported rates of aggravated robbery	702	0.48	0.21	0	1
Reported rates of theft	702	0.27	0.13	0	1

Note: The descriptive statistics are presented using ENUSC data at the municipality level for a total of 101 municipalities during 7 years (2007-2013).

Table 2: Determinants of reported rates of car theft in 101 Municipalities in Chile - Different specifications for Panel Data (2007-2013)

	Reported rate car theft	Reported rate car theft	Reported rate car theft	Reported rate car theft
Poverty incidence rate	0.042	-0.506	0.000	-0.321
	(0.181)	(0.437)	(0.187)	(0.484)
Ln of population			0.340	0.180
			(0.205)	(0.214)
Ln policeman per 100.000 hab			0.039	0.026
			(0.030)	(0.031)
N° of neighborhood associations per hab			-2.272**	-2.135**
			(0.979)	(0.989)
Constant	0.918***	0.977***	-3.184	-1.243
	(0.038)	(0.052)	(2.391)	(2.517)
Year fixed-effects	No	Yes	No	Yes
P-value joint F-test for year fixed effects		0.138		0.410
Observations	702	702	702	702
R-squared	0.000	0.012	0.012	0.019
Number of Municipio	101	101	101	101

*Note:**** p<0.01, ** p<0.05, * p<0.1 The descriptive statistics are presented at the municipality level for a total of 101 municipalities during 7 years (2007-2013).

Finally, note that although ENUSC data is superior to SPD data because the former is not affected by measurement error, it is only collected in 101 municipalities. Thus, although ENUSC data is adequate to quantify the extent of measurement error in SPD data and assessing whether the measurement error is correlated with poverty, its use is not appropriate in the main analysis because ENUSC data is not available for all municipalities and its use would restrict to less than one third the sample of municipalities in the analysis.

6.2 Poverty

The data on incidence of poverty is obtained from the Sistema Nacional de Información Municipal of Chile for the period 2007-2013 [7]. This institution, dependent from the Secretary of Regional and Administrative Development of the Government of Chile, publishes annual information at the municipality level on the number of people with a Social Protection Card. The Social Protection Card is given by municipalities to individuals that prove to be in a situation of risk of social

[7]The poverty data used for this study is available at http://www.sinim.cl/

exclusion, and not only to those below the poverty line. The Social Protection Card is a necessary condition to access social benefits such as free health attention or government cash transfers; and thus, there are large incentives for poor people to apply for a Social Protection Card. Also, it is important to note that the requirements to access the Social Protection Card are determined by the central government and are the same in all municipalities[8]. On the other hand, recent news reveal some notorious cases of non-poor people having a Social Protection Card [9]. The extent of the error in the delivery of Social Protection Cards in Chile remains unknown but is not believe to be large This is information I obtained talking with people in the Social Deverlopment Ministry. I have applied for specific numbers on this...still waiting and following up. In this study, the rate of Social Protection Cards in each municipality is used as the measure of poverty incidence.

6.3 Earthquake data

The 27th of February of 2010 at 03:34:08 local time an earthquake of 8.8 degrees in the Richter Scale shook the South of Chile. The epicenter was located at the geographical coordinates 36°17′23″ S and 73°14′20″ O, in front of the Chilean coast and approximately 90 km north west of Concepción, the second largest Chilean city. The earthquake and the tsunami following the earthquake causes 525 casualties (MIC, 2011) and economic losses estimated in USD 15,000-30,000 millions (UNEP, 2011). Although the economic losses affected a total of 6 regions, the regions of Biobio, Maule and Libertador O'Higgins were particularly affected (Larranaga and Herrera, 2010).

The Oficina Nacional de Emergencia del Ministerio del Interior y Seguridad Pública (ONEMI), dependent from the Chilean Ministry of Government and Public Security, is a public institution that studies the seismic activity in Chile. The ONEMI publishes for each earthquake in Chile the geographical coordinates of the epicenter and its magnitude using the Richter magnitude scale. This study uses municipality exposure to the 2010 earthquake shock based on year and distance to epicenter as the instrumental variable in the analysis.

However, the construction of variables aiming to measure exposure to the earthquake shock based on year and distance to the epicenter should be conducted with caution. Although the seismic incidence does not only depend on distance to epicenter but also on topographical factors, distance is a pretty well indicator of the Earthquake incidence (see CEPAL (2010);Larranaga and Herrera (2010)). Nonetheless, the relation between distance and exposure to shock is not linear. For example, after a certain distance, the earthquake incidence does not increase with distance to the epicenter. To cope with this problem, I construct a set of dummies to capture different levels of exposure to the Earthquake shocks. I code a dummy variable that has the value of 1 if the municipalities are below 200 km far from the epicenter for years 2010, 2011, 2012 and 2013 and 0 otherwise. These municipalities in these years are believed to be strongly affected by the 2010 earthquake shock. Then, I code a dummy variable that has a value of 1 if the municipality is above 200km and below 450km far from the epicenter for years 2010, 2011 and 2012 and 2013 and 0 otherwise. These municipalities in these years are believed to be moderately affected by the

[8]For details on the requirements to access to a Social Protection Card see http://www.fichaproteccionsocial.gob.cl/

[9]see http://www.emol.com/noticias/nacional/2014/03/17/650270/gobernadora-de-chiloe-sera-sumariada-por-su-polemica-ficha-de-proteccion-social.html

2010 earthquake shock. Municipalities above 450 km far from the epicenter are assumed not to be affected by the 2010 earthquake. Also, for the years 2007, 2008 and 2009, all municipalities are assumed to be not affected by the earthquake regardless of their distance to the earthquake epicenter. The selection of these distance thresholds for constructing the set of earthquake exposure dummy variables was based on the report CEPAL (2010) and on a personal communication with José Lopez, from ONEMI[10]. According to these sources, and although the exact Mercalli incidence might depend on the type of land, overall, the municipalities in a radio of 200 km were exposed to a seismic incidence of VIII in the Mercalli intensity scale[11]. Also, the municipalities in a radio above 200 km and below 450 km are overall exposed to a seismic incidence of VII in the Mercalli intensity scale[12]. Municipalities above 450 km far from the epicenter are overall exposed to a seismic incidence of less than VII in the Mercalli intensity scale. Below a seismic incidence of VII, the dwelling and civil constructions were not exposed to several damages and thus, I assume that poverty in these regions is not substantially affected by the earthquake. Figure 1 illustrates the municipality exposure to the earthquake shock according to our set of distance variables.

Section 8 tests the robustness of the results using directly the Mercalli intensity rather than distance to epicenter as the variable to measure exposure to the 2010 earthquake. The Mercalli intensity dataset is constructed by the author using the maps and information available in the United States Geological Survey (USGS)[13], which are not release at the municipality level and thus the Mercalli dataset constructed is not entirely accurate.

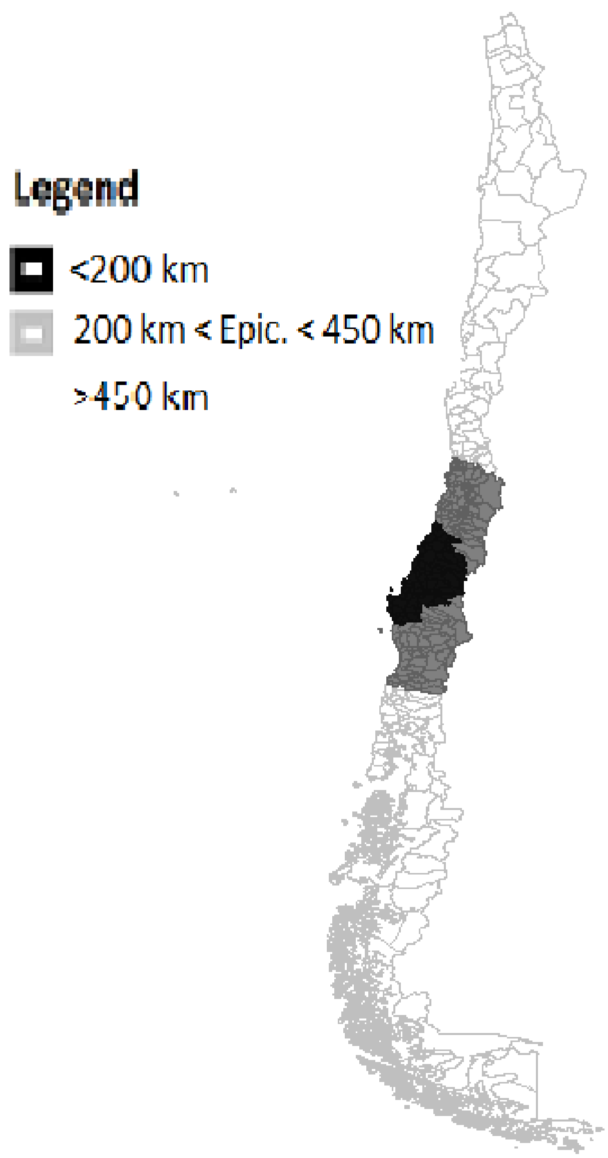
[10]Email:jlopez@onemi.gov.cl Telephone:(562) 22524366

[11]VIII Mercalli Scale: Damage slight in structures of good design, considerable in normal buildings with a possible partial collapse. Damage great in poorly built structures. Brick buildings easily receive moderate to extremely heavy damage. Possible fall of chimneys, factory stacks, columns, monuments, walls, etc. Heavy furniture moved.

[12]VII Mercalli Scale: Difficult to stand. Furniture broken. Damage light in building of good design and construction; slight to moderate in ordinarily built structures; considerable damage in poorly built or badly designed structures; some chimneys broken or heavily damaged. Noticed by people driving automobiles.

[13]http:earthquake.usgs.govearthquakespagereventsus2010tfanindex.html#cities

Figure 2: Municipality exposure to the February 27th 2010 Earthquake: Dist<200km; 200km<Dist<450km; Dist>450km



6.4 Control variables

In the analysis, the study also uses yearly information on municipality factors and characteristics that might be correlated with poverty incidence and demonstrated to be strong determinants of property crime in other studies. These municipality factors and characteristics include percentage of rural population, total population, number of policemen per 100,000 inhabitants and number of neighbourhood associations per 100 inhabitants as a proxy for social capital for the period 2007-2013. The information on these municipality characteristics is used in the regression equations as control variables. The information on total population, percentage of rural population and number of neighbourhood associations per 100 inhabitants is published by the Sistema Nacional de Información Municipal of Chile for the period 2007-2013 [14]. The information on the number of policemen per 100,000 inhabitants has been facilitated by the National Direction of Carabineros of Chile.

Section 8 tests the robustness of the results to the inclusion in the specification of additional control variables including gini index as a proxy for inequality, rate of male aged 15-29, unemployment rate and percentage of population with secondary education. These variables are constructed using the CASEN household surveys[15] applied in the years 2009 and 2011. Unfortunately, this information is not available yearly but only for two years in the period 2007-2013.

7 Results

7.1 Discussion of the Instrumental Variable

Section 5 presented the two validity conditions that an instrumental variable needs to satisfy: relevance and exogeneity.

The relevance assumption implies that the instrumental variable needs to be a strong and significant determinant of the endogenous variable. In this study, the assumption implies that the level of exposure to the earthquake shock substantially affects the incidence of poverty at the municipality level. Although the Chilean Government has conducted different reconstruction programmes, there is little doubt that the earthquake Richter magnitude 8.8 increased poverty in the areas around the epicenter. Different reports from the Chilean government, NGO's, Universities and International Organizations have tried to quantify the damages caused by the earthquake. For example, MIC (2011) reports that the earthquake and the tsunami that followed the earthquake caused a total of 525 casualties and 25 people missing. UNEP (2011) quantifies the economic damage of the earthquake in USD 15,000-40,000 millions, including 440,000 houses with severe damages (CEPAL, 2010). Although it was felt in all the country, the earthquake particularly affected six regions of the country: Maule, Biobio, Metropolitan Region of Santiago, Valparaíso, Araucanía and Libertador Bernardo O Higgins, including the 80% of the population (Larranaga and Herrera, 2010). Among these regions, Biobio, Maule and Libertador O'Higgins were the most damaged in terms of casualties and economic losses (Larranaga and Herrera, 2010).

[14]The data is available at http://www.sinim.cl/

[15]The data is available at http://www.ministeriodesarrollosocial.gob.cl/casen/bases$_d$*atos.html*

Furthermore, the relevance assumption can be tested empirically. A standard procedure to assess the fulfillment of this assumption is through checking the significance of the instrumental variables coefficients in the first stage regression. The coefficients of the instrumental variables in table 7 are largely statistically significant, with individual p-values<0.01 and a F-value for a joint significance test of instrumental variables well above 10; the relevance threshold typically used in the academia (Staiger and Stock (1997); Wooldridge (2012)). These results are in line with the reports from the Chilean government and other institutions that highlight the incidence of the earthquake on poverty, and remark that the instrumental variable selected fulfill the relevance condition.

On the other hand, the exogeneity condition requires that the instrumental variable should only affect the main outcome variable through affecting the endogenous variable. Thus, the exogeneity condition implies that exposure to earthquake should only affect property crime through increasing poverty. Since the exogeneity condition cannot be tested empirically, exogeneity condition requires a convincing argument on why exposure to earthquake only affects property crime through affecting poverty.

An earthquake is a complex phenomena and one may argue that exposure to earthquake may affects crime through other mechanisms. First, an earthquake generates immediate conditions such as temporary cuts in light or chaos situations that may temporally decrease the costs of all types of crime. Although this situation only last for some hours or a day, temporary increases in crime due to a temporary decrease in crime costs may lead to permanent increases in property crime. Second, given the lower quality of poor people assets and particularly dwellings, an earthquake would increase inequality through affecting more severely the assets and dwellings of poor people. Third, most of the reconstruction and humanitarian aid are delivered through neighbourhood councils, providing incentives for collaboration and organization among neighbours and arguably leading to increases in social capital. Fourth, the large damage on dwellings and assets caused by an earthquake may lead to migration in search of social networks protection, thus, decreasing population in affected areas and increasing cost of crime in those areas. Fifth, the government may deviate temporary or permanently police forces towards affected municipalities in order to prevent looting or chaos situations in affected areas. If inequality, social capital, population density, number of policemen and immediate temporary increases in crime are determinants of permanent property crime, the fulfillment of the exogeneity condition would require that the February 27th 2010 earthquake used as instrumental variable does not affect these factors other than through affecting poverty.

I test the previous channels as follows. First, the study uses monthly based administrative data on car theft and total crime to explore whether the earthquake lead to immediate transitory increases in crime. For this, the study regresses changes in total crime and car thefts between February 2010 and March 2010 at the municipality level on earthquake intensity. Furthermore, the study examines graphically the evolution of car theft and total crime the months immediately before and after the earthquake by exposure to the earthquake. Second, I test the inequality mechanism through regressing changes in the Gini index at municipality level between 2011 and 2009 on earthquake intensity. Third, the paper examines the social capital mechanism through regressing the change in the number of associations per 100 inhabitants at the municipality level between 2010 and 2009 on the earthquake intensity. Note that in this case, it is not possible to differentiate whether potential changes in social capital might be caused directly by the earthquake and its incentives for neighborhood cooperation or by any other mechanism (e.g. via changes in poverty if poverty is a determinant of social capital at a municipality level). In any case, a small and non-significant coefficient in the regression would suggest that the earthquake does not affect social capital either directly or presumably, via any other mechanism. Fourth, the migration mechanism -an earthquake may lead to a substantial and immediate migration movement towards non-affected areas- is test through regressing changes in population between the years 2011 and 2010 on earthquake intensity. The earthquake may have fostered immediate migration from heavily affected areas in search of protection networks or even, via increasing poverty in affected areas in a less immediate medium/long term. Because in principle only the presence of the former mechanism would challenge the validity of the instrument, it would have been preferred to explore changes in population the month of the earthquake. Nonetheless, although information on population is only available yearly, a small and non-significant coefficient would suggest that the earthquake have not a substantial effect on migration either directly or via poverty in the short term. Fifth, to test whether the earthquake lead to permanent changes in the number of policemen increasing the expected costs of crime, the study regresses the change in the number of policemen at the municipality level between the years 2010 and 2009 on earthquake intensity. Note that since policemen are paid by the state, the earthquake is not likely to affect differences between municipalities in terms of the number of policemen. Finally, and to better understand the dynamics generated by the earthquake, the study regresses the change between 2011 and 2009 in poverty and in a series of potential crime determinant variables including unemployment and percentage of population with secondary education on earthquake intensity.

The results of regressions exploring short term changes by exposure to earthquake are presented in table 3 and the evolution across time of poverty incidence, total crime and car theft are presented in figures 5, 8 and 10. Some additional figures on crime rate variation across time by exposure to shock are also presented in the Appendix. The results of the short term regressions in table 3, first stage panel data regressions reported in table 6 and to lesser extent the figure 5, suggest that earthquake has a relatively clear effect on poverty in the short term, particularly in highly exposed areas, creating poverty traps and increasing poverty permanently in municipalities highly and intermediately exposed to the earthquake. Also, there is a negative effect significant at the 90% confidence level of high exposure to earthquake on immediate crime, suggesting that during the month of the earthquake, the most affected areas were unexpectedly less affected by crime. It is also worth to mention that in the short term, the regression results do not provide evidence of any effect of earthquake exposure on inequality or unemployment. The lack of more data on inequality and unemployment prevent us from testing whether earthquake exposure may affects inequality or unemployment in the long term. For the rest of the variables, the earthquake exposure dummies are overall small and largely insignificant. These results suggest that in addition to the terrible loss of lives, the main social effect of the Chilean 2010 earthquake was the destruction of household assets that despite reconstruction programmes implemented in affected areas lead many households into poverty traps increasing poverty rates permanently in these areas. On the other hand, the data suggest that the looting episodes appeared in the media the days immediately after the earthquake seemed to be sporadic rather than generalized incidents. The results of the regression are also in line with the patterns emerged in the figures showing evolution across time in crime and car theft rates in affected and non-affected areas. Overall, despite the caveats due to the lack of further comprehensive data, these results suggest the exogeneity of the instrument and the validity of exposure to earthquake as an adequate instrumental variable.

Table 3: Robustness Checks: Instrumental variable exogeneity

	Δ Ln policemen per 100,000 inhab	Δ N associations per 100 inhab	Δ Ln Population	Δ Poverty incidence	Δ Gini index	Δ Rate of pop with secondary educ	Δ Unemployment rate	Δ N crimes (March 2010-Feb 2010)	Δ N car thefts (March 2010-Feb 2010)
High exposure to earthquake	0.060	0.016	-0.008	0.006**	-0.006	0.004	0.000	-9.591*	-0.108
	(0.039)	(0.136)	(0.005)	(0.002)	(0.012)	(0.012)	(0.008)	(5.445)	(0.486)
Intermediate exposure to earthquake	0.042	-0.030	0.001	0.003	-0.013	0.001	-0.007	5.080	0.543
	(0.032)	(0.110)	(0.004)	(0.002)	(0.010)	(0.010)	(0.007)	(4.452)	(0.397)
Observations	345	345	345	345	324	324	324	346	346
R-squared	0.008	0.000	0.011	0.018	0.005	0.000	0.005	0.024	0.008

Note: This table examines whether 2010 earthquake affected different time-variant characteristics in the short term. The table regresses the change in several variables from the most immediate value before the earthquake to the most inmediate value after the earthquake. The first, second and third columns use yearly data from SINIM for a total of 345 mnicipalities (change between 2010 and 2009). Fourth column uses data from SINIM for 345 municipalities (change between 2011 and 2009). The fifth, sixth and seventh columns use data from CASEN for a total of 324 municipalities (change between 2011 and 2009). The eighth and nineth columns use data from the SPD on monthly reported crimes for a total of 346 municipalities, including the Antartica.

Figure 3: Incidence of car theft: Number of car thefts per 1000 inhabitants

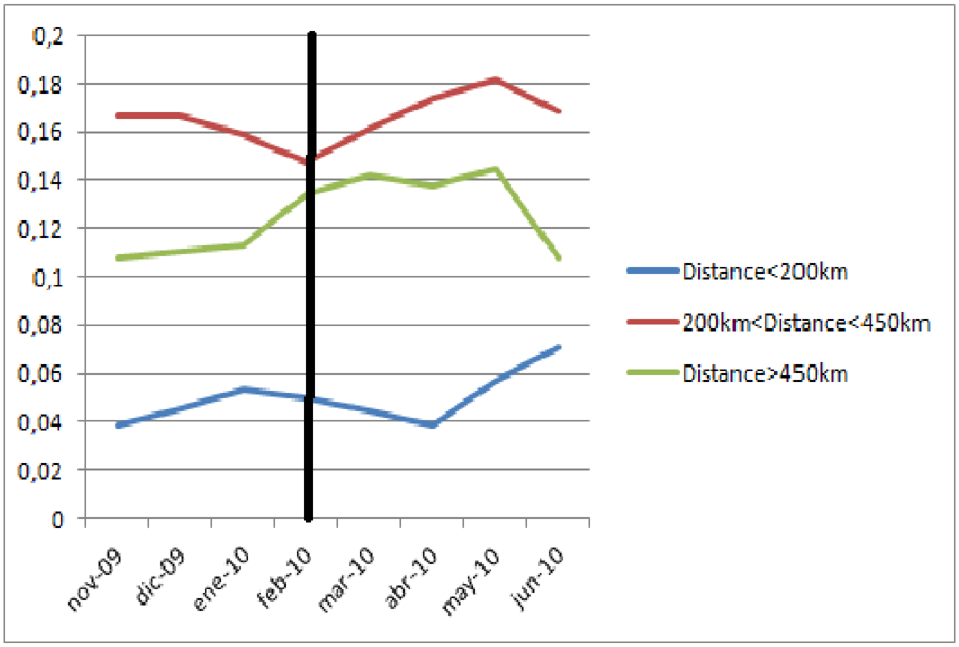


Figure 4: Incidence of crime: Numbers of crimes per 1000 inhabitants

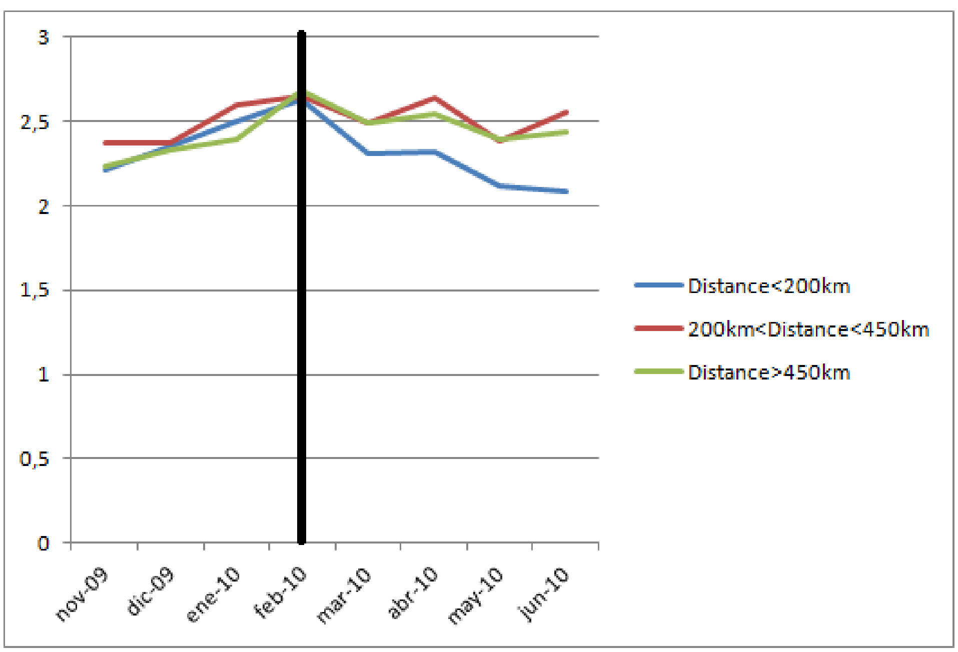
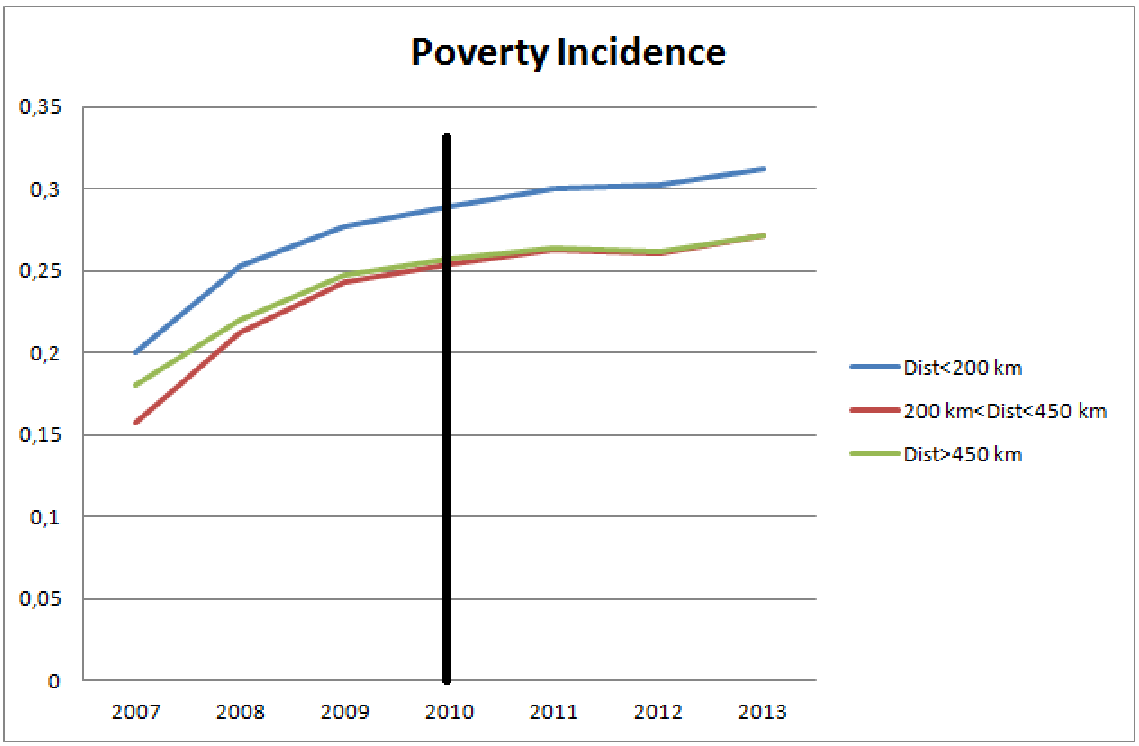


Figure 5: Poverty Incidence across time by Earthquake exposure



7.2 Descriptive Statistics

Table 4 presents the descriptive statistics at the municipality level for the main variables used in this paper for the 345 Chilean municipalities for the period 2007-2013. These variables are the rate of social protection cards as a proxy for poverty incidence, percentage of rural population, total population, the number of associations per 100 inhabitant as a proxy for social capital, the number of policemen per 100,000 inhabitants and the number of car theft per 1,000 inhabitants as a proxy for property crime.

Remarkably, the descriptive statistics show an average poverty incidence of 25%, which reflect not only the rate of poverty but also the population in risk of poverty. The large difference in terms of poverty incidence between minimum and maximum values also shows the spatial economic segregation in Chile with a municipality with 1% of poverty incidence and a municipality with more than 30% of poor people, both in the Metropolitan Area of Santiago. Large variations among municipalities are also found in the number of policemen per 100,000 inhabitants and in total population, with municipalities ranging from less than 300 inhabitants to municipalities with more than 900.000 inhabitants.

Table 4: Descriptive Statistics - Panel Data (2007-2013)

	N	Mean	Standard Deviation	Minimum	Maximum
Poverty incidence	2,415	0.25	0.07	0.01	0.51
Percentage rural pop	2,415	0.38	0.30	0	1
Population	2,415	49,520	85,242	243	931,211
N associations per 100 inhab	2,415	1.48	1.23	0.03	15.64
Policemen per 100,000 inhab	2,415	329	665	26	9,237
N of car thefts per 1,000 inhab	2,415	0.72	1.52	0	14.40

Note: The descriptive statistics are presented at the municipality level for a total of 345 municipalities during 7 years (2007-2013).

Table 5: Exposure to 2010 Earthquake at the Municipality Level

	Number of Municipalities	% of Municipalities
High exposure (Dist $<$ 200km)	72	0.21
Intermediate exposure (200km $>$Dist $<$ 450km)	162	0.47
Low exposure (Dist $>$ 450km)	111	0.32
Total Munic. in Chile	345	1

7.3 Effects of Poverty on Property Crime

Tables 6 and 7 presents the results of different models aiming to measure the effect of poverty on property crime in Chile during the years 2007-2013.

The Fixed-, Random- and First-difference models account for time invariant unobservable variables correlated with property crime and poverty. Among these specifications, the Wooldridge test on serial correlation ($F(4, 344) = 1.91$) and the Robust Hausman Test ($F(5, 344) = 7.17$) suggest that the fixed effect specification is more adequate. However, these three models are sensitive to endogeneity if there is a reverse causality between poverty and property crime or there are time variant unobservable variables correlated with property crime and poverty. To explore the existence of this, the study conducts a Durbin-Wu-Hausman Robust test. The results ($F(1, 344) = 8.97$) lead to the rejection of the null of exogeneity with a p-value<0.01, thus confirming the need to account for endogeneity in these models. Note however that the validity of this endogeneity test lies on the appropriateness of the instrumental variable discussed previously.

To account for endogeneity, the study also presents the results of an Instrumental Variable Fixed Effects (IV FE) estimated through a Limited Information Maximum Likelihood (LIML) procedure. LIML estimators are asymptotically equivalent to 2SLS but may have better finite-sample properties than the latter (Hahn and Inoue, 2002). The relevance of the instrumental variables used in this model is confirmed by the strong significance of the coefficients of the instrumental variables in the first stage equations, which satisfies by far the commonly accepted threshold of F>10. The exogeneity of the instrumental variable is examined in detailed in section 7.1.

However, as it is discussed in the previous section, even if the instrumental variables used are relevant and exogenous, the estimation of the effect of poverty on property crime though an IV FE would be biased and inconsistent under the null of a spatial dependence problem. The existence of spatial dependence is examined through Moran I tests. The results, with p-values<0.00 for all cross-sections, highlight the need to use a spatial econometric model. Table 7 assess the effect of poverty on property crime using the main FE spatial econometrics models: a FE Spatial Durbin Model (FE-SDM), a FE Spatial Error Model (FE-SEM) and FE Spatial Autoregressive Model (FE-SAR). Further examination of the nature of the spatial dependence through the conduction of Belotti tests confirms that the SDM is the preferred specification ($\chi^2(5) = 40.37$ in Belotti test I and $\chi^2(5) = 29.63$ in Belotti test II). In the last specification the author uses a FE-SDM S2SLS model that allows for endogenous covariates and a spatial lag. This specification is believed to be the strongest because it accounts for both endogeneity of the poverty regressor and spatial dependence.

The poverty coefficients are strong and statisticaly significant in all the specifications, pointing to poverty as a key determinant of property crime. The results suggest that an increase of 10 percentage points in the incidence of poverty significantly increases in 22-54 the number of car theft per 100,000 habitants depending on the econometric model used. Our preferred estimation, the FE-SMD S2SLS model yields the largest effects of poverty on property crime. Also, the indirect effects yield by the spatial models presented in table 7 highlight that property crime in a municipality is not only affected by poverty in the municipality but also by poverty in neighbour municipalities. In our prefer FE-SDM S2SLS model, an increase in 10 percentage points in the incidence of poverty in neighbour municipalities significantly increases in 41 the number of car theft per 100,000 habitants in a given municipality. Worth to mention, the indirect effect is larger and more significant than the direct effect. A possible explanation is that criminals respond to economic shocks through stealing cars in neighbour rather in their own municipalities.

Remarkably, the coefficients of poverty incidence in the IV models are larger than coefficients in non-IV models. This is unexpected because although the result of the Durbin-Wu-Hausman test confirms the presence of endogeneity, the authors expect this bias -arguably created by a reverse causality between poverty and property crime- to operate in the opposite direction. A possible interpretation for this is that an increase (decrease) in property crime does not seem to increase (decrease) poverty incidence, at least in the time period studied in this paper. Although more research is needed, in principle, these results do not provide evidence of the existence of a vicious (virtuous) cycle of poverty and property crime.

It is also worth to mention that overall, the statistical significance, magnitude and even the sign of the coefficients of the rest of property crime determinants examined is not homogeneous across the econometric models presented. Social capital does not affect significantly property crime in any specification and even the sign of the effect changes in every specification. Although small and non-statistically significant, the results of the different specifications show that overall, property crime and number of policemen correlate positively. This small and non-significant positive correlation might be driven by a reverse causality between property crime and number of policemen. Also, the coefficient of the effect of total population on property crime has the expected positive sign in most of the specifications although again the effect is non-significant in most of the specification. Finally, the effect of the percentage of rural population ranges substantially depending on the econometric model used.

Table 6: Non-spatial panel data estimations of the impact of Poverty on Property Crime: 2007-2013

	Fixed Effects	Random Effects	OLS First Difference	Fixed Effects LIML IV	
	N of car thefts per 1,000 inhab	N of car thefts per 1,000 inhab	Δ N of car thefts per 1,000 inhab	Poverty incidence (FS equation)	N of car thefts (SS equation)
Poverty incidence	3.213***	2.476***	2.192***		4.919***
	(0.399)	(0.331)	(0.367)		(0.828)
Percentage rural pop	0.634*	-0.555**	0.535	-0.085	0.996**
	(0.359)	(0.261)	(0.457)	(0.074)	(0.502)
N associations per 100 inhab	-0.010	-0.014	-0.008	0.003***	-0.020
	(0.012)	(0.012)	(0.011)	(0.001)	(0.014)
Ln Population	0.927	0.441***	0.953	-0.047	0.822
	(0.610)	(0.072)	(0.621)	(0.042)	(0.606)
Ln policemen per 100,000 inhab	0.066	0.258***	0.070	0.027***	-0.045
	(0.101)	(0.091)	(0.093)	(0.005)	(0.120)
High exposure to earthquake				0.051***	
				(0.003)	
Intermediate exposure to earthquake				0.054***	
				(0.002)	
Municipalities	345	345	345	345	345
N of periods	7	7	6	7	7
Observations	2,415	2,415	2,070	2,415	2,415
F-statistic χ^2	22.47	106.84	11.63	215.43	13.11

Note: In the FD specification explanatory variables are time differenced. In the FD, FE and RE specications, standard errors are adjusted for clusters in municipality. In the IV-FE specification, standard errors are adjusted for clusters and heteroskedasticity.***p<0.01;**p<0.05;*p<0.1

Table 7: Spatial fixed effects estimations of the impact of Poverty on Property Crime: 2007-2013

	FE-SDM	FE-SEM	FE-SAR	FE-SDM 2SLS	
	N of car thefts per 1,000 inhab	N of car thefts per 1,000 inhab	N of car thefts per 1,000 inhab	Poverty incidence (FS equation)	N of car thefts (SS equation)
Total					
Poverty incidence	3.731***	3.218***	2.020***		5.374**
	(1.020)	(0.415)	(0.496)		(2.215)
Percentage rural pop	0.412	0.634*	-1.321	-0.085	0.604
	(4.946)	(0.358)	(1.036)	(0.074)	(5.139)
N associations per 100 inhab	0.099*	-0.010	-0.011	0.003***	0.078
	(0.060)	(0.012)	(0.017)	(0.001)	(0.057)
Ln Population	0.185	0.927	0.064	-0.047	0.581
	(1.694)	(0.609)	(0.720)	(0.042)	(1.659)
Ln policemen per 100,000 inhab	-0.135	0.067	0.069	0.027***	-0.112
	(0.224)	(0.100)	(0.122)	(0.005)	(0.256)
High exposure to earthquake				0.051***	
				(0.003)	
Intermediate exposure to earthquake				0.054***	
				(0.002)	
Direct					
Poverty incidence	1.046		-1.195***		1.296
	(0.850)		(0.281)		(1.076)
Percentage rural pop	0.853		0.790		0.933
	(0.862)		(0.621)		(0.876)
N associations per 100 inhab	0.020		0.006		0.016
	(0.013)		(0.010)		(0.013)
Ln Population	0.442		-0.027		0.371
	(0.533)		(0.427)		(0.534)
Ln policemen per 100,000 inhab	-0.027		-0.039		-0.056
	(0.089)		(0.071)		(0.102)
Indirect					
Poverty incidence	2.685***		3.215***		4.077**
	(0.913)		(0.760)		(1.940)
Percentage rural pop	-0.441		-2.111		-0.329
	(4.567)		(1.651)		(4.727)
N associations per 100 inhab	0.079		-0.018		0.062
	(0.057)		(0.027)		(0.055)
Ln Population	-0.257		0.091		0.210
	(1.697)		(1.146)		(1.681)
Ln policemen per 100,000 inhab	-0.107		0.108		-0.056
	(0.228)		(0.192)		(0.255)
rho	0.304***		0.304***		0.304***
	(0.000)		(0.000)		(0.000)
lambda		-0.001			
		(0.005)			
Observations	2,415	2,415	2,415	2,415	2,415
Number of Municipio1	345	345	345	345	345

Note: Standard errors are adjusted for clusters in municipality. ***p<0.01;**p<0.05;*p<0.1

Figure 6: Car theft per 100,000 inhabitants (Average yearly rate for the period 2007-2013)

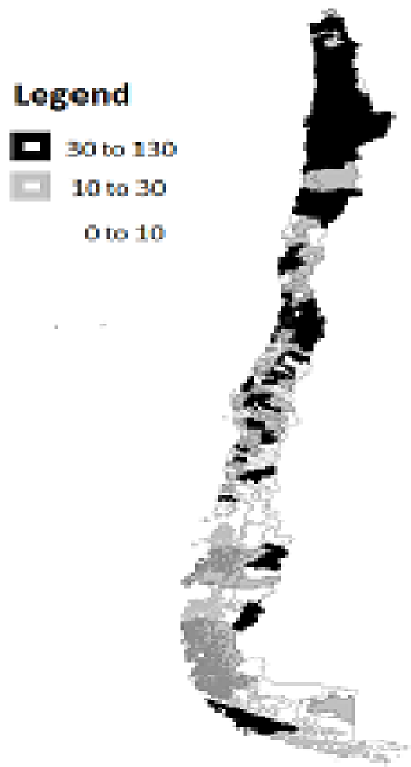


Table 8: Different Tests on Econometrics Models

	Wooldridge test on serial correlation in the error term	Robust Hausman Test	Durbin-Wu-Hauman Robust Test	Moran I Test	Belotti Test I	Belotti Test II
p-value	0.108	0.000***	0.003***	0.000***	0.000***	0.000***
H_0 :	No serial correlation in the error term	RE model is preferred to FE	Poverty variable is exogenous	No spatial dependence	SAR is preferred to SDM	SEM is preferred to SDM

Note: ***p<0.01;**p<0.05;*p<0.1

8 Robustness checks

This section examines the robustness of the results to different hypotheses.

8.1 Exclusion of municipalities with looting events after the Earthquake

The exogeneity condition of the instrumental variable model requires that exposure to earthquake only affects property crime through affecting poverty. One alternative channel through which earthquake may affect all types of crime is through transitory decreasing the cost of crime leading to permanent increases in property crime rates (e.g. transitory cuts of electricity may induce permanent enrolment into criminal activities of individuals that otherwise would have never commit a first crime). The crime data available and analyzed previously demonstrate that the earthquake did not lead to an immediate, direct and generalized increase in property or total crime in affected areas. However, it is worth to mention that although not generalized, there were some looting events the days immediately after the earthquake in some affected areas. The first two columns in table 10 re-estimate the effect of poverty on property crime using the FE-SDM S2SLS model, but dropping from the analysis the municipalities with looting events within ten days after the earthquake. Both the results of the first stage and of the second stage equation yields similar results confirming that the main conclusions of the study are robust to the exclusion of affected municipalities that suffered a looting event immediately after the earthquake.

8.2 Use of alternative definition of Earthquake intensity

The study has discussed in section 6.3 the potential problems associated to define municipality exposure to earthquake through year and distance to epicenter-based dummies. To check whether the results might be driven by this definition of the different levels of exposure to earthquake, the study re-estimates the results of the FE-SDM S2SLS model using yearly Mercalli intensity in each municipality as the variable to define municipality exposure to earthquake. The results of this analysis are reported in the third and fourth columns in table 10 and are very similar to those obtained when exposure variables based on distance to earthquake epicenter are used.

Unlike the Richter scale -which measure the energy released by an earthquake-, the Mercalli scale is a seismic scale used for measuring the intensity of an earthquake. Mercalli intensity does not only depend on distance to the earthquake epicenter but also on other factors such as type of soil or topography. In principle, Mercalli scale could reflect more accurately exposure to earthquake than distance to epicenter. However, the dataset on Mercalli intensity is constructed by the author using the maps and information available in the United States Geological Survey (USGS)[16], which are not release at the municipality level. Thus, the available Mercalli data for the 2010 Chilean Earthquake is not accurate and thus, in this analysis, the study considers superior the dummy exposure variables based on year and distance to epicenter.

[16]http:earthquake.usgs.govearthquakespagereventsus2010tfanindex.html#cities

8.3 Inclusion of additional control variables

In this section the study tests the robustness of the results to the inclusion in the specification of additional control variables that have been demonstrated determinants of property crime in different studies. These additional controls are inequality, rate of male aged 15-29, unemployment and secondary education.

These variables are constructed using two waves of CASEN household survey. Unfortunately, this national household survey is not collected annually and within the period of interest, CASEN data is only available for the year 2009 and 2011.

Thus, the inclusion of the additional controls require to reduce the panel to a two period panel. In the last column of table 10, the study assesses the link between poverty and property crime using a First Difference model and including in the specification the additional controls. In this specification, the poverty coefficient is very close to zero and no longer significant. Nonetheless, a few issues call for caution and place doubts in the validity of the specification and discourage the use of more complex econometric models. First, despite the substantial number of controls included in the regression, the joint F value of the specification is not significant at the 10% (Prob>F : 0.103). Second, descriptive statistics show that most of the additional variables including inequality and the rate of men aged 15-29 hardly change during the period of interest, discouraging the use of these variables in two periods panel data models. To illustrate the problem created by the inclusion of all the control variables in two period panel data models, this would be equivalent to the inclusion in cross-section models of control variables with little or no variation across observations, rendering the coefficients of the regressions misleading and inefficient.

Table 9: Descriptive Statistics - Two periods Panel Data (2009-2011)

	N	Mean	Standard Deviation	Minimum	Maximum
Δ Poverty incidence	324	-0.013	0.081	-0.371	0.300
Δ Percentage rural pop	324	-0.003	0.015	-0.064	0.049
Δ Population	324	985.383	5,450.029	-7,664	76,714
Δ N associations per 100 inhab	324	0.066	0.888	-3.166	4.462
Δ Policemen per 100,000 inhab	324	14.710	137.188	-2,083	911
Δ Gini index	324	-0.001	0.077	-0.181	0.393
Δ Rate of men between 15-29	324	-0.001	0.027	-0.081	0.085
Δ Rate of unemployment	324	-0.023	0.050	-0.155	0.164
Δ Rate of pop with secondary educ	324	-0.112	0.076	-0.390	0.137
Δ N of car thefts per 1,000 inhab	324	0.176	0.650	-1.666	5.892

Note: The descriptive statistics on change in variables are presented at the municipality level for a total of 324 municipalities for which data on inequality, secondary education, employment and rate of young male are available in year 2011 and year 2009.

Table 10: Spatial fixed effects estimations of the impact of Poverty on Property Crime: 2007-2013

	FE-SDM S2SLS		FE-SDM S2SLS		First Difference OLS
	Poverty incidence (FS equation)	N of car thefts (SS equation)	Poverty incidence (FS equation)	N of car thefts (SS equation)	Δ N of car thefts per 100 hab
Total					
Poverty Incidence		4.027*		5.871**	-0.026
		(2.247)		(2.768)	(0.305)
Percentage rural pop	-0.106	-0.275	-0.102	0.575	1.690
	(0.078)	(6.558)	(0.076)	(5.181)	(1.185)
N associations per 100 inhab	0.003***	-0.030	0.004***	0.076	-0.004
	(0.001)	(0.114)	(0.001)	(0.057)	(0.028)
Ln Population	-0.050	4.708*	-0.039	0.649	-0.312
	(0.044)	(2.568)	(0.042)	(1.629)	(1.315)
Ln policemen per 100,000 hab	0.027***	0.175	0.031***	-0.138	0.311
	(0.005)	(0.339)	(0.005)	(0.292)	(0.317)
High exposure to earthquake	0.053***		0.055***		
	(0.003)		(0.002)		
Intermediate exposure to earthquake	0.054***		0.044***		
	(0.003)		(0.006)		
Gini Index					-0.269
					(0.436)
Rate of male 15-29					0.916
					(1.318)
Rate of unemployment					0.661
					(0.631)
Rate of pop with sec. Educ.					-1.241***
					(0.389)
Direct					
Poverty Incidence		2.584***		1.760*	
		(0.958)		(1.061)	
Percentage rural pop		1.787**		1.040	
		(0.898)		(0.883)	
N associations per 100 inhab		-0.026*		0.014	
		(0.016)		(0.013)	
Ln Population		0.796		0.375	
		(0.516)		(0.535)	
Ln policemen per 100,000 hab		-0.041		-0.070	
		(0.110)		(0.102)	
Indirect					
Poverty Incidence		1.444		4.111*	
		(2.397)		(2.369)	
Percentage rural pop		-2.062		-0.466	
		(6.102)		(4.755)	
N associations per 100 inhab		-0.004		0.062	
		(0.105)		(0.055)	
Ln Population		3.912		0.274	
		(2.648)		(1.658)	
Ln policemen per 100,000 hab		0.217		-0.068	
		(0.348)		(0.284)	
rho		0.299***		0.304***	
		(0.000)		(0.000)	
Observations	2,191	2,191	2,415	2,415	324
Number of Municipio1	313	313	345	345	324

Note: The first two columns examines the effect of poverty on crime through an FE SDM IV model but excluding from the model those municipalities in which there were any looting the following days to the earthquake using the 7 year panel dataset. The third and fourth columns examines the effect of poverty on crime through an FE SDM S2SLS model but using an alternative measure of earthquake intensity, namely the mercalli scale. The last column examines the effect of poverty on crime through an FD OLS regression including additional control variables found to be relevant determinants of crime in other studies. These additional control variables are obtained from CASEN household datasets and are only available for 323 municipalities in two periods of time. Thus, the data used in this specification is only for years 2011 and 2009. ***p<0.01;**p<0.05;*p<0.1

9 Conclusions

An identification strategy to estimate causal effects of poverty on property crime would potentially need to account for reverse causality, time variant omitted variables and spatial dependence. To overcome these methodological difficulties, this study uses a spatial two stage least squares estimator allowing for endogenous regressors following Anselin and Lozano-Gracia (2008). Also, to account for potential measurement error in property crime correlated with poverty arising from the use of administrative crime data, the study uses a measure of property crime that is subject to a small measurement error and also uncorrelated with poverty: incidence of car theft. To the best of our knowledge, this is the first study using sub-national data that investigates the causal effect of poverty on property crime in a low- and middle-income countries accounting for spatial dependence and endogeneity. The distinction between high-income and low- and middle-income countries when assessing the link between poverty and crime is essential because the mechanisms through which the link operates might be different (Fafchamps and Minten, 2006).

The results of the study suggest that poverty has a strong and significant effect on our measure of property crime. Our preferred estimation suggests that an increase of 10 percentage point in poverty incidence increases in 54 the number of car thefts per 100,000 habitants. The significance of this effect is robust to the use of alternative variable definitions, econometric specifications and models and also to the exclusions of municipalities that suffered looting events the days after the earthquake. The results are in line with those found in Iyer and Topalova (2014) and Ivaschenko et al. (2012) for the effect of poverty on crime and with Fafchamps and Minten (2006) for the effect of poverty on some property crime measure such as crop theft. The study also points to large levels of spatial dependence and provides evidence that the incidence of property crime in a municipality is substantially determined not only by its poverty level but also and mainly by the poverty level of neighbour municipalities. An increase in 10 percentage points in poverty incidence of neighbour municipalities increases in 41 the number of car thefts per 100,000 inhabitants in a given municipality.

At the policy level, the results suggest that effective anti-poverty programmes might be optimal strategies to reduce property crime in low- and middle-income countries, particularly in the context of income shocks increasing poverty rates. Also, these anti-poverty programmes may have substantial effects in property crime in neighbour areas. Besides, the existence of neighbours effects of poverty on property crime suggests that reaching optimal levels of investments in muncipality anti-poverty programmes in Chile -mostly fund by municipalities- may require either non-depressed neighbor municipalities or the central government to share the costs of anti-poverty programmes in depressed municipalities. Finally, and although more research is needed, since the coefficient of the poverty variable is larger in IV models than in non-IV models, the study does not provide evidence of a virtuous cycle of poverty and property crime. The latter may suggest that programmes focusing on reducing property crime may not have a relevant effect on poverty at least in the short- or medium-term.

The theoretical framework presented in this paper enumerates different mechanisms through which poverty may affect property crime. First, poor people may have lower returns to legal jobs. Thus, involvement in property crime might be the result of a maximization decision of time allocation to an activity with high relative returns for poor people. Second, poor people might have smaller opportunity cost of time in prison if their returns to legal jobs are smaller. Thus, the cost of fine associated to apprehension might be smaller for poor people leading to a smaller expected cost of all types of crime for poor people. Finally, apprehension might be more difficult in poor areas leading to a smaller expected cost of both property and violent crime for poor people. On the other hand, poverty may also reduce property and violent crime if poor people are in average more risk averse. Also, the cost of property crime might be relatively higher for poor people, which may find more difficult to comply with the pecuniary fine associated to apprehension. Besides, at an aggregate level, the returns to property crime in non-poor areas might be larger than in poor areas (e.g. a successful theft committed in non-poor areas is likely to yield a higher economic benefit than a successful theft committed in a poor area) although investments in crime prevention might be also larger in non-poor areas making the success of property crime more difficult in these places. Worth to mention that in the presented theoretical framework on the effect of poverty on property crime, differences in the rates of property crime in poor and non-poor areas might be the consequence of different incentives of poor people and non-poor people to commit property crime rather than of intrinsic or moral differences between these two groups. The results suggest that the mechanisms operating a positive effect of poverty on property crime clearly dominates those operating a negative effect. However, this study does not investigate through which specific mechanisms the positive effect of poverty on property crime operates. More research is needed developing identification strategies to unpack the black box and investigate the mechanisms through which poverty affects property crime.

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A Evolution of crime and car theft rates across time

Figure 7: Incidence of car theft across time by exposure to Earthquake

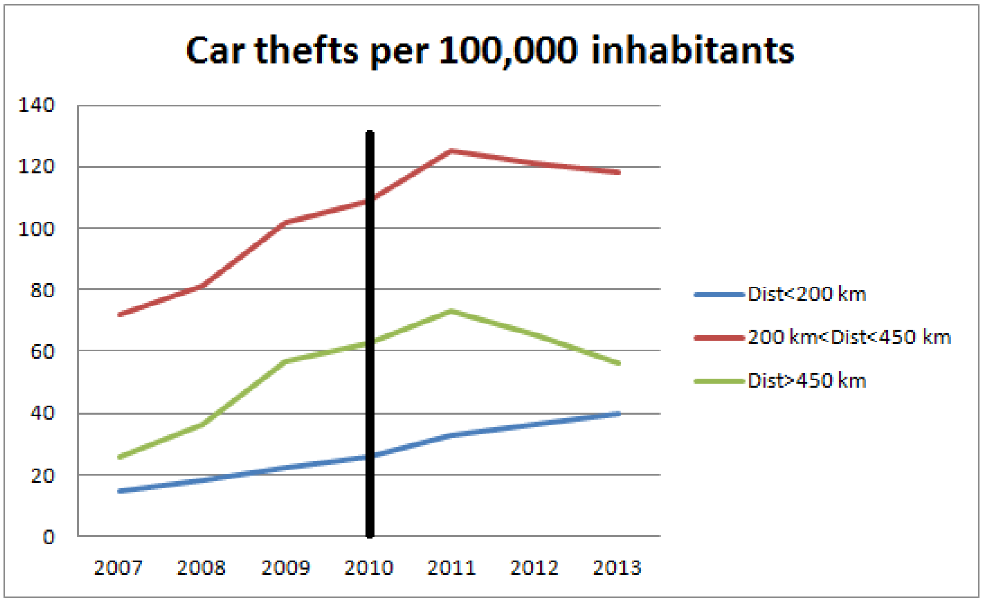

Figure 8: Incidence of car theft: Number of car thefts per 1000 inhabitants

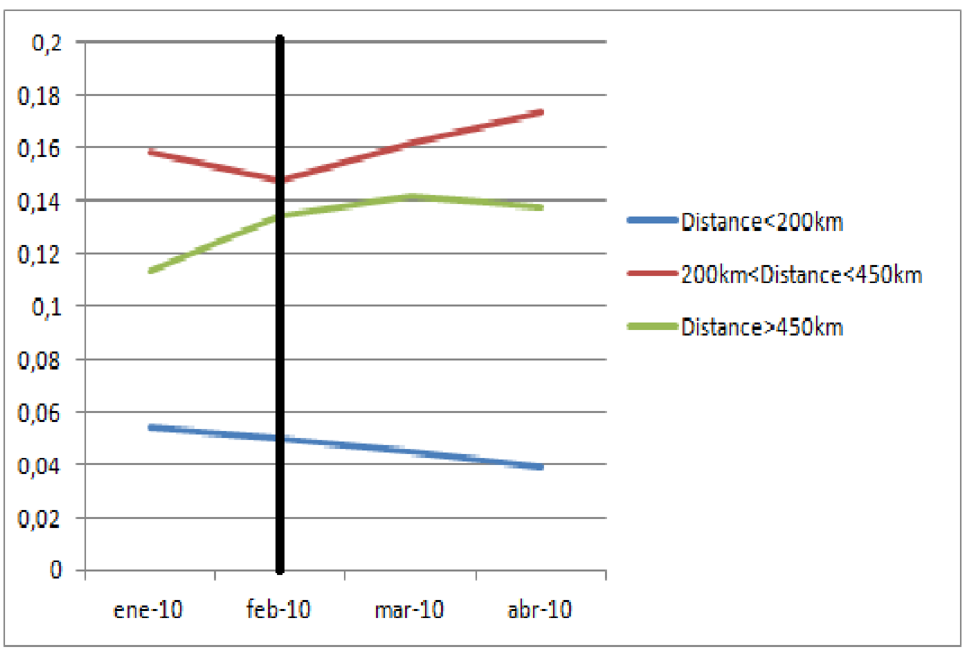

Figure 9: Incidence of car theft: Number of car thefts per 1000 inhabitants

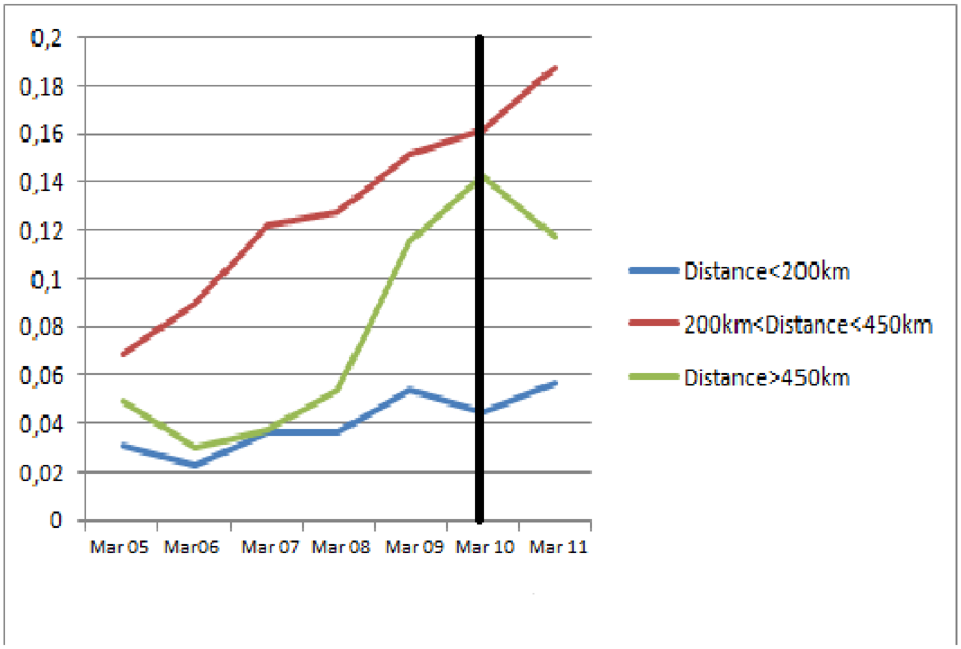

Figure 10: Incidence of crime: Numbers of crimes per 1000 inhabitants

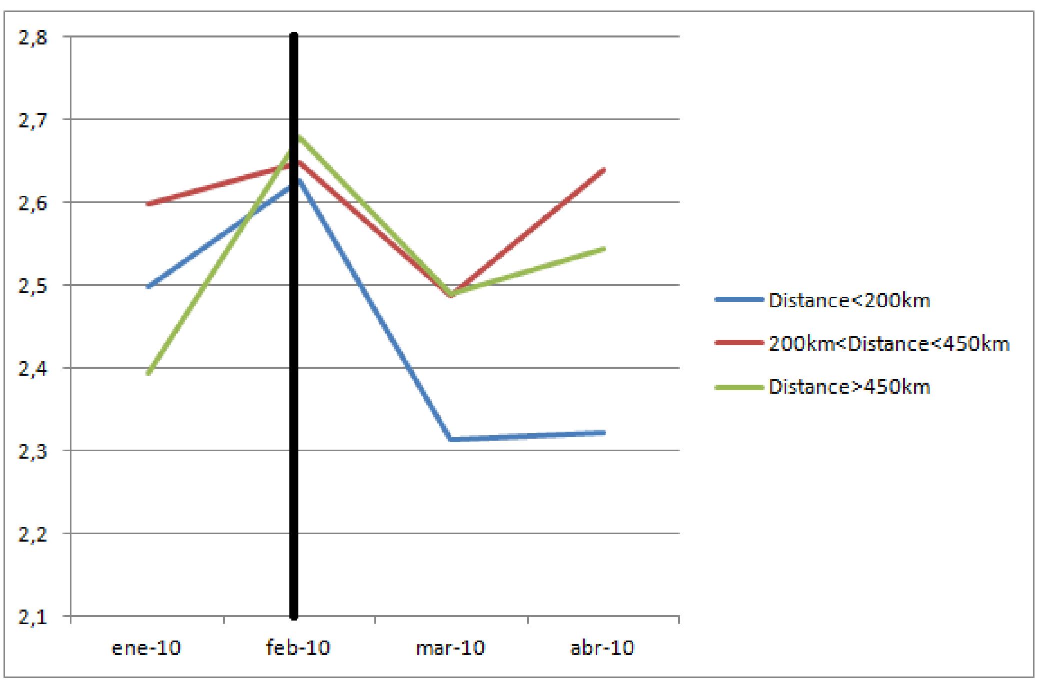

Figure 11: Incidence of crime: Numbers of crimes per 1000 inhabitants