Latin American Economic Review (2024), volume 33, article 8

RESEARCH ARTICLE

Does education reduce criminal activities? An aggregated empirical approach in Chile.

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Submission received: June 16, 2023
Final version received: April 23, 2024
Accepted: April 26, 2024
Published: September 10, 2024

Abstract

Social returns of education are all the benefits that accrue to society resulting from an increase in its citizens' overall education level. This paper addresses the relationship between regional criminal activities and the educational level in a city. We hypothesize that, at the aggregate level, higher education is related to low levels of criminal activities. We focus on Chile as a case study and build an unbalanced panel data from 2006 to 2017 with an average of 308 municipalities. We find that high human capital deters regional criminal activities while low human capital does not.

Keywords: Human capital; crime; schooling; developing countries; spatial analysis.

JEL codes: E24; J24; I26.

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1. Introduction

Literature has broadly addressed the relationship between education and its private returns, understood as wages. Economists have reached a consensus that, ceteris paribus, individuals with higher educational levels, earn higher wages (Mincer, 1962). However, in the presence of externalities, the social returns to education differ from the private ones. **?** states that education can reduce the probability of engaging in activities that generate negative externalities, such as criminal activities. If education reduces the incentive for people to commit a crime, then we can assume that education has a social return that is beyond the scope of a private one. From an urban perspective, cities with higher educational attainment tend to have lower crime rates (Lochner, 2004).

Empirical literature usually tests the relationship between human capital and criminal activity at the micro-level, finding a negative relationship between human capital and crime (Lochner, 2004, 2020; Lochner and Moretti, 2004). The few studies that test this relationship at the aggregate level, focus on developed countries (e.g., Buonanno and Leonida, 2009). To the best of the authors' knowledge, one exception is Nguyen (2019) who studies the effect of education on property crimes in Indonesia and finds that neighborhoods with more educated people present low levels of crime. This scarcity of literature at the aggregate level in developing countries is probably due to the lack of specific crime and education data as well as the presence of econometric problems that require more sophisticated strategies.

The aim of this article is to estimate whether education affects the number of local criminal activities in less developed countries. Our main hypothesis is that, at the aggregate level, the higher the educational level, the less the number of criminal events in a city.[1] To test our hypothesis, we focus on Chile as a case study. We build an unbalanced panel data from 2006 to 2017 with an average of 308 municipalities.[2] To build the database we used two main sources. The human capital variables are obtained from the Chilean National Socioeconomic Characterization (CASEN) Survey, waves 2006, 2009, 2011, 2013, 2015, and 2017, and the crime variables are taken from the Chilean Crime Study and Analysis Center (CEAD). These databases include variables representing municipalities' human capital level and criminal activities.

This article has three main contributions. First, it adds to the understanding of social aggregate returns to schooling in the context of less developed countries. Second, this article employs an econometric approach that addresses common econometrical issues between the human capital and crime levels relationship, such as the existence of aggregation bias, certain unobserved factors that condition the municipal educational levels, and reverse causality because the levels of human capital could be conditioned to the crime levels of the municipalities. To deal with this issue, we use a fixed effects panel specification and instrument our endogenous variable. Finally, a third contribution is that we address possible spatial spillover effects behind this relationship. Considering that the crime levels of a municipality not only affect the municipality itself but also neighboring municipalities, we perform a diagnostic for spatial dependence on our main variables of interest using panel spatial econometric techniques (Anselin et al., 2007).

Furthermore, this article addresses three mechanisms that underlie the relationship between aggregate human capital and crime levels. The first mechanism recognizes that cities with high unemployment rates have high rates of criminal activities (Speziale, 2014). The second mechanism states that, independently of the level of schooling, municipal rates of school attendance alone reduce the time available for participating in criminal activities (Anderson, 2014; Buonanno and Leonida, 2009). Finally, the last

[1]It is important to note that, following the work of **?**, human capital and education are used interchangeably in this article.
[2]The terms cities, and municipality are used interchangeably in this article.

mechanism recognizes wages as an opportunity cost that reduces crime rates or the propensity to commit crimes (Becker, 1968; Buonanno and Leonida, 2009).

Our findings suggest that education is negatively and significantly related to crime. Specifically, higher shares of high human capital in a municipality imply a lower number of criminal activities. In this sense, it is plausible to affirm that, in Chile, higher levels of education in a municipality generate social returns that are shared by the society. These results are in line with previous literature suggesting that education reduces crime at the local level through labor market opportunities like employment and wage rates or fewer opportunities to commit a crime due to time constraints (Buonanno and Leonida, 2009; Nguyen, 2019). The results confirm what previous studies have found in the Chilean context. For example, Berthelon and Kruger (2011) find that education can reduce crime through an incapacitation effect on young individuals. Therefore, if local governments want to intensify the benefits of having fewer criminal activities, then they could reinforce their public investment in education. Regarding the spatial spillover analysis, we find evidence of the existence of global spatial autocorrelation and local spatial distribution patterns in crime. Specifically, the spatially lagged crime variable indicates a positive correlation between the number of crimes in one municipality and the quantity of crimes in a neighboring municipality. The following section sets forth the theory and literature review. The data and empirical strategy are presented in section 3, the results are described in section 4, and section 5 offers conclusions and suggests possible lines for future research.

2. Theory and literature review

Private returns, understood as wages for an additional year of education, are highly studied in the economic literature (Stephens and Yang, 2014; Mincer, 1962). There is a consensus that individuals with higher levels of schooling have higher potential wages (Mincer, 1962). Nevertheless, schooling may also have other returns different from the private ones, which are the social returns. Social returns to education are an understudied topic in literature and even more in local geographical areas. **?** affirms that social returns are all the benefits that the society receives resulting from an increase in the overall level of education of its citizens, thus, social returns of education are observed at the aggregate level. Specifically, in this article, we address the reduction in crime as a potential social return of education. **?** affirms that education reduces the probability of an individual participating in activities that generate negative externalities, such as criminal activities. Therefore, the higher the educational level of a specific local geographical area, the lower the crime rates we can expect (Bell et al., 2022; Lochner, 2004).

We identify three mechanisms or channels through which education may affect aggregate crime rates. The first mechanism recognizes wages as an opportunity cost that reduces crime rates or the propensity to commit crimes (Lochner, 2004). The model of Becker (1968) states that individuals consider costs and benefits when deciding to commit a crime, including the opportunity costs of being detained for a crime. Therefore, at the aggregate level, municipalities' wages must be considered as an opportunity cost that reduces the propensity to commit crimes. Implying that higher levels of schooling in a municipality are associated with higher wages, increasing the opportunity cost of criminal behavior (Buonanno and Leonida, 2009; **?**). Therefore, we should expect an inverse relationship between wages and the number of crimes in a city.

The second mechanism states that, independently of the level of schooling, school attendance alone reduces the time available for participating in criminal activities (Anderson, 2014; Buonanno and Leonida, 2009). On the one hand, people who regularly attend classes have less time available to engage in criminal activities, especially at an early age. In fact, some studies such as Anderson (2014) examine the effect of school attendance on juvenile arrest rates by using state-level variation in minimum dropout age laws in the United States. They find that a minimum dropout age of 18 decreases arrest rates among 16- to 18-year-olds by approximately 17%, this holds for property crime, violent crime, and drug crime arrests.

On the other hand, people who go to school tend to improve their job skills, which in the long term allows them to aspire to better wages than those who are not in formal education (Lochner, 2020). In this regard, we should expect that the higher the rates of school attendance in a municipality, the lower the number of criminal activities.

Finally, the last mechanism states that municipalities with high unemployment rates are characterized by high criminal activity rates. Raphael and Winter-Ebmer (2001), for example, argue that criminal activities it is a "form of employment"; and people who are not employed in legal activities may be more likely to engage in non-legal activities to generate income. Using U.S. data, they find that a decrease in criminal activities is related to a decrease in unemployment levels. Likewise, using a dynamic specification for 103 Italian provinces over the period 2000 to 2005, Speziale (2014) finds that unemployment contributes to increased crime in Italian provinces. Under this context, we expect a positive relationship between unemployment and the number of criminal activities in a city. Additionally, Andresen et al. (2021) find that in the long run increases in unemployment are expected to increase crime, but this relation is not clear in the short run, especially at the local level. Table 1 presents a summary of these mechanisms and their expected relationship with education.

Table 1: *Mechanisms between education and crime*

Mechanism	**Relationship description**	**Expected sign**
Unemployment	The higher the unemployment in a municipality, the higher the number of crimes.	Positive
School attendance	The higher the school attendance in a municipality, the lower the number of crimes.	Negative
Wages	The higher the wages in a municipality, the lower the number of crimes.	Negative

Source: Own elaboration.

In Chile, to the best of our knowledge, the empirical relationship between education and crime has not been well documented. However, a few studies find that higher education is correlated with less crime (Benavente and Melo, 2006; Cuesta and Illanes, 2010). For example, Berthelon and Kruger (2011) find that education can reduce crime through an incapacitation effect on young individuals. This means that a teenager who goes to school has less chance of committing a crime. The authors analyze a 1997 school reform in Chile that generated an expansion of school hours by 30%, this reform caused a significant decline in youth crime. Gutiérrez et al. (2009) construct a socioeconomic and geographic profile of crime in Chile, and find, unexpectedly, that the number of people charged with crimes tends to be higher in cities with higher levels of education. Under this context, there is a need to evaluate the relationship between the levels of education and criminality in Chilean municipalities. This article takes this challenge and makes an empirical approach to this issue.

3. Data and empirical strategy

3.1. Data

To test the relationship between crime levels and human capital we build an unbalanced panel data from 2006 to 2017 with an average of 308 Chilean municipalities.[3] This database includes variables representing municipalities' human capital level and criminal activities; and is nourished by two main sources. First, human capital variables are obtained from the Chilean National Socioeconomic Characterization (CASEN) Survey, waves 2006, 2009, 2011, 2013, 2015, and 2017. This survey is developed by the Chilean Ministry of Social Development, and it is representative of Chilean's population at a regional and municipality level. These datasets are the main source for Chile's socioeconomic statistics such as wages, unemployment rate, and educational level. As reference criteria to evaluate the precision and reliability of the estimates, the Ministry of Development recommends using the sampling weights given by the CASEN. In our database, we follow this recommendation and aggregate the data at the municipal level using the sampling weights defined by the municipal expansion factor provided in the survey. Second, crime data was obtained from the Chilean Crime Study and Analysis Center (CEAD), which includes police complaints at the municipal level for the years under study.

Table 2 shows more database details and descriptive statistics for the main variables included in the analysis. On average, there is a higher share of the population with low levels of human capital in Chilean municipalities (57.2%), and the average schooling level is 9.40 years. Regarding the crime variables, there are higher number of property crimes (857.88) than violent crimes (748.31) on average in Chilean municipalities, adding up to a mean of approximately 1606 total crimes. As mentioned, the sample consists of 308 municipalities (n) over 6 time periods (T), adding up to a total sample size of 1794 (N).

Table 2: *Descriptive statistics for various variables*

Variable	**Mean**	**SD**	**Min**	**Max**	**N**	**n**	**T**
Share of high HC	0.090	0.076	0.000	0.691	1794	308	6.000
Share of low HC	0.572	0.131	0.054	0.897	1794	308	6.000
Schooling	9.408	1.379	6.024	15.880	1794	308	6.000
Total crime	1606.202	3012.973	2.000	27057.000	1794	308	6.000
Property crime	857.889	1684.363	1.000	15802.000	1794	308	6.000
Violent crime	748.313	1366.432	1.000	11913.000	1794	308	6.000
Unemployment rate	8.752	4.857	0.521	51.852	1794	308	6.000
Wages (thousands of CLP)	329.563	161.130	107.281	1958.184	1794	308	6.000
Attendance rate	88.515	3.530	54.490	96.770	1794	308	5.997
Schools	17.785	18.086	2.000	567.000	1794	308	5.928
Population (thousands)	56.597	88.073	0.928	931.211	1794	308	6.000
Poverty rate	17.495	8.994	0.030	57.050	1794	308	5.975

Notes: CLP stands for Chilean pesos. Given that we are dealing with unbalanced panel data we have included some panel descriptive statistics: N represents the number of observations, n represents the number of municipalities, and T represents the number of times each municipality appears.

Our dependent variable is criminal activities. The criminal activities variable consists of the sum of police complaints about different criminal categories for each municipality. We follow the literature and consider two categories of crime, which are violent crime and property crime. The violent crime category considers crimes such as rape, robbery in residence place, robbery with violence, robbery from a vehicle, other violent robberies, aggravated assault, homicides, and sexual assault; while the property

[3]Chile has a total of 345 municipalities, but due to the lack of information on the main variables for some municipalities, we work with an unbalanced panel of 308 municipalities (89% of the total).

crime category includes activities such as livestock theft, burglary and other types of theft (Lochner, 2004). In addition to these variables, we calculate the total number of crimes in each municipality by adding the two previous variables.

The main explanatory variable is education which is represented by two variables: the share of the population with low human capital and the share of the population with high human capital in each municipality. We focus on the working-age population, that is, people at least 15 years old. The low level of human capital refers to people without secondary education, and the high level refers to people with complete tertiary education. To test the robustness of the results, we also create another variable of education that considers the average years of schooling for each municipality.

Figure 1 depicts the share of each human capital level by year. We can observe a decline in the low human capital share through the years of study. We can also observe that both medium and high shares of human capital have been increasing in these years, but especially since 2011. In fact, in 2017, the high human capital share had a value of more than twice the value of 2006 and 2009. This evidences that, on average, the share of people with higher education in Chile has doubled from 2006 to 2017. Figure 1 also presents the average number of crimes divided into violent and property crimes by year. Note that both categories, but especially the property crime category, show a pronounced positive trend from 2006 to 2011. After 2011, the year in which the high level of education started to truly increase, the crime rates started to decline.

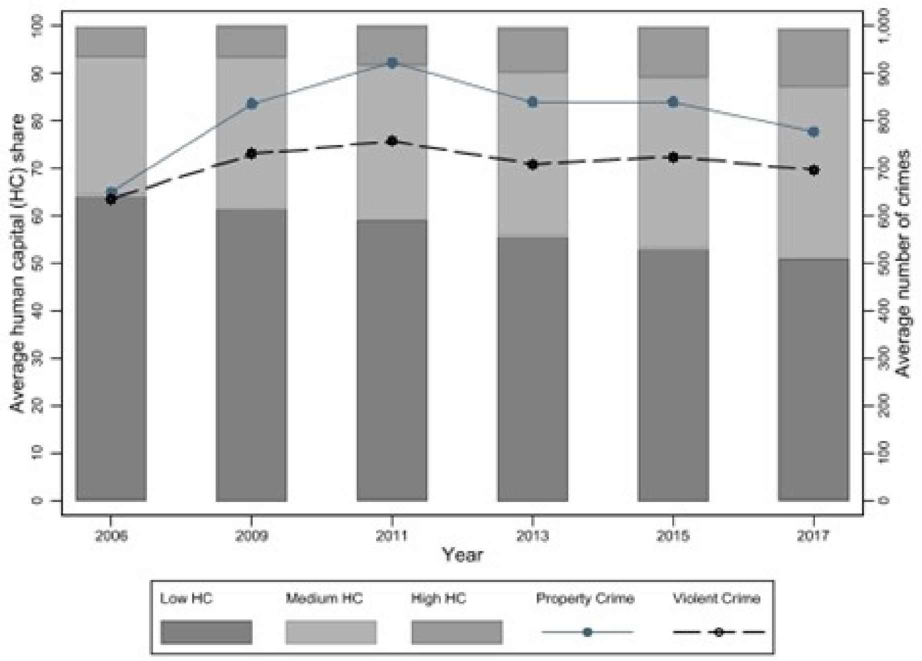

Figure 1: *Dynamic of human capital levels and crime in Chile.*
Notes: The figure shows the average human capital share for each level by year (Data obtained from the CASEN surveys). It also shows the average number of total crimes, both violent and property, by year (Data obtained from the CEAD).

Before performing any empirical exercise, it is important to undertake a descriptive analysis of the relationship between the level of crime and human capital at the municipal level. We perform this analysis for the 2006, 2009, 2011, 2013, 2015, and 2017 waves. Contrary to our expectations, we find a strong positive relationship between crimes per 1000 inhabitants and the average years of schooling by municipality (Figure 2). This positive relationship could be explained by the potential bias caused by the key empirical difficulties discussed in the theory and literature review. Therefore, we need to address this relationship through an adequate empirical analysis.

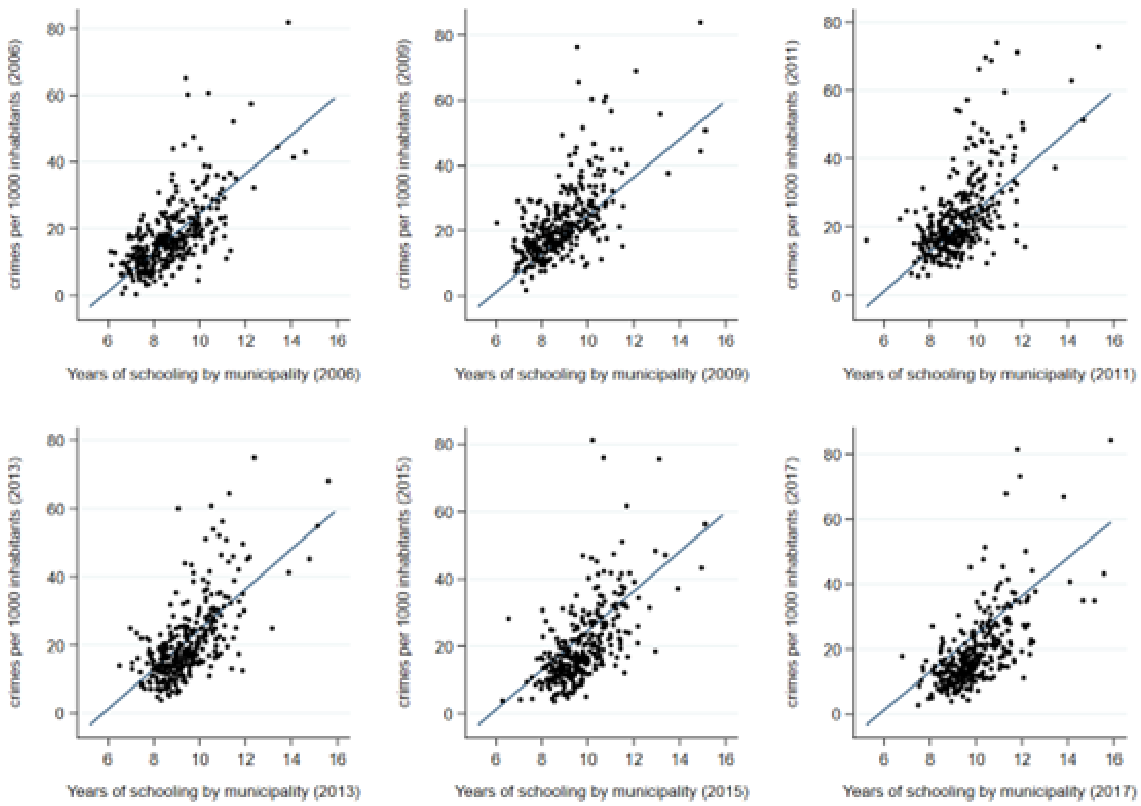

Figure 2: *Crimes per 1000 inhabitants and years of schooling by municipality in 2006, 2009, 2011, 2013, 2015, and 2017*

Notes: Schooling data obtained from the CASEN surveys. Crime obtained from the CEAD.

3.2. Empirical strategy

To address the common econometrical issues between the human capital and crime levels relationship we divide the empirical strategy into two parts. First, we use a fixed effects panel specification and instrument our endogenous variable. Second, we address possible spatial spillover effects behind this relationship by using panel spatial econometric techniques.

3.2.1 Panel data model and instrumental variables (IV)

We begin our empirical strategy by addressing (1) the potential aggregation bias (Cherry and List, 2002) that occurs when analyzing a variable that contains different categories. The variable total crime includes property crimes and violent crimes. We also address (2) the presence of unobserved factors that likely condition the municipality level of education (Lochner and Moretti, 2004), and (3) the possible bias due to reverse causality, where both variables are co-determined (e.g., schooling levels could depend on crime levels and vice versa). Specifically, human capital is endogenous because there can be unobserved time-varying shocks in the human capital levels of a municipality that may affect our results (e.g., changes in (des)amenities that include, in addition to crime, the quality of schools, local public services, and local taxes). As far as we know, literature has no empirical evidence about the sign that this bias may have, because it will depend on the possible correlation between shocks, omitted variables, and human capital levels. To deal with these three difficulties, we first estimate a naïve panel data model with fixed effects. This general specification is defined as:

$$\log(\text{Crime}_{it}) = \beta_0 + \beta_1 \log(\text{education}_{it}) + \beta_2 X_{it} + \alpha_i + \epsilon_{it} \tag{1}$$

Where $Crime_{it}$ represents the number of criminal activities in municipality i at time t. To deal with the aggregation bias, we define three different dependent variables: (i) the total crime in a municipality, and the division of total crimes into (ii) violent crimes and (iii) property crimes (Lochner, 2004). To deal with the potential bias due to unobserved factors, we use three strategies. First, we define two alternative measures for $Education_{it}$, as explained above. Second, we include X_{it}, which is a vector of time-variant control variables that potentially condition municipal levels of criminal activity, all measured in logarithms.[4] It includes unemployment rate, wages, school attendance rate, number of schools, population, and poverty rate. Third, we include α_i, which represents municipality fixed effects that capture cross-sectional heterogeneity. ϵ_{it} represents the disturbance term.

To address the reverse causality bias, we instrument our endogenous variable, which is human capital, and create a Bartik-style instrument, which has been widely used in the literature (Bartik, 1991; Broxterman and Larson, 2020; Goldsmith-Pinkham et al., 2020; Rodríguez-Puello and Iturra, 2022; Hernández et al., 2023). We use historic human capital levels obtained from CASEN 2003 and create a Bartik-style instrument following Moretti and Thulin (2013) for human capital. The instrument is an index that captures exogenous shifts in the relative demand for different education groups that are predicted by each municipality, as follows:

$$iv_{it} = \log HC_{i,2003} \left(\ln(HC_t - HC_{it}) - \ln(HC_{2003} - HC_{i,2003}) \right) \tag{2}$$

Specifically, the index isolates the variation that comes from changes at the national level since they are calculated excluding the municipality (i). To build this instrument, first, we calculate the human capital levels in each municipality (i) obtained from CASEN 2003. Second, we compute the growth in human capital levels in the municipality (i) over time (t).

The difference within the brackets in Equation (2) represents the percentage change of the difference between the national median human capital and the median human capital of the municipality. The change in the national median human capital excludes municipality (i), therefore, the variation comes from different human capital levels in the municipalities that depend on regional specialization or different exposure to external shocks. Finally, this is multiplied by the logarithm of the initial median human capital of the municipality. The exclusion restriction for this type of instrument is that the national growth rates of human capital are not correlated with the internal conditions of any municipality. Under this context, we argue that our instrument is exogenous because human capital levels must vary unevenly among industries, regions, and over time. For example, human capital levels depend on regional specialization or the level of exposure to external shocks.

[4] Using the logarithm of continuous independent variables in the model has several reasons. First, it improves the fit by transforming the distribution to a more normally shaped curve. Second, it improves the interpretation of the results, and third, it reduces the variability of data, especially when the data includes outlying observations, among other factors (Wooldridge, 2015).

3.2.2 Spatial econometrics model

In addition, we address the spillover effects conditioning the relationship between human capital and the levels of crime in a municipality. Schooling and crime levels are not uniformly distributed around space, and crime presents high geographic mobility in Chile (Gutiérrez et al., 2009). Additionally, the idea that education not only rewards the individual per se living in a certain municipality, but also generates spillovers that are shared by society at the aggregate level has great political and social implications. For example, if education has a positive effect in diminishing local crime rates at neighboring municipalities, then local governments could reinforce their public investment in education to enjoy the social spillovers of having a better-educated population.

We start with a LM test statistic on an OLS estimation to select the best spatial specification for our data (Anselin, 1988; Florax et al., 2003). After analyzing the LM-error test, LM-lag test, and the robust version of each test for Equation (1), we conclude that a spatial error model (SEM) best specifies our analysis. The SEM model (Equation 3) includes a spatial lag on the error term and addresses interaction effects among error terms. However, as a robustness test, we also perform the spatial autoregressive model (SAR), which includes a spatial lag on the dependent variable and addresses endogenous interaction effects, that is, the relationship between the dependent variable of municipality (i) and that of municipality (j) (Equation 4); and the Spatial Autoregressive Combined Model (SAC) which includes a spatial lag of both the error term and the dependent variable (Equation 5).

$$\text{Log}(Crime_{it}) = \beta_0 + \beta_1 \text{Log}(education_{it}) + \beta_2 X_{it} + \alpha_i + \tau_t + \mathbf{u}_{it} \tag{3}$$
$$\mathbf{u} = \theta W \mathbf{u}_{it} + \epsilon_{it}$$

$$\text{Log}(Crime_{it}) = \beta_0 + \rho W \text{Log}(Crime_{jt}) + \beta_1 \text{Log}(education_{it}) + \beta_2 X_{it} - \alpha_i + \tau_t + \epsilon_{it} \tag{4}$$

$$\text{Log}(Crime_{it}) = \beta_0 + \rho W \text{Log}(Crime_{jt}) + \beta_1 \text{Log}(education_{it}) + \beta_2 X_{it} + \alpha_i + \tau_t + \mathbf{u}_{it} \tag{5}$$
$$\mathbf{u} = \theta W \mathbf{u}_{it} + \epsilon_{it}$$

4. Results

4.1. General Results

The estimation results of the different variants of the naïve panel data model with fixed effects are presented in Table 3 and 4. In both tables, columns 1 to 3 present the results using the share of high and low human capital as the main independent variables. Columns 4 to 6 present the results using years of schooling as the main explanatory variable. In both cases (Tables 3 and 4), we also made the estimations for the aggregated total crime variable (columns 1 and 4) and splitting the variable into property (columns 2 and 5) and violent crimes (columns 3 and 6).

In general, human capital, measured as the share of people with tertiary education or as the average years of schooling, is negatively correlated and statistically significant at the 1 percent level with the level of crimes in a municipality (Table 3). On the one hand, when we compare high and low human capital, the results are as follows: (i) high human capital is negatively correlated and statistically significant with total crimes in a municipality, and (ii) low human capital is positively and statistically significantly correlated with crime levels in a municipality. Specifically, a ten percent increase in the high human capital share is correlated with a reduction of total crimes by around nine percent (column (1)). When splitting the sample between property crimes (column (2)) and violent crimes (column (3)), property crimes are more sensitive to the increase in human capital than violent crimes. On the other hand, focusing on years of schooling as our education variable, a ten percent increase in average years of schooling is correlated with a 6.4 percent reduction in the average total crimes (column (4)). In columns (5) and (6), we disaggregate the sample between property and violent crimes, and the magnitude and significance of the coefficients are very similar. These results support our main hypothesis that the higher the level of human capital in a municipality, the lower the number of crimes.

Table 3: *Human Capital and crime levels – Panel specification with fixed effects.*

	(1) Total b/se	(2) Property b/se	(3) Violent b/se	(4) Total b/se	(5) Property b/se	(6) Violent b/se
Share of high HC (Log)	-0.092***	-0.107***	-0.079***			
	(0.021)	(0.023)	(0.025)			
Share of low HC (Log)	0.183***	0.106	0.273***			
	(0.068)	(0.077)	(0.083)			
Schooling (Log)				-0.642***	-0.631***	-0.700***
				(0.127)	(0.147)	(0.168)
Unemployment rate (Log)	0.048***	0.056***	0.035**	0.048***	0.055***	0.034*
	(0.014)	(0.016)	(0.016)	(0.014)	(0.016)	(0.016)
Wages (Log)	0.376***	0.430***	0.330***	0.324***	0.383***	0.276***
	(0.040)	(0.045)	(0.051)	(0.038)	(0.043)	(0.049)
Attendance rate (Log)	-0.780***	-1.271***	-0.249*	-0.744***	-1.251***	-0.197
	(0.177)	(0.241)	(0.218)	(0.174)	(0.239)	(0.212)
Schools (Log)	0.075	0.073	0.102*	0.076	0.073	0.103*
	(0.049)	(0.052)	(0.059)	(0.048)	(0.052)	(0.058)
Population (Log)	0.190***	0.153*	0.246***	0.164***	0.133	0.212**
	(0.071)	(0.084)	(0.084)	(0.072)	(0.084)	(0.088)
Poverty rate (Log)	-0.022	-0.005	-0.050**	-0.015	-0.001	-0.041*
	(0.019)	(0.022)	(0.023)	(0.018)	(0.021)	(0.022)
Constant	2.630*	3.790***	-0.472	4.932***	6.114***	1.902
	(1.128)	(1.457)	(1.369)	(1.087)	(1.423)	(1.335)
Observations	1794	1794	1794	1794	1794	1794
Groups	308	308	308	308	308	308
P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R2	0.109	0.124	0.061	0.096	0.114	0.051
F statistic	17.674	20.429	11.320	18.031	20.796	9.899

Note: Significant at the *10 percent; **5 percent; ***1 percent. Robust standard errors in parenthesis.

However, we have not fully addressed the issue of endogeneity that we discussed earlier. Therefore, in Table 4, we show the results of the panel model with fixed effects and instrumental variables. On the one hand, high human capital is correlated negatively and statistically significant at 1 percent with crime levels (columns (1) to (3)). This result is very similar when we split the sample between property and violent crimes. Low human capital, on the contrary, is correlated positive and statistically significant at 5 percent with an increase of crime levels in a municipality. On the other hand, the average years of schooling are correlated negatively and statistically significant with the municipal crimes level (columns (4) to (6)). When we split the sample between property and violent crimes, violent crimes experience

Table 4: *Human Capital and crime levels. Panel specification with instrumental variable.*

	(1) Total b/se	(2) Property b/se	(3) Violent b/se	(4) Total b/se	(5) Property b/se	(6) Violent b/se
Share of high HC (Log)	-0.353***	-0.359***	-0.318***			
	(0.085)	(0.095)	(0.102)			
Share of low HC (Log)	0.367**	0.122	0.722***			
	(0.170)	(0.196)	(0.197)			
Schooling (Log)				-1.966***	-1.015**	-3.093***
				(0.425)	(0.466)	(0.533)
Unemployment rate (Log)	0.036**	0.047***	0.021	0.036**	0.052***	0.013
	(0.015)	(0.016)	(0.017)	(0.015)	(0.016)	(0.018)
Wages (Log)	0.773***	0.759***	0.787***	0.586***	0.459***	0.749***
	(0.100)	(0.106)	(0.119)	(0.093)	(0.100)	(0.118)
Attendance rate (Log)	-0.969***	-1.401***	-0.514**	-0.886***	-1.292***	-0.454**
	(0.213)	(0.271)	(0.230)	(0.198)	(0.249)	(0.224)
Schools (Log)	0.012	0.021	0.027	0.017	0.056	-0.003
	(0.041)	(0.046)	(0.050)	(0.040)	(0.046)	(0.050)
Population (Log)	0.228***	0.173**	0.308***	0.162***	0.133*	0.208**
	(0.068)	(0.077)	(0.085)	(0.063)	(0.071)	(0.082)
Poverty rate (Log)	-0.017	0.003	-0.052**	-0.002	0.003	-0.018
	(0.019)	(0.021)	(0.022)	(0.016)	(0.019)	(0.020)
Observations	1794	1794	1794	1794	1794	1794
Groups	308	308	308	308	308	308
R2	-0.050	0.031	-0.081	0.027	0.110	-0.119
F statistic	16.356	18.225	11.461	16.624	18.755	11.174
F statistic for weak identification	53.095	53.095	53.095	126.331	126.331	126.331

Notes: Significant at the *10 percent; **5 percent; ***1 percent. Robust standard errors in parenthesis.

a higher reduction (with 1 percent statistical significance) compared to property ones (with 5 percent of statistical significance). In fact, the magnitude of the coefficient is almost three times greater (columns (5) and (6)). Our results are consistent with the literature. Buonanno and Leonida (2009) for example, find that both high school and average years of schooling reduce criminal activity in Italian regions. They show that this effect is stronger in property crimes than in theft. These results allow us to not reject our main hypothesis that human capital deters crime activities in Chilean municipalities.

As a heterogeneity analysis, we split the sample into the minimum categories of crime that the data allows us to. Table A2 and Table A3 of the appendix present results for the different categories of violent crimes and property crimes, respectively. Both tables show that, as expected, schooling is negatively correlated with crime. This correlation is statistically significant for most types of violent crimes: rape, robbery in residence place, other violent robberies, and aggravated assault; as well as for most types of property crimes: theft in a non-residential place and livestock theft. This result is robust even when the model we present is the most rigorous in our article (iv specification).

Finally, Modrego and Berdegué (2015) state the sampling carried out by the CASEN for municipalities with a small population size might not be representative of selected variables and could therefore introduce bias into the estimates. To address this, we have decided to build on the work of Rodríguez-Puello et al. (2022) and use different estimates in terms of the population size of the municipalities: (a) using the whole available sample, (b) considering only those municipalities with at least 10,000 inhabitants, (c) considering only those municipalities with at least 25,000 inhabitants and (d) considering only those municipalities with at least 50,000 inhabitants. The greater the population size of the analyzed observable units, the smaller the sample. The results in Appendix Table A4, where our dependent variable is the logarithm of total crimes per municipality, show that our main dependent variable of interest, the share of high human capital, remains negative and significant for all population sizes. This suggests that even though some municipalities may be smaller/larger than others, the expected results remain generally stable through the different sizes.

4.2. Mechanisms discussion

The first mechanism we test is unemployment. According to our expectations, the unemployment rate is positively correlated with crime levels for all specifications, and it is statistically significant at 1 percent for total crimes and property crime. This result is in line with the literature. Speziale (2014), for example, finds in Italy that unemployment rates have a positive corretation with crime rates. This result is also positve when focused on juvenile unemployment rates. Raphael and Winter-Ebmer (2001), using U.S. state data, also find positive effects of unemployment on property crime rates. The positive relationship between unemployment and property crimes catches our attention. Our results suggest that unemployed individuals, who are excluded from obtaining legal income, may see property crimes as a short-term alternative to generate income (Speziale, 2014). That is, if we assume that an unemployed person has some commitment to being the economic support for his or her family, he or she is more likely to commit property crimes in the short term. This finding opens the opportunity for policy makers to focus on employment protection programs or Keynesian measures that ensure family income in economic recession or increased unemployment times.

Second, in line with our expectations, municipal attendance rates at school are negatively correlated with crime levels. This result is consistent in all specifications (columns (1) to (6)). This can be explained by two main reasons. On the one hand, people who attend school reasonably have less time to engage in criminal activities because of the school time. On the other hand, the interests of people who attend schools can be directed toward controlled extracurricular activities (e.g., sports, book clubs) that potentially keep young people away from being exposed to criminal activity. Prior studies such as Buonanno and Leonida (2009) show similar results. They find in Italy using a panel data specification that enrollment rate is correlated negatively and statistically significant with criminal activities. Other studies such as Anderson (2014) using a Diff-in-Diff-in-Diff specification find that minimum dropout age requirements deter juvenile crime. In this line, our result gives some light to promote educational policies that ensure school attendance by young people. As Deming (2011) states, schools can play a crucial role in preventing future crimes, especially for high-risk youth. In their article, they observed that many of these at-risk young individuals drop out of school at a very early age and become involved in serious criminal activities before even completing high school. Therefore, for these marginalized youth, public schools may represent the most effective point of intervention.

Third, contrary to our expectations, wages are correlated positively and statistically significantly with crime levels in all specifications. Although this result takes us by surprise, it is not an isolated case. For example, Doyle et al. (1999) finds a positive relationship between wages and crime in the United States. They argue that on the one hand richer cities (which offer higher wages) can carry a higher opportunity cost that deter criminal activities; but, in the other hand, they also offer a better attractiveness (value of properties) that incentivize taking the risk of committing crimes. A second explanation lies in the following context. Wages in less developed countries, like Chile, are low compared to more developed countries and still do not represent an opportunity cost strong enough to deter criminal activity. In fact, the Chilean average annual wages are 84% less than the OECD average (OECD, 2022).

Other control variables behave as expected, population is correlated positive and statistically significant in all specifications. This result is in line with **?** who recognizes this result as a negative externality of agglomeration economies, where the largest municipalities tend to concentrate higher levels of criminal activity as a product of the concentration of economic agents. Poverty rates and the number of schools have no apparent relationship with crime levels in the municipalities. Finally, the results for the first stage of the IV regression are in Table A1 in the appendix. It should be noted that the different diagnostic tests provided by the instrument variable panel data with fixed-effects model (at the end of Table 4 in column (4)) support our Bartik-style instrument. The Kleibergen-Paap under-identification test rejects under-identification (p-value= 0.000) and the weak instrument F statistic (126.331) is above the Stock-Yogo critical value, even for a 10% relative bias (16.38). Both tests discard a problem of weak instrument, and thus indirectly discard any model misspecification errors. Summarizing, these results support our main hypothesis that higher education deters criminal activity in a municipal level.

4.3. Spatial spillover effects of crime

To address the spatial interdependence between neighboring municipalities, we begin by performing a diagnostic for spatial dependence on the crime variable. The first step is to define a spatial weight matrix that describes the neighborhood structure, we follow the literature and define a normalized inverse distance weight matrix (Anselin, 1995; Chávez and Rodríguez-Puello, 2022).[5] We then proceed to analyze the Moran's I , which is a coefficient that measures the global spatial autocorrelation of a variable. Its null hypothesis is that there exists spatial randomness, that is, rejecting this null hypothesis indicates the existence of global spatial association in crime (Anselin, 1995). Table 5 presents the results for the estimated Moran's I for each year of our sample. The results suggest that there is enough evidence to reject the null hypothesis at a 1% significance level. Therefore, with this preliminary analysis, we can affirm that there exists global spatial autocorrelation in the prevalence of crime in the Chilean municipalities, and the spatial distribution of criminal activities is not random across space.

Table 5: *Moran's I statistic for global spatial autocorrelation in total crime.*

Year	Total crime Moran's I statistic	z-value	Pseudo p-value
2006	0.173	28.728	0.000
2009	0.179	29.809	0.000
2011	0.190	31.624	0.000
2013	0.195	32.316	0.000
2015	0.194	32.170	0.000
2017	0.203	33.639	0.000

Notes: Analysis performed using a normalized inverse distance weight matrix. The number of permutations is set at 999, indicating precision of 0.000.

Deeping in our diagnostic for spatial dependence, we use the Local Indicators of Spatial Association (LISA) to determine the geographic location and significance level of local spatial distribution patterns.[6] These clusters are classified as high–high, low–low, low–high and high–low. A high-high cluster means, for example, that a municipality with significant high levels of total crime has neighbor municipalities

[5] We use the geographic coordinates of the municipalities m and j to compute the distance d_{mj}. The distance matrix has the advantage of reflecting proximity in the distance logic, which is not represented by a contiguity matrix.

[6] Also known as clusters or hotspots (Anselin, 1995; Anselin et al., 2007)

with significant high levels of total crime. Figure 3 presents LISA maps for crime clusters at a 10% significance level for 2017. We observe that most high-high clusters are concentrated in the central municipalities of Chile.[7] A fact that has striking implications in fighting crime, as it means that the decisions and measures taken by a municipality affects neighboring municipalities, thus, regional place-based measures must be taken to diminish local crime levels.

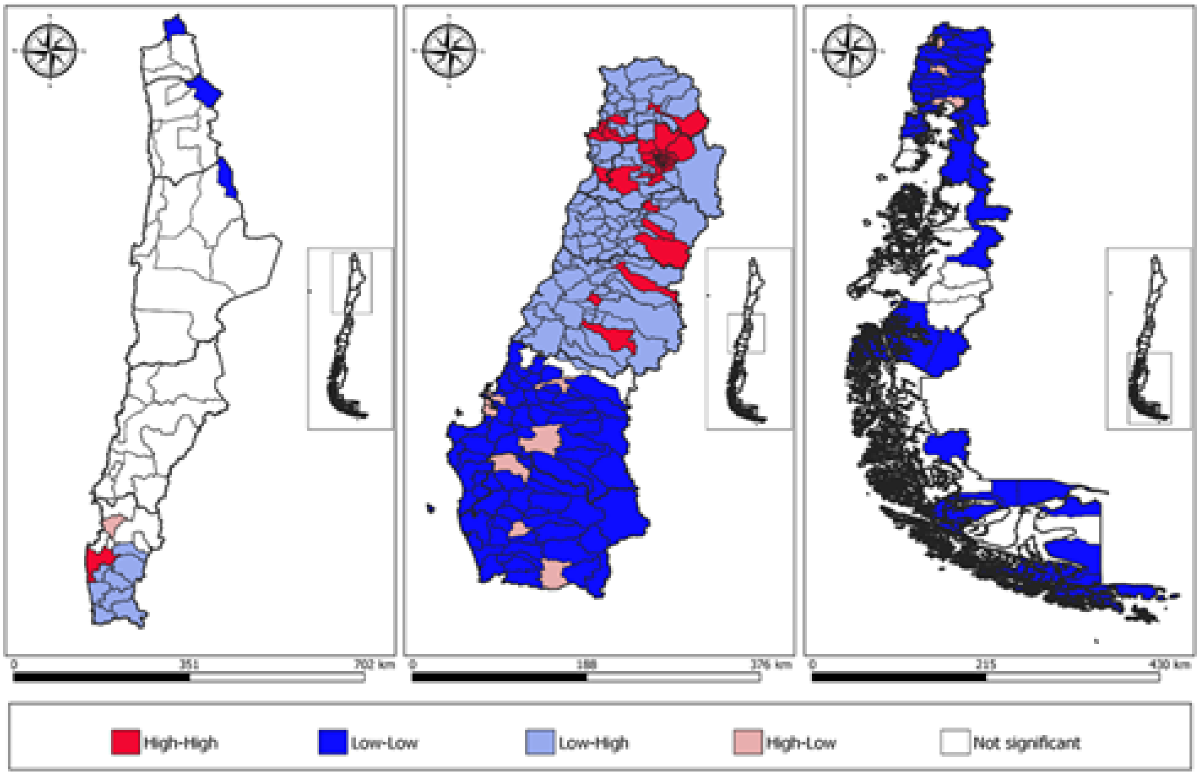

Figure 3: *Local indicators of spatial association (LISA) for crime in 2017.*
Note: Clusters at a 10% significance level. Total crime variable obtained from the Chilean Crime Study and Analysis Center (CEAD).

Until now, we have established the existence and importance of global spatial autocorrelation and local spatial distribution patterns in total crime. We now use LM test statistics on Equation 3 to guide and select the best spatial specification for our data (Florax et al., 2003). After analyzing the LM-error test, LM-lag test, and the robust version of each test, we conclude that a spatial error model (SEM) represented by Equation 3 best specifies our analysis. As a robustness test, we also perform the spatial autoregressive model (SAR) specified Equation 4; and the Spatial Autoregressive Combined model (SAC) specified in Equation 5.

The panel data has been strongly balanced for the purpose of these spatial estimations. We use normalized inverse distance weight matrices at the municipal level. Results are presented in Table 6. We use property crimes (columns 1 to 4) and violent crimes (columns 5 to 8) as the dependent variable and high and low human capital as our main independent variable. Given that we have balanced our dataset, columns 1 and 5 present results for the non-spatial (panel with fixed effects) specification to compare with spatial results. Columns 2 and 6 present results for the SEM specification, columns 3 and 7 do it for the SAR and, finally columns 4 and 8 present results for the SAC specification.

[7] We also performed this analysis for 2006 and obtained similar results. LISA maps for all years are available upon request from the authors.

First, it is worth noting that when the spatial lag is included results for the share of low and high human capital are non-significant for violent crimes (columns 6, 7 and 8), however, the share of people with high human capital is correlated negative and statistically significant with the level of property crimes for both the SAR and SAC models (columns 3 and 4). That is, the higher the share of high human capital in a municipality, lower the level of property crimes crime of that same municipality. To explore the correlation between neighboring municipalities, let us focus on the spatial lag section of table 6. We can observe that the error lag is positive and significant for all models (columns 2, 4, 6 and 8). Given that, according to their nature, spatially correlated errors do not induce spatial spillover effects in the covariates, we focus on the analysis of the crime lag variable. We observe that the lag crime variable is positive and significant for the SAR model for both property and violent crimes (columns 3 and 7), and for the SAC model for the property crimes (column 4), but not for the violent crimes (column 8).

In conclusion, when analyzing the spatial spillover effects in the relation between education and crime we find evidence for the existence of global spatial autocorrelation and local spatial distribution patterns in total crime. We also find that both the error lag and the crime lag are positive and significant for all models. Thus, in general, we find evidence of a positive correlation between the quantity of crimes of one municipality and the quantity of crimes of a neighboring municipality. This is in line with some existent literature that demonstrates the importance of social interactions for determining criminal activity. For example, Billings et al. (2019) find evidence that neighborhood spillovers in crime based on exposure to same race and gender peers are larger when those peers are assigned to the same school for North Carolina.

Table 6: *Human Capital and crime levels – Spatial specification with fixed effects.*

	Property crimes				Violent crimes			
	(1) Panel B / SE	(2) SEM B / SE	(3) SAR B / SE	(4) SAC B / SE	(5) Panel B / SE	(6) SEM B / SE	(7) SAR B / SE	(8) SAC B / SE
Share of high HC (Log)	-0.118***	-0.027	-0.041**	-0.034*	-0.080***	0.007	-0.010	0.004
	(0.020)	(0.020)	(0.020)	(0.020)	(0.024)	(0.022)	(0.021)	(0.023)
Share of low HC (Log)	0.092	-0.053	-0.021	-0.034	0.282***	0.050	0.128	0.064
	(0.074)	(0.078)	(0.072)	(0.076)	(0.083)	(0.085)	(0.079)	(0.088)
Unemployment rate (Log)	0.046**	0.009	0.013	0.011	0.038**	0.001	0.007	0.002
	(0.020)	(0.013)	(0.012)	(0.012)	(0.016)	(0.014)	(0.013)	(0.014)
Wages (Log)	0.455***	0.074	0.087**	0.088**	0.379***	0.135**	0.112***	0.135**
	(0.046)	(0.051)	(0.040)	(0.045)	(0.062)	(0.054)	(0.043)	(0.053)
Attendance rate (Log)	-1.473***	-0.375	-0.410**	-0.425*	-0.433*	-0.027	-0.076	-0.042
	(0.267)	(0.254)	(0.209)	(0.234)	(0.255)	(0.274)	(0.222)	(0.270)
Schools (Log)	0.077	0.010	0.043	0.019	0.108*	0.011	0.060	0.015
	(0.052)	(0.047)	(0.045)	(0.048)	(0.061)	(0.051)	(0.049)	(0.053)
Population (Log)	0.057	0.168**	0.133**	0.152**	0.147	0.236***	0.182**	0.223***
	(0.111)	(0.073)	(0.068)	(0.071)	(0.102)	(0.079)	(0.073)	(0.080)
Poverty rate (Log)	0.001	-0.008	-0.009	-0.009	-0.031	-0.002	-0.016	-0.003
	(0.022)	(0.015)	(0.014)	(0.015)	(0.022)	(0.016)	(0.015)	(0.017)
Constant	5.441***				0.746			
	(1.745)				(1.505)			
Spatial lag								
Error lag		0.923***		0.429*		0.906***		0.748***
		(0.028)		(0.229)		(0.035)		(0.245)
Crime lag			0.891***	0.821***			0.881***	0.507
			(0.035)	(0.085)			(0.042)	(0.372)
Constant		0.236***	0.236***	0.236***		0.256***	0.256***	0.256***
		(0.004)	(0.004)	(0.004)		(0.005)	(0.005)	(0.005)
Observations	1926	1926	1926	1926	1926	1926	1926	1926

Note: Dependent variable is the logarithm of total crime. Standard errors in parentheses. The model specifies spatial lags using normalized inverse distance weighting matrices at the municipal level. All models specified with fixed effects and a balanced dataset. Key: * p¡0.05, ** p¡0.01, *** p¡0.001

5. Conclusion

This article contributes to the understanding of social returns to schooling that accumulate in local geographical areas. The research tests whether education affects the number of local criminal activities in Chilean municipalities. Using an unbalanced panel data from 2006 to 2017, we find that high human capital is negatively and significantly related to the number of total, property, and violent criminal activities; while low human capital is positively and significantly related to them. Thus, we provide evidence that at the aggregate level, higher levels of education in a municipality deter criminal activity. This finding holds robust after performing several actions to solve some econometric issues addressed by the literature, such as aggregation bias, unobserved factors, endogeneity by simultaneity as well as the presence of spatial spillover effects. Consequently, our final econometric approach that allowed us to test this relationship is a panel model with fixed effects and instrumental variable. We also performed some tests to analyze the spatial spillover effects in the relation between education and crime. We provide evidence for the existence of global spatial autocorrelation and local spatial distribution patterns in total crime. Our results indicate a positive correlation between the number of crimes in one municipality and the number of crimes in a neighboring municipality.

This article also tests three mechanisms that explain the relationship between education and criminal activity, which are: unemployment rates, school attendance rates and wages. We find that unemployment is positive and significantly related to total and property crimes, but not to violent crimes. This result is in line with previous studies (Raphael and Winter-Ebmer, 2001). Regarding the school attendance mechanism, we find that municipal attendance rates are negatively correlated with total, property, and violent criminal activities. This result is also in line with previous literature (Buonanno and Leonida, 2009). Finally, contrary to our expectations, wages are correlated positively and statistically significant with crime levels in all specifications. Doyle et al. (1999) finds a similar relation in the United States and argue that richer cities could offer a better attractiveness (value of properties) that incentivize taking the risk of committing crimes. A second explanation is that wages in less developed countries, like Chile, are low compared to more developed countries and still do not represent an opportunity cost strong enough to deter criminal activity.

Understanding these associations is relevant from a policy perspective as it suggests a direct way for policymakers to reduce crime. Policy makers should support policies that promote employability and ensure the access of people to education to enjoy the social spillovers of having a better-educated population. To conclude, this article also opens several avenues for future research. This study focuses on the aggregated analysis of education and crime. It would be interesting to see results from individual-level data, which up to this date is not available for Chile. Also, it would be interesting to use natural experiments as a source of exogenous variation in human capital or unemployment to give some insight of the causal relationship with crime.

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Appendix

Table A1: *Human Capital and crime levels. Panel specification with instrumental variable (first stage).*

	(1,2,3) Share of low HC (Log)	(4,5,6) Schooling (Log)
	b/se	b/se
IV high HC (Log)	0.027***	
	(0.005)	
IV low HC (Log)	-1.028***	
	(0.105)	
IV Schooling (Log)		0.244***
		(0.022)
Controls	Yes	Yes
Observations	1794	1794
Groups	308	308
R^2	-0.050	0.027
F statistic	16.356	16.624
F statistic for weak identification	53.095	126.331

Note: Significant at the *10 percent; **5 percent; ***1 percent. Robust standard errors in parenthesis.

Table A2: *Human Capital and Property crime categories. Panel specification with instrumental variable.*

	Dependent Variables								
	Violent crimes (log)	Rape (log)	Robbery in residence place (log)	Robbery with violence (log)	Robbery from a vehicle (log)	Other violent robberies (log)	Aggravated assault (log)	Homicide (log)	Sexual Assault (log)
	b/se								
Schooling (Log)	-3.106***	-3.498***	-2.758***	-0.798	-0.824	-8.139***	-9.811***	-0.622	0.490
	(0.535)	(0.827)	(0.687)	(0.675)	(0.873)	(1.321)	(1.056)	(0.762)	(0.656)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1798	1798	1798	1798	1798	1798	1798	1798	1798
Groups	308	308	308	308	308	308	308	308	308
R^2	-0.119	-0.047	-0.085	0.061	0.167	-0.159	-0.802	0.012	0.061
F statistic	11.328	4.238	6.658	13.883	28.729	21.568	31.868	2.698	12.101
F stat. for weak id.	126.345	125.791	125.791	125.791	125.791	125.791	125.791	125.791	125.791

Note: Column (1) is the sum of the total violent crimes. Columns (2) to (9) refers to the minimum categories of violent crimes. Significant at the *10 percent; **5 percent; ***1 percent. Robust standard errors in parenthesis.

Table A3: *Human Capital and Property crime categories. Panel specification with instrumental variable.*

	(1) Property crime (log)	(2) Theft in a non-residential place (log)	(3) Burglary (log)	(4) Livestock theft (log)
		b/se		
Schooling (Log)	-1.192**	0.463	-1.090**	-7.562***
	(0.491)	(0.614)	(0.493)	(1.133)
Controls	Yes	Yes	Yes	Yes
Observations	1798	1798	1798	1798
Groups	308	308	308	308
R^2	0.109	0.103	0.072	-0.271
F statistic	17.626	21.628	12.304	10.527
F statistic for weak id	125.791	125.791	125.791	125.791

Note: Column (1) is the sum of the total property crimes. Columns (2) to (4) refers to the minimum categories of property crimes. Significant at the *10 percent; **5 percent; ***1 percent. Robust standard errors in parenthesis.

Table A4: *Human Capital and population levels. Panel specification with instrumental variable.*

	Sample 1				Sample 2			
	Full sample	Pop. >= 10,000	Pop. >= 25,000	Pop. >= 50,000	Full sample	Pop. >= 10,000	Pop. >= 25,000	Pop. >= 50,000
	b/se				*b/se*			
Share of high HC (Log)	-0.359***	-0.474***	-0.700***	-0.241*				
	(0.085)	(0.087)	(0.155)	(0.140)				
Share of low HC (Log)	0.383**	0.199	-0.110	0.060				
	(0.172)	(0.187)	(0.221)	(0.213)				
Schooling (Log)					-2.165***	-2.144***	-1.881***	-0.334
					(0.464)	(0.440)	(0.698)	(0.753)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1795	1425	823	516	1798	1425	823	516
Groups	308	249	144	90	308	249	144	90
R^2	-0.119	-0.047	-0.085	0.061	0.167	-0.159	-0.802	0.012
F statistic	15.949	14.794	8.099	8.123	13.793	14.600	7.956	8.277
F stat. for weak id.	53.313	44.124	19.544	13.550	125.791	89.030	45.177	39.542

Note: Column (1) is the sum of the total property crimes. Columns (2) to (4) refers to the minimum categories of property crimes. Significant at the *10 percent; **5 percent; ***1 percent. Robust standard errors in parenthesis. fdffdf