Do Immigrants Increase Crime? Spatial Analysis in a Middle-Income Country

ABSTRACT

The last decade has seen a significant global increase in immigration. This large growth has caused an increasing opposition to immigration in local populations in many parts of the world, partly because of a commonly held belief that immigration increases crime. Using data from Chile, spanning 10 years, from 2005 to 2015, we analyze the relationship between immigration and crime through a dynamic Spatial Durbin Model (SDM), which accounts for the possible bias for omitted variables. As the spatial model is dynamic and based on panel data, it is possible to identify direct and indirect effects on both the short- (the same period) and long-term (next period) bases. Our results show that there is no statistical evidence to link an increase in the number of immigrants to a rise in the rate of any type of crime. If any, we found a negative relationship between the number of immigrants and crime for only one out of the eight crime types analyzed.

Keywords: Crime, immigration, spatial econometrics.

JEL codes: C21, J15, K49

I. Introduction

In this study, we evaluate the hypothesis that immigration increases the crime rate using a spatial-temporal econometric approach. Globally, immigration has significantly increased over the last decade. A report by the International Organization for Migration (2018) shows that in 1980, there were around 102 million people (2.3% of the world's population) living in a country different from their country of birth. This value increased to 153 million by 1990 (2.9% of the world's population), 173 million in 2000 (2.8%), and 244 million in 2015 (3.3%). The same phenomenon has been observed in Latin America, where the number of immigrants has increased by approximately 50% since 2000 (United Nations, 2017).

In response to this phenomenon, the local population in many countries is increasingly opposed to immigration, in part because of a commonly held belief that immigration increases different types of crime. Simon and Sikich (2007) implemented a cross-country public poll to assess public perception about the relationship between immigration and crime rate. They found mixed results. In Japan, 72% of respondents thought that immigration increases crime. The proportion was 64% in Germany, 44% in France, 40% in the United Kingdom (UK), 35% in Australia, while it was 27% in the United States of America (USA).

Since the seminal work done by Becker (1968), who defined the theoretical framework commonly used in the economics of crime literature, and its first application by Ehrlich (1973), many researchers have studied the relationship between crime and economic incentives, including income inequality and deterrent variables, while others have analyzed the relationship between crime and gender, and crime and immigration, among other topics. The economic model of crime suggests that the participation in criminal activities (in the margin) will depend on the relationship between the potential benefits of crime activities and the earnings associated with participation in formal labor markets (Freeman, 1999). Extensive work has been carried out addressing the relationship between crime and labor market outcomes, including studies analyzing the relationship between crime and unemployment, crime and wages, and crime and education (Fougère et al., 2009; Gould et al., 2002; Lin, 2008; Machin et al., 2011; Machin and Meghir, 2004) For an extensive review on crime and economic incentives, see Draca and Machin (2015).

The theory suggests that the economic incentives to participate in criminal activities are transmitted to individuals by both the level and the distribution of income (Danziger and Wheeler, 1975). Regarding income level, evidence suggests a positive relationship with crime (Allen, 1996; Scorzafave and Soares, 2009), whereas results associated with the relationship between crime and income inequality are controversial. Kelly (2000) found that inequality does not influence property crime; however, its impact on violent crime is high. Similar results related to violent crimes are reported by Enamorado et al. (2016) in Mexico. Scorzafave and Soares (2009) found a positive relationship with pecuniary crimes, while Fajnzylber et al. (2002) reported a relationship between crime and inequality for both property crimes and violent crimes. Further, Chintrakarn and Herzer (2012) found a negative relationship between inequality and crime.

Another fruitful strain of research on crime is the one related to deterrence variables, which are those associated with the probability of being captured and the severity of punishment, determining the expected returns of crime. The research on the deterrence effect includes those addressing the effect on crime of an increase in the probability to be apprehended, which depends upon policing intensity; and those addressing the responsiveness of criminal activities to an increase in punishment, which depends on the severity of sanctions. Empirical evidence suggests that an increase in policing intensity will reduce crime (Levitt, 2002; Lin, 2009), with a larger effect on violent crime than on property crime (Chalfin and McCrary, 2018). For an extensive review on crime and deterrence variables, see Chalfin and McCrary (2017), and Nagin (2013).

Regarding gender, there is evidence suggesting that women are less involved in criminal activities than men. Moreover, women's criminal behavior is less serious and less violent (Becker and McCorkel, 2011; Lauritsen et al., 2009). Finally, in recent years, the economic analysis of crime has expanded to include its relationship with immigration, gaining increasing attention from scholars because of the relevance of immigration in public policy and political quarrels (Card, 2001, 2005).

In this article, we analyze the relationship between immigration and crime through a dynamic Spatial Durbin Model (SDM). This method allows us to capture the interdependence of observations and solve the possible bias for omitted variables, as it captures the spatial lags of both the dependent and explanatory variables (LeSage and Pace, 2009). The model is dynamic, as it captures the temporal lag of the dependent variable (Elhorst, 2014). We use the number of immigrants into Chile at the municipality (county) level during the period 2005-2015. Our results show that there is no statistical evidence to link an increase in the number of immigrants with a rise in the rate of all types of crime.

Most of the research analyzing the immigration-crime relationship has been conducted in developed countries, using either the Ordinary Least Square (OLS) or the Instrumental Variables (IV) method (Alonso-Borrego et al., 2012; Baker, 2015; Bell et al., 2013; Bianchi et al., 2012; Chalfin, 2013; Cracolici and Uberti, 2009; Fasani, 2018; Light and Miller, 2018; Martinez et al., 2010; Piopiunik and Ruhose, 2017; Spenkuch, 2013). Our literature review shows that there are only three studies using spatial analysis in their estimations (Cracolici and Uberti, 2009; Fasani, 2018; Kakamu et al., 2008). The current literature also includes studies using a fixed effects negative binomial model (Martinez et al., 2010), the Generalized Method of Moments (GMM) (Alonso-Borrego et al., 2012), or a meta-analysis (Ousey and Kubrin, 2018).

The evidence on the relationship between immigration and crime is controversial, as some studies do not find any effect of immigration on crime, or find only a small effect on economic crimes, while others find a positive relationship. For instance, Bianchi et al. (2012) analyzed the immigration-crime relationship at the provincial level in Italy using both the OLS and IV models. In general terms, they did not find a relationship between immigration and crime, with a minor influence of immigration on theft. Using the same methods, at the local authority level in the UK, Bell et al. (2013) found a positive effect of immigration only on property crimes, and only in the case of refugee immigrants or those seeking asylum.

The relationship between crime and immigration in the USA is the subject of many studies. Martinez et al. (2010) look at the effects of immigration on homicides, specifically for the city of San Diego, California. Using a fixed effects negative binomial model, they found that neighborhoods with a higher proportion of immigrants have fewer homicide victims. Other studies using panel data (fixed-effects) at county-level show some effect of immigration on crimes with *economic* motives but not in relation to "*crimes of passion,"* such as homicide, assault, or rape (Spenkuch, 2013). Using OLS and IV models at the metropolitan level, Chalfin (2013) found that Mexican immigrants have no effect on crime in the USA. Using a fixed effect panel and IV model, Light and Miller (2018) analyzed illegal immigration in the 50 States and Washington D.C. during the period of 1990-2014; the authors concluded that an increase in the number of immigrants did not raise the amount of violent crime. Using census data for the years 1980, 1990, and 2000 for the USA, including the probability of incarceration, Butcher and Piehl (2007) found no effect of immigration on crime, while Baker (2015) suggests that improving the working conditions of immigrants, for example, legalizing those who have illegally entered the country, could decrease the crime rate in the USA. Implementing a meta-analysis from 1994 to 2014, Ousey and Kubrin (2018) found a negative, though weak, relationship between immigration and crime.

In contrast with these previous studies, evidence also suggests a positive effect between immigration and crime. For instance, Kakamu et al. (2008), using spatial models for Japan, across 47 prefectures, found that an increase in the immigrant population was positively correlated with various types of crimes. Cracolici and Uberti (2009) conducted a study in Italy at the provincial level, using OLS, IV, and Spatial models, and found that immigration affects mainly economic crimes. In Spain, Alonso-Borrego et al. (2012) also found positive effects, using provincial-level panel data with OLS and GMM models. Piopiunik and Ruhose (2017) found similar results in Germany (county-level with panel data with fixed effects) when analyzing immigrants of German descent with lower levels of education, less-favorable working conditions, and a poorer understanding of the German language.

A common problem when using crime data is the potential interdependence across spatial units of analysis, as the behavior of the dependent or explanatory variable in one area could be correlated with the behavior of this variable in a neighboring area. For instance, people living in one area could travel to another area to commit a crime (see Elhorst (2014) chapter 1). Thus, we need an estimation method able to deal with this interdependence of observations. Although both OLS and IV can be used to estimate these types of models (e.g., using spatial lag of only the explanatory variables or spatial lag models), a SDM approach offers a richer interpretation of the interdependence of observations (Elhorst, 2014; LeSage and Pace, 2009)

In this article, we contribute to the economic literature on the crime-immigration relationship by (i) analyzing the immigration phenomena in a developing country, and (ii) increasing the infrequent evidence based on the spatial econometric approach. To the best of our knowledge, this is the first study to analyze immigration to a high-income developing country.

II. Econometric approach

Information constraints make it impossible to observe the real delinquency level within an area. To solve this issue, the common practice is to use the formal complaints made to the police by citizens as a proxy variable of the delinquency rate. Notwithstanding, the specification of panel data with an area fixed effect, and the use of a logarithm for the crime rate variable (the dependent variable) could help eliminate the bias between areas across time (Bianchi et al., 2012; Ehrlich, 1996; Gould et al., 2002; Levitt, 1996). Another problem when using crime data is the possible correlation across spatial units of analysis, as the behavior of the dependent or explanatory variable in one area could be correlated with the behavior of this variable in a neighboring area (Elhorst, 2014). To address the potential spatial correlation in crime across areas, we use several spatial models whose more general expression is as follows (Anselin, 1988):

$$\begin{gathered}\boldsymbol{Y_t} = \boldsymbol{\rho W Y_t} + \boldsymbol{\alpha l_N} + \boldsymbol{\tau Y_{t-1}} + \boldsymbol{X_t \beta} + \boldsymbol{W X_t \theta} + \boldsymbol{u_t} \\ \boldsymbol{u_t} = \boldsymbol{\lambda W u_t} + \boldsymbol{\varepsilon_t}\end{gathered} \qquad [1]$$

In equation [1], $\boldsymbol{Y_t}$ indicates a vector N x 1 of observations of the crime rate for each unit in the sample $(i = 1, \dots, N)$; $\boldsymbol{l_N}$ is a vector N x 1 of those associated with the constant of the parameter $\boldsymbol{\alpha}$ which will be estimated; $\boldsymbol{X_t}$ denotes a matrix N x K of exogenous explanatory variables; $\boldsymbol{\beta}$ is a vector N x 1 associated with the explanatory variables with unknown parameters to be estimated; $\boldsymbol{\varepsilon_t} = (\varepsilon_1, \dots, \varepsilon_N)^T$ is a vector of error terms, where ε_i is assumed to be independent and identically distributed throughout all of the observations i, with zero median and variance σ^2 (For more details, see Elhorst (2014)).

The effects of the spatial interaction correspond to $\boldsymbol{WY_t}$ that denotes the effect of the endogenous interaction between the dependent variable; $\boldsymbol{WX_t}$ is the effect of the exogenous interaction between the independent variables; and $\boldsymbol{Wu_t}$ is the effect of the interaction in terms of the error of the different units. Finally, $\boldsymbol{\rho}$, $\boldsymbol{\theta}$, and $\boldsymbol{\lambda}$ represent the coefficients that capture the spatial effects, and $\boldsymbol{\tau}$ represents the coefficient that captures the temporal effects of the dependent variable in the previous period $(\boldsymbol{Y_{t-1}})$.

Based on equation [1], it is possible to define several spatial models. Following Elhorst (2014), we use the following formulations: (1) Spatial Autoregressive Model (SAR): if $\lambda = 0$ y $\theta = 0$, (2) Spatial Error Model (SEM): if $\rho = 0$ y $\theta = 0$, (3) Spatial Autoregressive Model with Autoregressive Disturbance (SAC): if $\theta = 0, (4)$ Spatial Durbin Model (SDM): if $\lambda = 0$ and (5) Static Model: if $\tau = 0$; Dynamic Model: if $\tau \neq 0$. Using the Moran's I test we check for the presence of spatial correlation to each type of crime and explanatory variable in every year. The selection of the most suitable spatial model is based on a series of tests proposed by Belotti et al. (2017).

To build the matrix W of spatial weights, the literature suggests different forms, mainly (i) contiguity criteria, (ii) criteria of the k-nearest neighbors, and (iii) Euclidian distance or inverse distance (Anselin, 1988; Elhorst, 2014; LeSage and Pace, 2009). Given that the spatial units used correspond to polygons (in our case municipalities), we use the first order queen contiguity criteria (queen contiguity spatial weight). These criteria consider neighbors to be all the adjacent geographic units (i.e., those with which the unit in reference is adjoined by borders and vertices). For robustness analysis, we run estimations using the k-nearest neighbor criteria with five neighbors, being the average of the municipalities, we obtained when we contrasted the matrix with the queen continuity criteria[1]. The estimation of these models is implemented using the maximum likelihood (ML) method (Elhorst, 2003), using panel data specifications with individual fixed effects in all of them.

[1] In the construction of the matrix W, it was row-standardized.

Finally, considering the geographic extension of Chile, it is possible that certain heterogeneity exists between municipalities within the country. This heterogeneity is tested using the Chow spatial test, which is an adaptation of the traditional Chow test (over time) to test structural change, assessing the existence of spatial heterogeneity between different geographical areas (Anselin, 1990). In case of heterogeneity, for a robustness analysis, we divide the country into four macro-zones: Northern, Center (including the Metropolitan Region), Southern, and Metropolitan Region (only). With this, we estimate the selected spatial model with a first order queen contiguity matrix for each macro-zone separately.

III. Case Study

During the last decade, Chile has shown not only an increase in its economic performance but also an improvement in its institutional stability. Proof of the latter is the country's acceptance into the Organization for Economic Co-operation and Development (OECD) in 2010, as the first South American country to be included (OECD, 2010). While Chile improved its economic and social performance indicators, the political stability of several Latin-American and Caribbean countries, such as Haiti, Venezuela, Bolivia, Peru, and Argentina, diminished within the same period (Doña, 2018; Hierro, 2016). These two facts could explain why Chile has attracted a significant number of immigrants, especially in the last ten years. According to the last Population Census (INE, 2017), there were 746,465 immigrants (4.35% of the total population) living in the country, a large increase from the 187,008 immigrants (1.27% of the total population) represented in the 2002 census.

Using data from the Sub-secretary of Crime Prevention for the period of 2005 to 2016, and the data on immigrants from the Socioeconomic Characterization Survey (CASEN) for the period of 2006 to 2015, we built a panel of crime rates for 330 municipalities in Chile. In this article, we used the CASEN survey classification in which immigrants are those who were born in a different country than Chile. As we relied on the CASEN survey to collect information about foreigners, we avoid the problem of under-reporting due to illegal immigration. This is because the survey does not ask for the legal status of the person or household surveyed. As the CASEN survey is not conducted on a yearly basis, our panel data contain information for 330 municipalities across five temporal periods (2006, 2009, 2011, 2013, and 2015). The models with temporal lag (Y_{t-1}) includes the year 2005.

The information on crime reported by the Sub-secretary of Crime Prevention is obtained through the official complaints received by the police from citizens. Following examples from the literature on crime economics (Bianchi et al., 2012; Gould et al., 2002; Light and Miller, 2018), we use the rate of complaints per 100,000 inhabitants as a proxy to measure the quantity of crimes committed in a certain period and area. This study focuses on the Crimes with Greater Social Connotation (DMCS in Spanish), a definition given by the Chilean Sub-secretary of Crime Prevention. These crimes are grouped into "property crimes" and "crimes against people (violent crimes)". *Property crimes* include forced robbery (robbery of motorized vehicles, robbery of vehicle accessories, burglary of an inhabited place, burglary of an uninhabited place, and other robberies using force) and theft. *Violent crimes (crimes against people)* include robbery with violence or intimidation, robbery by deception, injuries, homicides, and rape. Figure 1 shows the evolution of the DMCS rate per 100,000 inhabitants for the period of 2005-2016.

[FIGURE 1 AROUND HERE]

From 2005 to 2011, the DMCS rate rose (with the exception of the years 2009 and 2010), reaching its peak in 2011 with a crime rate of slightly over 3,000 per 100,000 inhabitants. After 2011, the rate began to decrease until 2016. In 2016, the crime rate was similar to that of 2005, at slightly over 2,500 crimes per 100,000 inhabitants, on a national level. It is also possible to see the evolution by crime group in Figure 1. Property crimes show a similar pattern to the total DMCS rate, whereas a slight decrease can be seen in violent crimes between the years 2005 and 2016. A possible explanation may be the changes in the government administration and different crime policies. In this period, three government administration changes can be observed in 2006, 2010, and 2014.

Table 1 shows the number of immigrants in Chile on a national and regional level for the period 2006-2015. As expected, the largest number of immigrants is located in the Metropolitan Region (RM), which also accounts for the largest share of the total population. Our analysis of data shows that immigrants are, on average, younger, more educated, and receive large salaries than the Chilean population.

[TABLE 1 ABOUT HERE]

Although in some regions the number of immigrants has decreased, the national total has constantly risen. In relative terms, the number of foreigners living in Chile increased more than 200% between 2006 and 2015. It is important to point out that, because of a lack of data availability, it is impossible to observe all of the periods between 2005 and 2015 (as we can do with the crime rate), as the CASEN survey is carried out only every 2 to 3 years.

Figure 2 shows both the geographic distribution of crimes in Chile and the number of immigrants per municipality (on average). The left panel shows the distribution of the average of the total DMCS (2005 to 2016), while the right panel shows the average number of immigrants.

[FIGURE 2 ABOUT HERE]

We built a panel data including 330 municipalities for the years 2006, 2009, 2011, 2013, and 2015 in which the crime rate for every 100,000 inhabitants is the explanatory variable. We estimated a model for each type of crime (forced robbery, thefts, robbery with violence or intimidation, robbery by deception, injuries, homicides, and rape), as well as the total of DMCS (sum of the total crimes types). Following previous literature, we use several explanatory variables. First, we use i) the number of immigrants (foreigners) reported by the CASEN survey. Evidence on the relationship between crime and number of immigrants is controversial, with studies showing positive relationship, negative relationship, or no relationship between immigrants and crime (Bianchi et al., 2012; Chalfin, 2013; Cracolici and Uberti, 2009; Kakamu et al., 2008). We evaluate the hypothesis that immigration increases crime rate. The second explanatory variable is ii) the police efficiency, which captures the ratio between the people arrested and the number of crimes for each of the types. This variable is relevant as the probability of capture could be dissuasive for committing crimes (Becker, 1968; Ehrlich, 1973). As previous evidence suggests (Chalfin and McCrary, 2017; Lin, 2009), we expect a negative relationship between crime rate and police efficiency. The third explanatory variable we use is iii) average income (*income*) in each municipality reported by the CASEN survey. With this variable, we wanted to know whether an increase in wealth would attract certain types of crimes, mainly those of an economic nature. We expect that an increase in the average income will increase the rate for crimes related to robbery and theft (Scorzafave and Soares, 2009). The fourth explanatory variable is iv) the proportion of men in each municipality. This variable is added because in Chile most of the people in jail are men (Gendarmería de Chile). Furthermore, according to the Chilean Police (Carabineros) 82.4% of people arrested in 2016 were men (Carabineros de Chile, 2016). Similar to previous literature (Becker and McCorkel, 2011), we expect that the municipalities with higher proportions of men will tend to have higher crime rates. Finally, we use v) the Gini index for each municipality, as a measure of income inequality. As previous literature shows, we expect a positive relationship between the Gini index and the crime rate (Fajnzylber et al., 2002; Scorzafave and Soares, 2009).

IV. Results

Table 2 shows the descriptive statistics for the total DMCS crimes and the different types of crimes. As shown, the largest share of crimes consists of those associated with forced robbery (which includes different forced crimes), followed by theft and injuries.

[TABLE 2 AROUND HERE]

Table 3 shows the descriptive statistics for the following variables: *foreigners*, average income by municipality (*income),* and the proportion of men by municipality (*men by municipality*). We can observe that the average number of foreigners by municipality is around 850, with the maximum level reported for Santiago (the capital city) in 2015 (more than 100,000 foreigners).

[TABLE 3 AROUND HERE]

All spatial models addressed in equation [1] capture the spatial effects, either in the spatial lag of the dependent variable, in the error, or in the explanatory variables. Through the Moran's I test applied to each type of crime and explanatory variables in every year, we found that all variables (crimes and explanatory variables) present spatial autocorrelation in at least one year of the panel data. Following Belotti et al. (2017), we selected the best spatial model among SAR, SEM, SAC, SDM specifications. First, we estimated the more general specification (in our case the SDM), then we tested whether $\rho \neq 0$ and $\theta = 0$ (testing SAR specification), $\theta = -\beta\rho$ (testing SEM specification), whereas for the SAC specification we used information criteria (AIC and BIC), as both SAC and SDM are not nested. We found that for seven out of the eight crime types, the best modelling approach is the SDM. For the remaining crime type (rape), we found that SDM is better than SAC, but we cannot prefer the SDM above both SAR and SEM. As the SDM provides richer interpretation compared with other spatial models, we selected this approach.[2]

[2] In the Appendix, we show the results using all the modeling approaches.

To address the possible spatial correlation in the crime rate throughout the municipalities, we used the dynamic SDM as the main modeling approach. The SDM model largely solves the potential bias for omitted variables, such as certain amenities or area characteristics that could affect the foreigners' decisions when choosing certain areas over others to establish themselves in (LeSage and Pace, 2009).

As our spatial model is dynamic, it is possible to identify direct and indirect effects, on both the short- (the same period) and long-term (next period) bases. The direct effects are those affecting the same area, while the indirect effects are those affecting neighboring areas (Elhorst, 2014).

After transforming all the variables into natural logarithms, except for the *men by municipality* variable, the model specification can be expressed as follows:

$$ln(Crime\ rate)_t = \alpha l_N + \tau ln(Crime\ rate)_{t-1} + \rho W ln(Crime\ rate)_t + W ln(Foreigners)_t \theta + WX_t\theta + ln(Foreigners)_t \beta + X_t\beta + u_t \quad [2]$$

where τ, ρ, θ, and β represent the parameters to be estimated, W represents the matrix of spatial weights, and X_t represents the following control variables: $ln(Police\ Efficiency)_t$; $ln(Income)_t$; *men by municipality; and Gini index (by municipality).* To measure income inequality, the Gini index was calculated. The Gini index range is $0 \leq G \leq 1$, where a value that tends to 1 represents a higher index of inequality and the opposite when the value tends to zero. The Gini coefficient was calculated at the municipality level for the years 2006, 2009, 2011, 2013, and 2015.

We keep the crime rate at $t-1$, and we incorporate it as an explanatory variable with the aim of capturing the dynamic (temporal) effect, i.e., the temporal lag of the dependent variable. The ρ coefficient is interesting on its own, as it captures the spatial effect for the spatial lag of the dependent variable.

Following Elhorst (2014), we rewrite equation [1] to capture both the direct (short and long term) and indirect effects (short and long term):

$$Y_t = (I - \rho W)^{-1}(\tau I)Y_{t-1} + (I - \rho W)^{-1}(X_t\beta + WX_t\theta) + (I - \lambda W)^{-1}\mu_t \qquad [3]$$

The direct effects are the effects on crime in municipality *i,* of changes in the explanatory variables on municipality *i*. Mathematically, the direct effects could be modeled in the short term as $[I - \rho W)^{-1}(\beta I + \theta W)]^{\bar{d}}$, or in the long term as $[\left((1-\tau)I + \rho W\right)^{-1}(\beta I + \theta W)]^{\bar{d}}$. The indirect effects, or spatial spillovers, are the effects on crime in municipality *i*, of changes in the explanatory variables on municipality *j,* and the effect on crime in municipality *j*, of changes in the explanatory variables on municipality *i.* Mathematically, the indirect effects could be modeled in the short term as $[I - \rho W)^{-1}(\beta I + \theta W)]^{\overline{rsum}}$ or in the long term as $[\left((1-\tau)I + \rho W\right)^{-1}(\beta I + \theta W)]^{\overline{rsum}}$. The total effects are the sum of the direct and indirect effects: the effects on crime in municipality *i* and in municipality *j* of changes in explanatory variables in municipality *i*. In the abovementioned expressions, "*the superscript* $\bar{d}$ *denotes the operator that calculates the mean diagonal element of a matrix and the superscript* $\overline{rsum}$

denotes the operator that calculates the mean row sum of the non-diagonal elements" (Elhorst, 2014).

Table 4 shows both the spatial and temporal effects. For the spatial effects, we report the direct and indirect effects of different variables on the crime rate, while the temporal effects are represented by both the short-term and long-term effects. The total effects represent the sum of both the direct and indirect effects.

[TABLE 4 AROUND HERE]

In the short term, we did not find evidence that an increase in the number of immigrants increases the crime rate (for all the crime types considered). Furthermore, our results show that the direct effect of an increase in the number of immigrants (*Foreigners*) is negative and statistically significant only for injuries (Table 4). This means that an increase in the number of immigrants on municipality *i,* in period *t,* will decrease the number of injuries in municipality *i*. The indirect effect of an increase in the number of immigrants (*Foreigners*) is negative and statistically significant only for robbery by deception. This means that an increase in the number of immigrants on municipality *i,* in period *t,* will decrease the number of robberies by deception crimes in municipality *j*. Because of the spillovers, the total effect of an increase in the number of immigrants (*Foreigners*) is negative and statistically significant only for robbery by deception. Thus, an increase in the number of immigrants on municipality *i*, will decrease the number of robberies by deception crimes in municipality *i* and its neighboring municipalities. The same results hold for the long term.

At aggregated level, the ρ coefficient is statistically significant and positive for the total DCMS, robbery with violence or intimidation, rape, injuries, forced robbery, and thefts. Suggesting that, as the crime rate increases in municipality i, it also does so for municipality j.

Our results show that, in the short term, an increase in police efficiency will reduce the crime rate for all crime types. Furthermore, the direct effect of an increase in police efficiency is negative and statistically significant for all types of crimes (including Total DMCS). Meaning that an increase in the ratio between the people arrested and the number of crimes for each of the crime types on municipality *i,* in period *t,* will decrease the number of crimes (all of them) in municipality *i*. The indirect effect of an increase in police efficiency is negative and statistically significant for homicides, injuries, forced robbery, and thefts. Because of the spillovers, the total effect of an increase in police efficiency is negative and statistically significant for all types of crimes (including Total DMCS). The same results hold for the long term.

In the short term, we found a positive relationship between income and some of the crime types. The direct effect of an increase in average income is positive and statistically significant for economic crimes, injuries, and total DMCS. The indirect effects show the same pattern, but they include a negative effect on homicides. When considering the total spatial effects, there is a positive and statistically significant relationship between average income and some economic crimes, injuries, and total DMCS; and there is a negative statistically significant relationship between income and homicides. Similar results hold for the long term.

The direct effect of an increase in the number of men by municipality, in the short term and the long term, is positive and statistically significant only for robbery with violence or intimidation. However, the total effect is not statistically significant. Whereas, the total effect of an increase in inequality will increase six out the of the eight crime types analyzed. This result holds for both the short and long terms.

In Appendix I, we report a robustness analysis of our results for different econometric specifications: SAR, SEM, and SAC models (queen contiguity spatial weight), as well as for the SDM, SAR, SEM, and SAC models using the W matrix with the five nearest neighbors. According to these models there is no evidence to support that immigration increases the rate of any type of crime.

Chile is quite large, and for this reason, it is possible to expect heterogeneity across geographical zones. We confirm this hypothesis through the Chow spatial test, which confirms the heterogeneity at 1% of significance. To address this point, we performed a second robustness analysis by separating the country into 4 macro-zones: Northern, Central and Southern Zones; we also considered the Metropolitan Region alone as it is the region with the largest number of immigrants[3]. The Northern Zone includes 5 regions, from Arica and Parinacota to the region of Coquimbo, which include 44 municipalities. The Central Zone includes the regions from Valparaíso to Bio-Bio (including the Metropolitan region), with

[3] Following a reviewer's suggestion, we performed a third robustness analysis (standard panel analysis with unit fixed effects), and the main conclusions remain the same (see Appendix III).

204 municipalities, while the Southern Zone contains the regions between La Araucania and Aysen, with 82 municipalities. In addition, we estimate the Metropolitan region separately, which includes 52 municipalities[4].

The results for the macro-zones are consistent with our main estimations, in which we reject the main hypothesis that immigration increases the crime rate. If any, the total effect of the number of immigrants is negative and statistically significant, only for the northern zone, for both the short and long term. Detailed results are shown in Appendix II.

V. Discussion and Conclusions

Our results show that there is no statistical evidence to link an increase in the number of immigrants with a rise in the rate of most type of crimes. If any, we found a negative relationship between the number of immigrants and only one type of crime (robbery by deception). Similar results are reported by Martinez et al. (2010), Spenkuch (2013), Chalfin (2013), Light and Miller (2018), Butcher and Piehl (2007), and Ousey and Kubrin (2018), who also found negative or no effect of immigration on crime rates. Moreover, our results are consistent with those studies relating educational level and crime rate (Lochner and Moretti, 2004), as on average the educational level of the immigrants is higher than the average educational level of the Chilean population.

[4] We built the panel data for each macro-zone considering 5 years (same as that for our main estimation).

In contrast, other studies using spatial models such as that of Cracolici and Uberti (2009) found a positive effect of immigration on economic crimes, and that of Kakamu et al. (2008) found positive effects in 12 out of the 18 crime types analyzed, while Fasani (2018) found that crime rates will decrease in the next period if immigrants' legalization is carried out. Unlike all previous evidence using spatial models, we did not find evidence that relates the number of immigrants to an increase in most of the crime categories. Regarding the other variables, our results are consistent with previous studies that found a positive relationship between crime and income (Allen, 1996; Scorzafave and Soares, 2009), as well as those that found a positive relationship between crime and inequality (Enamorado et al., 2016; Kelly, 2000).

In conclusion, in this article, we evaluated the hypothesis that immigration increases the crime rate. We tested this hypothesis using a spatial-temporal econometric approach, and on the basis of our results we rejected the hypothesis. Moreover, we found a negative relationship between the number of immigrants and crime for one out of the eight crime types analyzed. We found that the short-term/direct effect of an increase in immigration is negative only for one type of crime (injuries). The indirect effect in the short term is negative only for robbery by deception, while the total spatial effect is not significant for most types of crime (it is negative only for robbery by deception).

It is important to highlight that the crime rate could be under-reported, as the information available to the police and the Sub-secretary of Crime Prevention is obtained from the complaints made by citizens, meaning that the real crime rate could be higher than what is observed. This is a widely known issue in the literature on crime economics.

Based on our findings, we suggest that the focus in controlling and reducing delinquency should not be associated with closing borders to the immigrant population, as there is no evidence supporting that their arrival increases crime. Instead, attention should be focused on the police force and the judicial system in other areas, such as police intelligence and surveillance services, with the aim of increasing efficiency and reducing crimes.

Tables

Table 1: Number of Foreigners by Region

Region	Year				
	2006	2009	2011	2013	2015
Arica and Parinacota	4,134	6,594	6,810	8,018	7,982
Tarapacá	6,533	9,898	16,760	18,069	30,520
Antofagasta	5,412	8,257	9,953	26,624	30,528
Atacama	1,705	1,871	1,196	2,997	4,675
Coquimbo	2,555	2,907	2,832	7,076	10,897
Valparaíso	9,848	14,128	16,476	25,510	25,457
O'Higgins	1,803	2,025	3,599	4,743	4,509
Maule	3,881	3,442	2,884	2,743	3,188
Biobío	4,694	3,401	7,028	6,760	5,547
Araucanía	6,261	8,108	6,273	6,076	7,824
Los Lagos	1,100	1,094	1,760	1,346	3,257
Los Ríos	4,279	3,791	4,422	5,696	4,951
Aysén	644	679	1,410	1,505	1,853
Magallanes	3,422	966	1,954	1,808	2,570
Metropolitan	98,372	141,561	154,543	235,610	321,561
Total Annual	154,643	208,722	237,900	354,581	465,319

Source: Authors` elaboration based on CASEN survey.

Table 2: Descriptive statistics of Crimes in Chile (2005 to 2016). Dependent variable.

Crime rate per 100,000 inhabitants	Mean	Standard Deviation	Min.	Max.	Observations
DMCS Crimes	2072.177	1387.882	0	19223.22	N = 3960
Robbery with violence or intimidation	150.7644	228.7328	0	2790.063	N = 3960
Robbery by deception	67.64745	145.2925	0	2392.441	N = 3960
Forced Robbery	848.8821	722.6829	0	7287.329	N = 3960
Thefts	521.9703	369.2967	0	5455.036	N = 3960
Injuries	466.4495	212.1276	0	1804.368	N = 3960
Homicides	1.377693	6.212406	0	323.1018	N = 3960
Rape	15.08575	13.60085	0	177.305	N = 3960

Source: Authors` elaboration.

Note: Variables are represented as the crime rate per 100,000 inhabitants. The construction is provided by the Sub-secretary for Crime Prevention (Chile), who calculates it with the ratio of the total number of reports (for each crime) per municipality on the population per municipality, multiplied by 100,000. The table shows the average, the standard deviations, and the minimum and maximum values for the whole country. For all types of crime: n = 330 (municipalities), T = 12 (years).

Table 3: Descriptive statistics: Foreigners, Average income of workers by municipality and Proportion of men by municipality (Years 2006, 2009, 2011, 2013 and 2016)

Variable	Average	Standard Dev.	Min.	Max.	Observations
Foreigners	853.2879	3901.14	0	107149	N = 1650
Income	357152.7	166634.7	126040.9	2068662	N = 1650
Men by municipality	0.5120521	0.0384445	0.4317	0.8708	N = 1650
Gini index (by municipality)	0.4912566	0.0636396	0.237	0.86489	N = 1650

Source: Authors` elaboration.

Note: For the variables of foreigners, average salaries by municipality (income), the proportion of men by municipality (Men by municipality) and Gini index. For all variables: n = 330 (municipalities), T = 5 (years).

Table 4: Spatial Effects Dynamic SDM with Fixed Effects. Dependent Variable: ln(Crime Rate)

	(1) Total DMCS	(2) Robbery with violence or intimidation	(3) Robbery by deception	(4) Homicides	(5) Rape	(6) Injuries	(7) Forced Robbery	(8) Thefts
Direct spatial effects (Short-term)								
ln(Police	-0.2216***	-0.4111***	-0.2787***	-0.3377***	-0.3209***	-0.2663***	-0.1105***	-0.1419***
Efficiency)	(0.0287)	(0.0286)	(0.0273)	(0.0588)	(0.0321)	(0.0315)	(0.0135)	(0.0174)
ln(Income)	0.1246***	0.0357	0.5274***	-0.1044	-0.1426	0.1651*	0.1382*	0.1668***
	(0.0462)	(0.1816)	(0.1908)	(0.1126)	(0.1901)	(0.0844)	(0.0785)	(0.0632)
ln(Foreigners)	-0.0072	-0.0021	-0.0049	0.0016	-0.0080	-0.0101**	-0.0073	-0.0089
	(0.0048)	(0.0107)	(0.0126)	(0.0097)	(0.0140)	(0.0050)	(0.0078)	(0.0063)
Men by	0.4353	4.3928**	-2.1136	-0.3072	2.1960	-3.0499	1.8821	0.1333
municipality	(0.6851)	(2.1476)	(2.3643)	(0.7705)	(3.3644)	(3.4899)	(1.1833)	(2.0623)
Gini index	0.1774	1.1542**	-0.2067	0.5259	1.0772*	-0.0927	0.4180*	0.1138
	(0.1242)	(0.4981)	(0.4871)	(0.3402)	(0.5833)	(0.1777)	(0.2423)	(0.1954)
Indirect spatial effects (Short-term)								
ln(Police	-0.0142	-0.0329	-0.0508	-0.2153**	-0.1447	-0.0660*	-0.1187***	-0.0645**
Efficiency)	(0.0400)	(0.1074)	(0.0755)	(0.0954)	(0.1032)	(0.0369)	(0.0400)	(0.0324)
ln(Income)	0.2470	0.5238**	1.0474***	-0.3692**	0.1584	0.0408	0.3256**	0.4153***
	(0.1593)	(0.2244)	(0.2173)	(0.1507)	(0.2304)	(0.1672)	(0.1488)	(0.1348)
ln(Foreigners)	0.0065	0.0438	-0.0518*	0.0052	0.0241	-0.0164	0.0193	0.0176
	(0.0100)	(0.0267)	(0.0283)	(0.0224)	(0.0370)	(0.0202)	(0.0151)	(0.0146)
Men by	0.4957	-7.8433	7.6524	3.1532	-3.2947	1.0685	1.1855	-1.4729
municipality	(1.5507)	(4.7891)	(5.5771)	(3.9791)	(5.5366)	(2.6936)	(1.9953)	(2.0484)
Gini index	0.6938**	0.0963	-1.3281	0.6220	1.6904	1.3963***	0.5249	0.1453
	(0.2888)	(1.0157)	(1.1346)	(0.6357)	(1.1946)	(0.3648)	(0.3859)	(0.3881)
Total spatial effects (Short-term)								
ln(Police	-0.2359***	-0.4439***	-0.3295***	-0.5531***	-0.4656***	-0.3323***	-0.2292***	-0.2064***
Efficiency)	(0.0565)	(0.1111)	(0.0797)	(0.1164)	(0.1114)	(0.0498)	(0.0435)	(0.0394)
ln(Income)	0.3716***	0.5596***	1.5748***	-0.4736***	0.0158	0.2058	0.4638***	0.5821***
	(0.1303)	(0.1780)	(0.1806)	(0.1087)	(0.1963)	(0.1424)	(0.1151)	(0.1269)
ln(Foreigners)	-0.0007	0.0417	-0.0566*	0.0069	0.0161	-0.0265	0.0120	0.0087
	(0.0108)	(0.0297)	(0.0316)	(0.0238)	(0.0405)	(0.0232)	(0.0162)	(0.0165)
Men by	0.9310	-3.4505	5.5388	2.8460	-1.0987	-1.9813	3.0676	-1.3396
municipality	(1.7571)	(5.2969)	(5.8040)	(4.0080)	(6.7558)	(4.0977)	(2.7833)	(3.1620)

Gini index	0.8713***	1.2506	-1.5348	1.1479**	2.7676**	1.3036***	0.9429**	0.2591
	(0.3275)	(0.9956)	(1.0761)	(0.5337)	(1.2945)	(0.4203)	(0.3733)	(0.4309)
Direct spatial effects (Long-term)								
ln(Police	-0.3404***	-0.4264***	-0.3273***	-0.3379***	-0.3228***	-0.4158***	-0.1292***	-0.1828***
Efficiency)	(0.0445)	(0.0297)	(0.0321)	(0.0588)	(0.0323)	(0.0486)	(0.0157)	(0.0224)
ln(Income)	0.2017***	0.0375	0.6186***	-0.1044	-0.1435	0.2572**	0.1621*	0.2185***
	(0.0665)	(0.1882)	(0.2243)	(0.1126)	(0.1912)	(0.1266)	(0.0912)	(0.0806)
ln(Foreigners)	-0.0107	-0.0022	-0.0057	0.0016	-0.0080	-0.0165**	-0.0084	-0.0112
	(0.0074)	(0.0111)	(0.0148)	(0.0097)	(0.0141)	(0.0083)	(0.0091)	(0.0081)
Men by	0.6881	4.5506**	-2.4875	-0.3073	2.2088	-4.6679	2.1977	0.1551
municipality	(1.0605)	(2.2280)	(2.7768)	(0.7708)	(3.3846)	(5.3895)	(1.3827)	(2.6516)
Gini index	0.3026	1.1973**	-0.2418	0.5261	1.0838*	-0.0723	0.4890*	0.1476
	(0.1931)	(0.5165)	(0.5723)	(0.3404)	(0.5867)	(0.2799)	(0.2820)	(0.2508)
Indirect spatial effects (Long-term)								
ln(Police	-0.0915	-0.0359	-0.0586	-0.2154**	-0.1458	-0.2182***	-0.1420***	-0.0948**
Efficiency)	(0.0738)	(0.1118)	(0.0883)	(0.0954)	(0.1039)	(0.0642)	(0.0472)	(0.0436)
ln(Income)	0.4778*	0.5453**	1.2259***	-0.3693**	0.1593	0.1303	0.3865**	0.5646***
	(0.2704)	(0.2331)	(0.2553)	(0.1508)	(0.2319)	(0.2917)	(0.1742)	(0.1791)
ln(Foreigners)	0.0095	0.0456	-0.0606*	0.0052	0.0242	-0.0340	0.0226	0.0229
	(0.0179)	(0.0278)	(0.0332)	(0.0224)	(0.0373)	(0.0387)	(0.0178)	(0.0195)
Men by	1.0103	-8.1451	8.9743	3.1545	-3.3146	0.9106	1.4306	-1.9598
municipality	(2.8097)	(4.9850)	(6.5385)	(3.9808)	(5.5721)	(5.0481)	(2.3652)	(2.7609)
Gini index	1.2976**	0.1048	-1.5555	0.6223	1.7017	2.5714***	0.6266	0.2002
	(0.5325)	(1.0562)	(1.3307)	(0.6360)	(1.2022)	(0.7103)	(0.4545)	(0.5184)
Total spatial effects (Long-term)								
ln(Police	-0.4319***	-0.4623***	-0.3858***	-0.5533***	-0.4686***	-0.6340***	-0.2712***	-0.2776***
Efficiency)	(0.1017)	(0.1158)	(0.0932)	(0.1165)	(0.1121)	(0.0887)	(0.0515)	(0.0531)
ln(Income)	0.6795***	0.5828***	1.8445***	-0.4738***	0.0159	0.3875	0.5485***	0.7831***
	(0.2340)	(0.1855)	(0.2132)	(0.1087)	(0.1976)	(0.2675)	(0.1355)	(0.1711)
ln(Foreigners)	-0.0012	0.0434	-0.0663*	0.0069	0.0162	-0.0504	0.0142	0.0117
	(0.0199)	(0.0309)	(0.0371)	(0.0238)	(0.0408)	(0.0444)	(0.0191)	(0.0222)
Men by	1.6984	-3.5945	6.4868	2.8472	-1.1058	-3.7573	3.6283	-1.8047
municipality	(3.2317)	(5.5177)	(6.8002)	(4.0097)	(6.7997)	(7.8761)	(3.2937)	(4.2554)
Gini index	1.6002***	1.3022	-1.7972	1.1484**	2.7855**	2.4991***	1.1157**	0.3478
	(0.6124)	(1.0366)	(1.2610)	(0.5339)	(1.3029)	(0.8330)	(0.4422)	(0.5803)

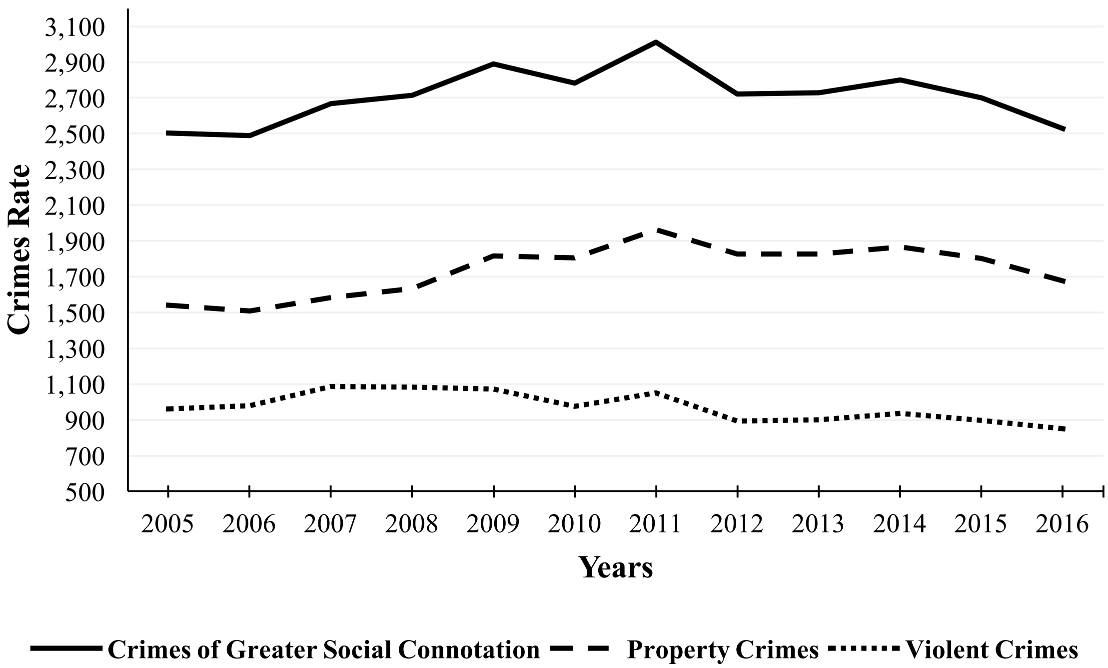
Spatial: ρ	0.2491***	0.0958***	0.0188	0.0027	0.0743***	0.2747***	0.0813***	0.1423***
	(0.0306)	(0.0284)	(0.0296)	(0.0300)	(0.0272)	(0.0323)	(0.0240)	(0.0232)
N	1650	1650	1650	1650	1650	1650	1650	1650
Log Likelihood	-20.6455	-1808.1151	-1971.5210	-1288.6442	-2181.9483	-556.8252	-758.1862	-818.7659

Note: *<0.1; **<0.05; ***<0.01
Standard errors in parentheses per cluster (municipalities).
W Matrix: queen contiguity.
Source: Authors` elaboration.

Figures

Figure 1: Crimes of Greater Social Connotation

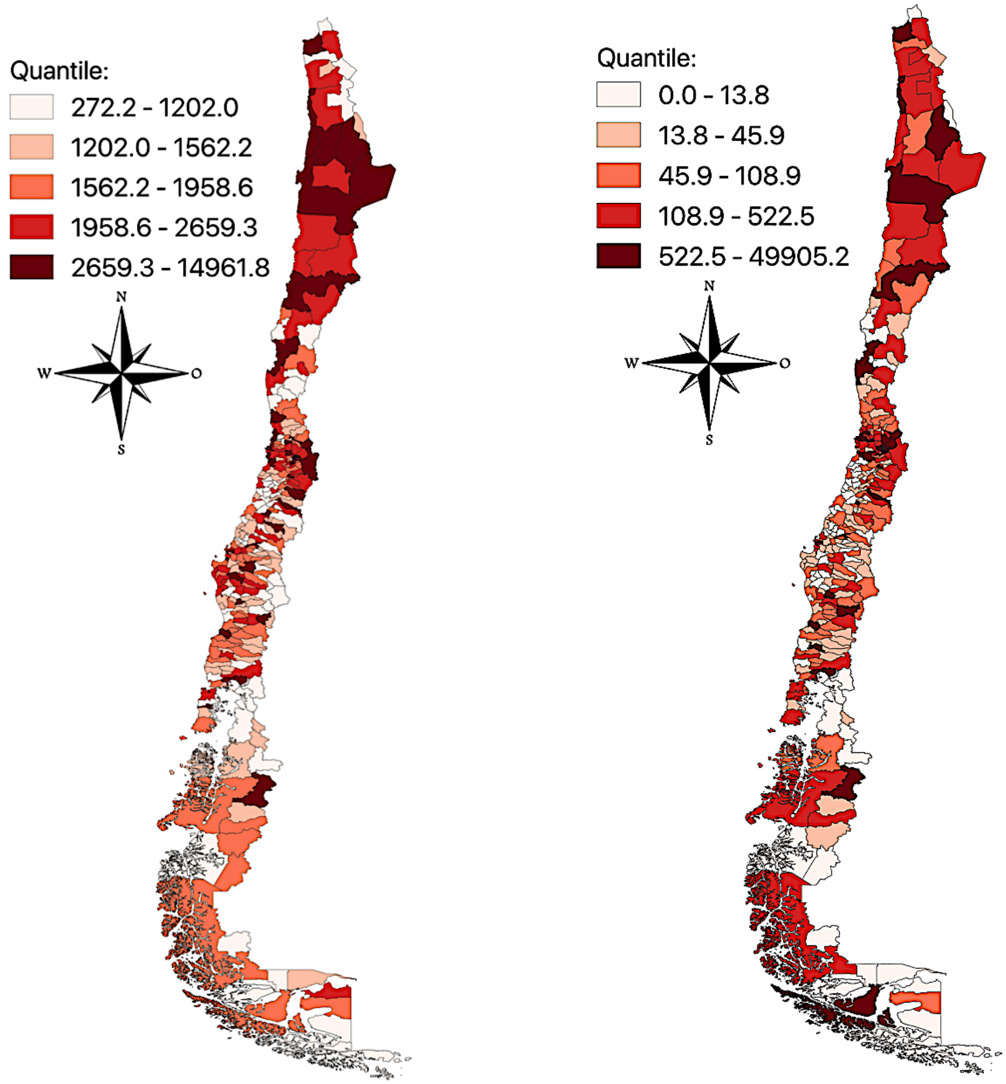
Country-Level Data 2005-2016 (Chile)



Source: Authors` elaboration based on *Sub-secretary for Crime Prevention* (Chile).

Figure 2: Distribution of Crime and Immigration by Municipality

Average of Total DMCS Crimes **Average of Immigrants**



Source: Authors` elaboration based on geographic information system of Albers (2012)

For the total DMCS per municipality (left graphic), the average was calculated for 12 years [2005 to 2016], while the average number of immigrants per municipality was computed using the years (2006, 2009, 2011, 2013, 2015), which are those for which the CASEN survey is available.

References

Allen, R.C., 1996. Socioeconomic conditions and property crime: A comprehensive review and test of the professional literature. American Journal of Economics and Sociology 55, 293-308 %@ 0002-9246.
Alonso-Borrego, C., Garoupa, N., Vázquez, P., 2012. Does immigration cause crime? Evidence from Spain. American law and economics review 14, 165-191.
Anselin, L., 1988. Spatial Econometrics: Methods and Models.
Baker, S.R., 2015. Effects of immigrant legalization on crime. American Economic Review 105, 210-213.
Becker, G., 1968. Crime and Punishment: An Economic Approach. Journal of Political Economy 76, 169-217.
Becker, S., McCorkel, J.A., 2011. The gender of criminal opportunity: The impact of male co-offenders on women's crime. Feminist criminology 6, 79-110.
Bell, B., Fasani, F., Machin, S., 2013. Crime and Immigration: Evidence from Large Immigrant Waves. Review of Economics and Statistics 95, 1278-1290.
Belotti, F., Hughes, G., Mortari, A.P., 2017. Spatial panel-data models using Stata. The Stata Journal 17, 139-180.
Bianchi, M., Buonanno, P., Pinotti, P., 2012. Do Immigrants Cause Crime? Journal of the European Economic Association 10, 1318-1347.
Butcher, K.F., Piehl, A.M., 2007. Why are Immigrants' Incarceration Rates so Low? Evidence on Selective Immigration, Deterrence, and Deportation. National Bureau of Economic Research.
Carabineros de Chile, 2016. Informe Anual.
Card, D., 2001. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. Journal of Labor Economics 19, 22-64.
Card, D., 2005. Is the new immigration really so bad? The Economic Journal 115, F300-F323.
Chalfin, A., 2013. What is the Contribution of Mexican Immigration to U.S. Crime Rates? Evidence from Rainfall Shocks in Mexico. American Law and Economics Review 16, 220-268.
Chalfin, A., McCrary, J., 2017. Criminal deterrence: A review of the literature. Journal of Economic Literature 55, 5-48.
Chalfin, A., McCrary, J., 2018. Are US cities underpoliced? Theory and evidence. Review of Economics and Statistics 100, 167-186.
Chintrakarn, P., Herzer, D., 2012. More inequality, more crime? A panel cointegration analysis for the United States. Economics Letters 116, 389-391.
Cracolici, M.F., Uberti, T.E., 2009. Geographical distribution of crime in Italian provinces: a spatial econometric analysis. Jahrbuch für Regionalwissenschaft 29, 1-28.
Danziger, S., Wheeler, D., 1975. The economics of crime: Punishment or income redistribution. Review of social economy 33, 113-131.
Doña, C., 2018. Amid Record Numbers of Arrivals, Chile Turns Rightward on Inmigration. Migration Information Source. Migration Policy Institute. January 17.
Draca, M., Machin, S., 2015. Crime and economic Incentives. Annual Review of Economics 7, 389-408.
Ehrlich, I., 1973. Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. Journal of Political Economy 81, 521-565.

Ehrlich, I., 1996. Crime, Punishment, and the Market for Offenses. Journal of Economic Perspectives 10.
Elhorst, J.P., 2003. Specification and Estimation of Spatial Panel Data Models. International Regional Science Review 26, 244-268.
Elhorst, J.P., 2014. Spatial Econometrics from Cross-Sectional Data to Spatial Panels.
Enamorado, T., López-Calva, L.F., Rodríguez-Castelán, C., Winkler, H., 2016. Income inequality and violent crime: Evidence from Mexico's drug war. Journal of Development Economics 120, 128-143.
Fajnzylber, P., Lederman, D., Loayza, N., 2002. Inequality and violent crime. The journal of Law and Economics 45, 1-39.
Fasani, F., 2018. Immigrant crime and legal status: evidence from repeated amnesty programs. Journal of Economic Geography.
Fougère, D., Kramarz, F., Pouget, J., 2009. Youth unemployment and crime in France. Journal of the European Economic Association 7, 909-938.
Freeman, R.B., 1999. The economics of crime. Handbook of labor economics 3, 3529-3571.
Gendarmería de Chile, Estadísticas.
Gould, E., Weinberg, B., Mustard, D., 2002. Crime Rates and Local Labor Market Opportunities in the United States: 1979-1997. Review of Economics and Statistics 84, 45-61.
Hierro, M., 2016. Latin American migration to Spain: Main reasons and future perspectives. International Migration 54, 64-83.
INE, 2017. Censo Nacional de Población y Vivienda. Instituto Nacional de Estadisticas.
Kakamu, K., Polasek, W., Wago, H., 2008. Spatial interaction of crime incidents in Japan. Mathematics and Computers in Simulation 78, 276-282.
Kelly, M., 2000. Inequality and crime. Review of economics and Statistics 82, 530-539.
Lauritsen, J.L., Heimer, K., Lynch, J.P., 2009. Trends in the gender gap in violent offending: New evidence from the National Crime Victimization Survey. Criminology 47, 361-399
LeSage, J., Pace, R.K., 2009. Introduction to Spatial Econometrics.
Levitt, S.D., 1996. The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation. 111, 319-351.
Levitt, S.D., 2002. Using electoral cycles in police hiring to estimate the effects of police on crime: Reply. American Economic Review 92, 1244-1250.
Light, M.T., Miller, T.Y., 2018. Does Undocumented Immigration Increase Violent Crime?*. Criminology 56, 370-401.
Lin, M.-J., 2008. Does unemployment increase crime? Evidence from US data 1974–2000. Journal of Human resources 43, 413-436.
Lin, M.-J., 2009. More police, less crime: Evidence from US state data. International Review of Law and Economics 29, 73-80.
Lochner, L., Moretti, E., 2004. The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. American economic review 94, 155-189.
Machin, S., Marie, O., Vujić, S., 2011. The crime reducing effect of education. The Economic Journal 121, 463-484.
Machin, S., Meghir, C., 2004. Crime and economic incentives. Journal of Human resources 39, 958-979.
Martinez, R., Stowell, J.I., Lee, M.T., 2010. Immigration and crime in an era of transformation: A longitudinal analysis of homicides in San Diego neighborhoods, 1980–2000. Criminology 48, 797-829.

Nagin, D.S., 2013. Deterrence: A review of the evidence by a criminologist for economists. Annual Review of Economics 5, 83-105
OECD, 2010. Chile signs up as first OECD member in South America.
Ousey, G.C., Kubrin, C.E., 2018. Immigration and Crime: Assessing a Contentious Issue. Annual Review of Criminology 1, 63-84.
Piopiunik, M., Ruhose, J., 2017. Immigration, regional conditions, and crime: Evidence from an allocation policy in Germany. European Economic Review 92, 258-282.
Scorzafave, L.G., Soares, M.K., 2009. Income inequality and pecuniary crimes. Economics Letters 104, 40-42.
Simon, R.J., Sikich, K.W., 2007. Public attitudes toward immigrants and immigration policies across seven nations. International migration review 41, 956-962.
Spenkuch, J.L., 2013. Understanding the Impact of Immigration on Crime. American Law and Economics Review 16, 177-219.
United Nations, 2017. International Migration Report 2017: Highlights., in: Department of Economic and Social Affairs, P.D. (Ed.).