Chapter 2

Territorial distribution of crime

Statistical evidence suggests that crime is a territorial phenomenon. Indeed, beyond national averages, regional differences within countries in criminal activities are often important and crime rates tend to be concentrated around the same geographic areas. This chapter presents some evidence on the territorial patterns of criminal activities within OECD countries and discusses the main socio-economic variables associated with different levels of crime in a sample of OECD countries. Due to the relevance of evidence-based policies, the chapter discusses the main constraints associated with measuring security and provides some orientations to increase the availability of internationally comparable statistics at sub-national level. Finally, a framework is proposed to describe the multi-level governance needed in the design and measurement of prevention and security policies.

Introduction

Statistical evidence suggests that crime is a territorial phenomenon. Indeed, beyond national averages, regional differences in criminal activities within countries are often important and crime rates tend to be concentrated or clustered around the same geographic area. Moreover, adaptation of crime activities to new environments can happen quite quickly, resulting in territorial concentration or expansion over time.

The forces driving these geographical patterns seem to be related to the interaction of different social, economic, institutional and physical factors. Authors like Vilalta (2012b) suggest that territorial disparities in crime could be explained by two alternative approaches. The first considers that regional differences are due to the aggregate effect of individual characteristics interacting with the attributes of a particular location. The second approach suggests that geographic patterns result from similar people facing different levels of government and experiencing different trust in institutions and law enforcement, depending on where they live. In both cases, the analysis of criminal statistics disaggregated at different geographical scales can provide appropriate information to public policies to detect and anticipate changes in criminal activity. Considering that a significant share of criminal activities in Mexico is caused by the presence of organised crime in specific geographic areas of the country, this approach could be of particular interest for Mexican authorities. Indeed, drug cartels are established in certain regions of the country, while their domains extend across states. Moreover, these domains do not necessarily respect political boundaries and seem to be reactive to different security policies implemented at different moments in time. Thus, understanding the dynamics of the geographical patterns of criminal activities can contribute to enhancing the design of security policies.

Geographical patterns provide information on the way criminal activities interact across regions in a country. Indeed, assuming that criminal activities do not respect political boundaries, it seems plausible that crimes sharing the same type of drivers may be present in groups of neighbouring regions. In other words, a region's crime rate may be correlated with the criminal rates of surrounding regions. This phenomenon – known as spatial dependency – can change over time, signalling a reorganisation of crime activities in the territory. A spatial approach to crime statistics can also help identify the interaction of criminal activities with socio-economic characteristics and whether the relevance of certain characteristics differs across places (so-called spatial heterogeneity analysis).

The study of criminal activities following a spatial approach has gained a place among social scientists during the past decades. Improvements in data collection and the availability of geographic information systems (GIS) have contributed to the increase of such empirical studies in the most recent years. For instance, Curry and Spergel (1988) use community level data to identify different geographical patterns in intentional homicides and common types of crimes, finding that while intentional homicides are associated to areas of poverty and lack of social control, common crimes are mostly related to a measure of social disorganisation. Tita *et al.* (1999) find that gangs tend to form in areas characterised by low values of informal social control. Authors like Messner *et al.* (1999), Canter (2000) and Santtila *et al.* (2007) have made significant contributions to the literature by analysing intentional homicide statistics through GIS. Canter (2000) argues that one of the main advantages of using GIS for analysing homicides is the possibility to better understand offender patterns. Messner *et al.* (1999)

and Santtila *et al.* (2007) analyse the spatial patterns of homicides through time; these two studies are focused on concentration patterns. In both cases, the authors reject the existence of a random spatial pattern, *i.e.* homicides seem to be clustered in particular areas within a community. Following a similar approach, Vilalta (2012b) suggests the existence of a spatial match between metropolitan judicial activity rates and the levels of both institutional and urban infrastructure development in 60 Mexican metropolitan areas. These studies not only highlight the importance of considering the spatial nature of criminal activities, but they also show the significant role better territorial indicators play in policy design, implementation and evaluation.

This chapter will first present some evidence on the territorial patterns of criminal activities in OECD countries, drawing on the indicators available in the *OECD Regional Database*. The second and third sections provide some evidence on the main socio-economic variables associated with different levels of crime within countries in a sample of seven OECD countries that includes Mexico.

Even though regional differences are important in crime activities, it is often difficult to measure them satisfactorily and to identify what socio-economic, institutional and cultural conditions are associated or responsible for crime. The fourth section discusses the main constraints of measuring security and provides some orientations to increase the availability of internationally comparable statistics at the sub-national level.

Finally, better data do not automatically translate into **actionable evidence**, that is to say evidence that can provide guidance to policy making, because the indicators can be far away from the policy intervention, or because the institutional conditions are not known or difficult to change, or because causality and correlation links are difficult to be established given the many stakeholders (national, local policy makers, citizens and business), with different information needs, different objectives and capacity. The territorial dimension of crime activity, thus, requires coherent policies across levels of government and government bodies. The multi-level governance issue is particularly important not only because states have broad-ranging powers in the organisation of police and courts of law, but because, given the strong local dimension of crime, the alignment of policy objectives across levels of government is essential to increase the effectiveness of prevention and security policies. The chapter will address this aspect in its final section.

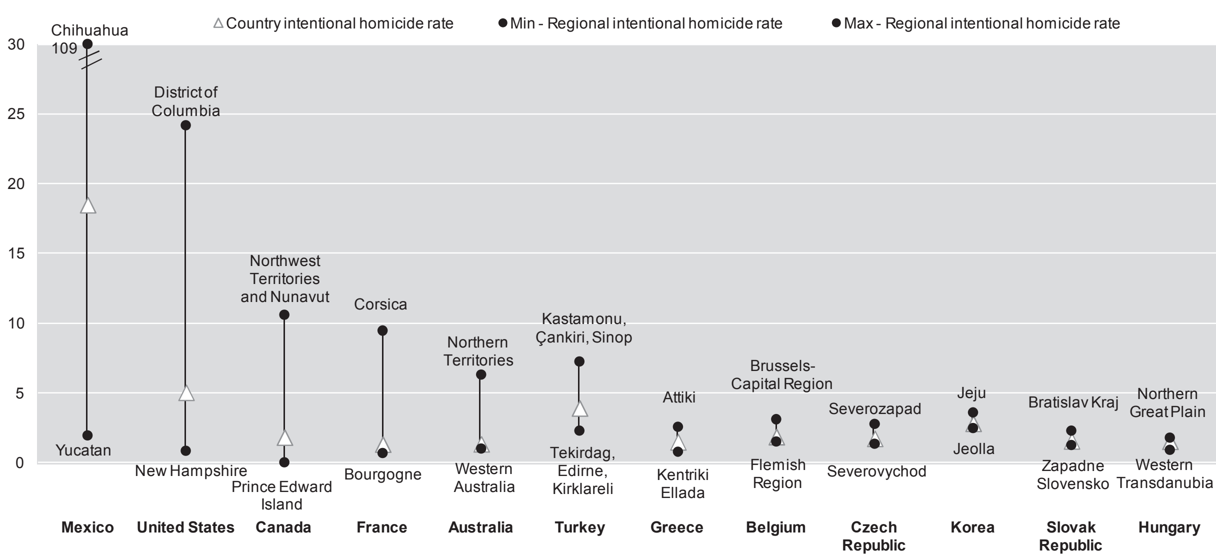
Regional crime statistics in OECD countries

Despite crime being a territorial phenomenon, the collection of comparable sub-national statistics within this domain tend to be scarce. Considering this constraint, the *OECD Regional Database* (RDB) has focused on two widely used variables that account for criminal activities: the number of reported intentional homicides and the number of reported crimes against property. The RDB stores this information for the states or regions in 26 OECD countries on an annual basis. Both variables are collected on the basis of official statistics provided by national statistical offices or the corresponding national agency in charge of collecting sub-national data.

Under the definition used by the RDB, intentional homicide is considered as **the unlawful killing of a human being with malice aforethought**; in other words murder. Crimes against property, on the other hand, refer to the set of crimes that includes forgery, arson, burglary, theft, robbery and malicious damage of property. In order to control for differences in population sizes and promote comparability, both variables are usually expressed as rates with respect to the regional population. Both variables refer to the number of crimes reported to the police; underestimation of crimes, due to under-reporting, is a common problem in crime statistics and quite important in Mexico, as the recent victimisation survey carried out by the national Institute of Statistics and Geography (INEGI) highlights. To understand the actual criminal activity, reported crimes should be complemented by people's perception of an area's security. However, the RDB does not include any subjective measure due to poor cross-country comparability of these measures.

Regional crime statistics show that national averages often mask strong differences within countries. This is particularly the case in Mexico. Mexico is not only the OECD country with the highest national intentional homicide rate, but it is also the one with the greatest regional disparities in intentional homicides. In 2009, the national intentional homicide rate was close to 18 per 100 000 inhabitants. However, the intentional homicide rate of the state of Chihuahua (109 intentional homicides per 100 000 inhabitants) was 56 times higher than in the state of Yucatán. The intentional homicide rate of Yucatán is close to, or even less than, that of many European regions (Figure 2.1).

Figure 2.1. **Regional differences in intentional homicide per 100 000 inhabitants in selected OECD countries (2009)**



Source: OECD Regional Database (2009).

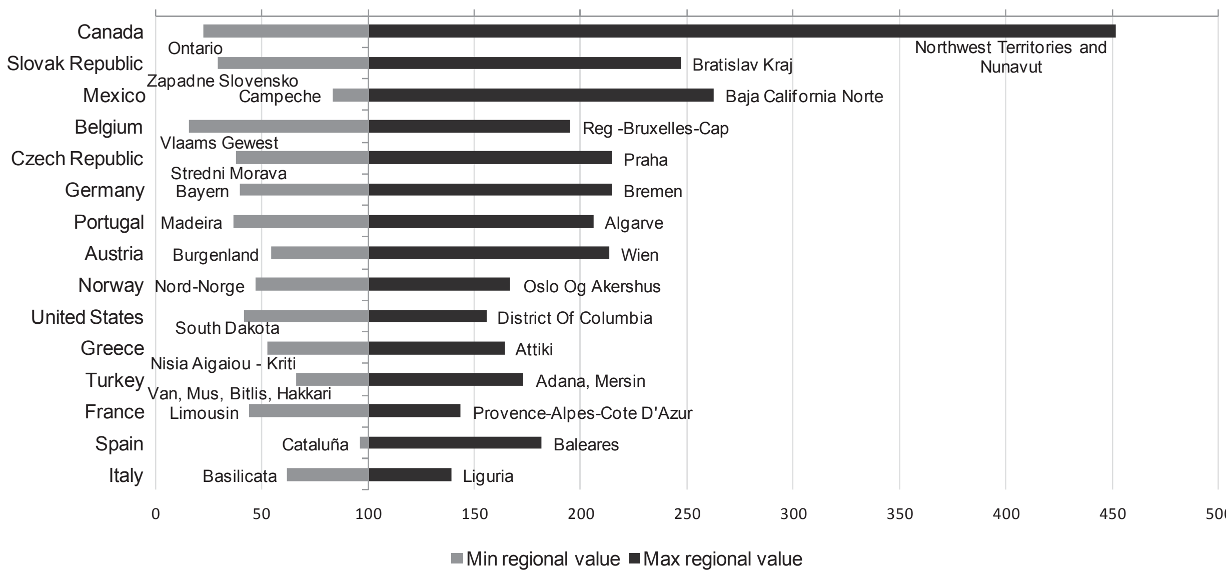
Similarly, big differences can be observed across regions in different OECD countries; for instance, during the same year in the United States, the intentional homicide rate of the District of Columbia (24 intentional homicides per 100 000 inhabitants) was almost 30 times higher than in New Hampshire. This pattern can also be found in countries like Canada and France, where regions like Northwest Territories and Nunavut (Canada) and Corsica (France) have intentional homicide rates significantly higher than the rest of the country.

OECD countries also show high regional disparities regarding crimes against property. In 2009, Canada had the largest disparities in crimes against property; the region Northwest Territories and Nunavut had a rate almost five times higher than the national value. For the same year, Mexico also showed significant regional disparities.

Moreover, these disparities seem to follow a geographical pattern similar to the one of intentional homicide rates. The northern state of Baja California Norte (neighbour of Chihuahua) had a rate of crime against property almost three times higher than the national value, while the southern state of Campeche (neighbour of Yucatán) had a rate five times smaller than the national value.

Crimes against property are usually higher in urban areas. Indeed, in some European countries like Austria, Belgium, Greece, Great Britain, Norway, Spain and Sweden, the region where the capital city is located features a rate of crimes against property particularly high compared to the other regions in the country (Figure 2.2).

Figure 2.2. **Regional differences in crimes against property (Country value =100) – 2009**



Note: Each bar represents the ratio between the regions with the highest and lowest values of property crimes rates and the national value (multiply by 100). For instance, in Italy the region of Liguria has a rate of crimes against property 40% higher than the national value, whilst the region of Basilicata has a rate of crimes against property representing only 60% of the national value.

Source: OECD Regional Database (2009).

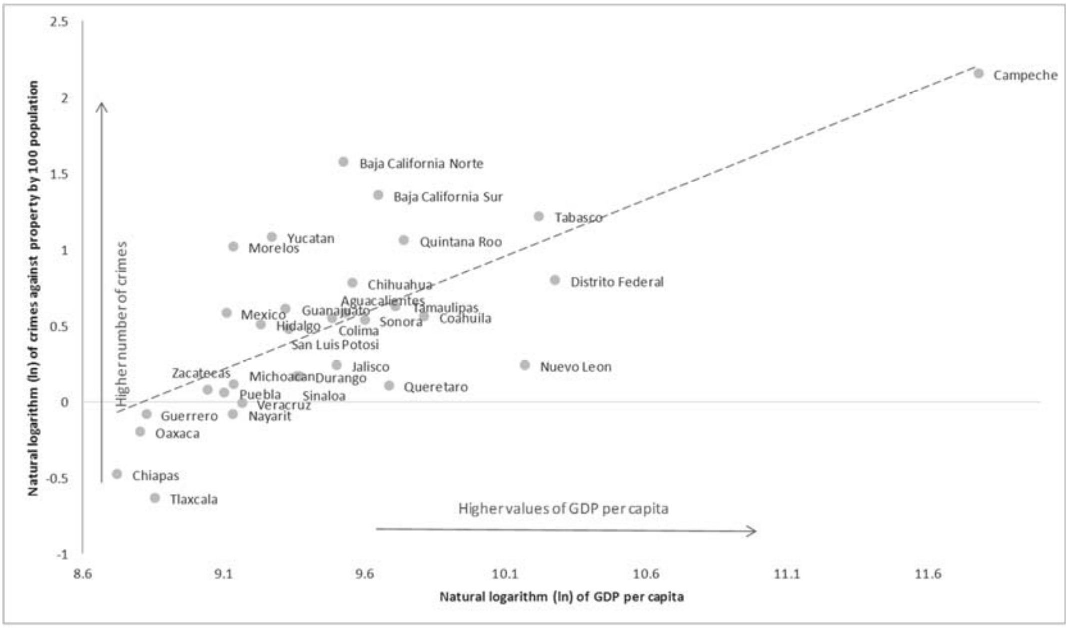
Understanding the linkages between socio-economic conditions and crime activities is not easy. At first glimpse, property crimes tend to be concentrated in cities and reported property crimes tend to increase with regional *per capita* GDP in many OECD countries (see Figure 2.3 for Mexican states).

However, as described in the following paragraphs, analyses following a spatial approach can provide insights to the way criminal activities interact across regions and help to better understand the incidence of certain socio-economic variables on different crime activities in different regions.

The geography of intentional homicide rates[1]

Intentional homicides represent the most extreme form of violence. It should be noted that intentional homicide rates do not provide information on more common security conditions. However, since the phenomenon they represent has one of the biggest impacts on people's well-being, they are considered to be one of the most important indicators when analysing criminal activity.

Figure 2.3. **GDP *per capita* and crimes against property in Mexican states (2008)**



Note: The region of Campeche is excluded from this figure as an outlier. The region's GDP includes the most important share of oil production activities; hence its GDP *per capita* is the one of highest in Mexico but does not necessarily reflect the wealth of the population on the state.

Source: OECD Regional Database; information provided by INEGI.

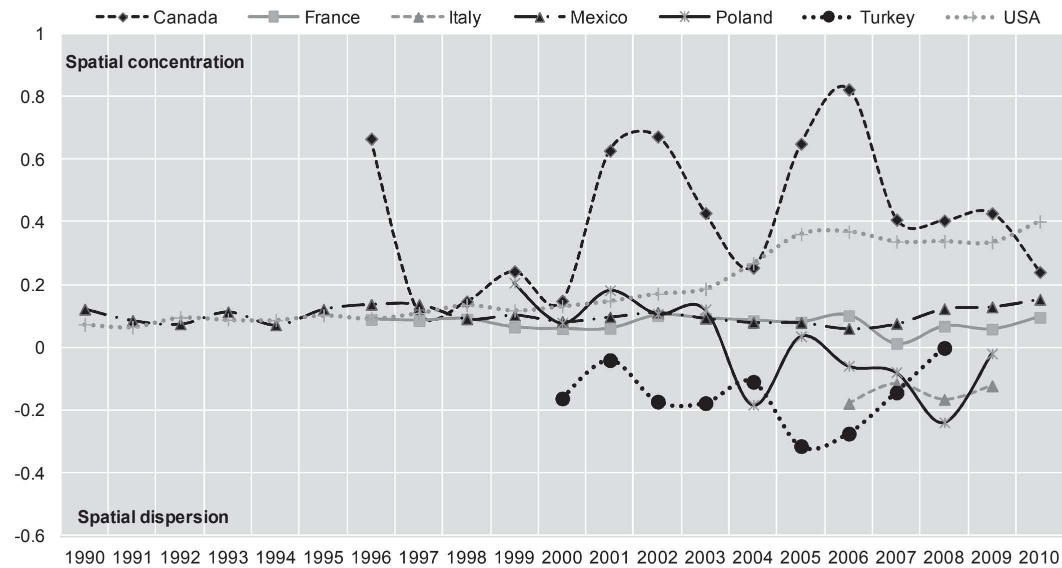
Understanding the way in which intentional homicide rates are distributed across regions is key in the design of any security strategy. Moreover, identifying the socio-economic factors that influence their spatial distribution could help sub-national governments to implement policies intended to eradicate some of the actual drivers of criminal activity.

The following paragraphs present the results from the spatial dependency and spatial heterogeneity analysis applied to seven OECD countries: Canada, France, Italy, Mexico, Poland, Turkey and the United States.

Spatial dependence of intentional homicide rates

The strength of spatial dependency, *i.e.* the degree in which neighbouring regions can influence each other, varies according to distance and time. The closer two regions are, the higher their interaction or dependency. However, spatial dependency may be present at certain periods of time and lacking at others. Criminal activities are dynamic and highly reactive; thus, depending on changes in monitoring efforts and law enforcement across regions, criminal activities may be concentrated or dispersed throughout a territory at different points in time. The patterns of spatial dependency for the seven countries in the sample are presented in Figure 2.4. In this figure, spatial dependency is expressed through an autocorrelation coefficient, which takes a positive value in the presence of regional concentration and a negative value in the presence of regional dispersion.

Figure 2.4. **Spatial autocorrelation coefficients over time per country**



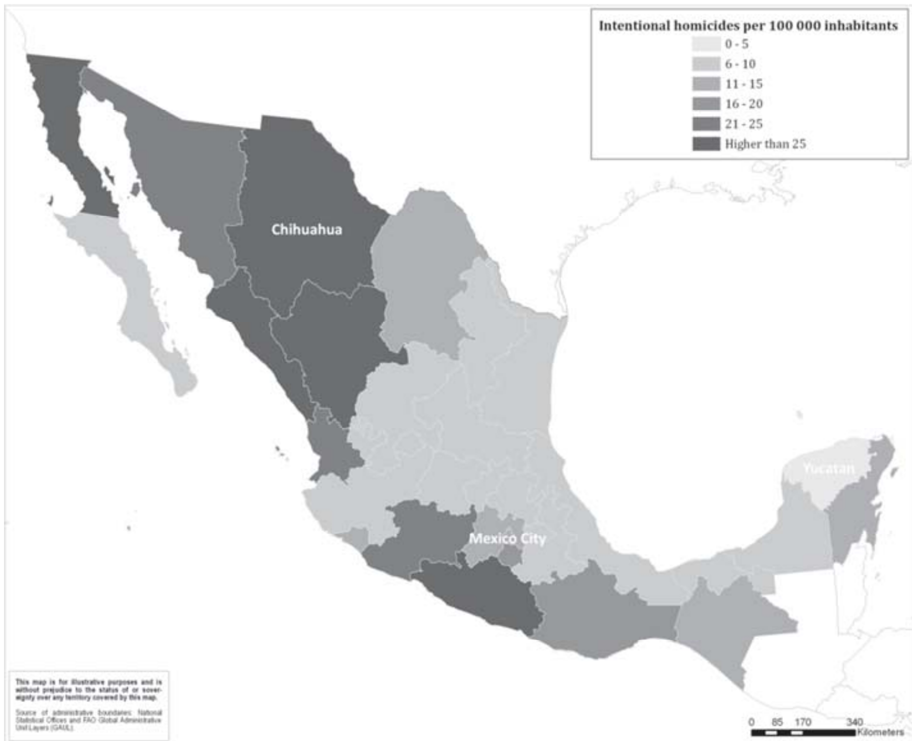
Note: Based on an inverse distance function, with the exception of the United States, for which calculations were based on a squared inverse distance function.

The results from the spatial dependence analysis show a wide variety in geographical patterns among the seven OECD countries. In general terms, these results suggest that in Canada, France, Mexico and the United States intentional homicides tend be clustered in certain geographical areas; while in Italy, Poland and Turkey intentional homicides tend to be dispersed across regions. Nevertheless, due to the different geographic dynamics of each country, it is more adequate to discuss each case independently.

The results in Figure 2.4 show that the Mexican geography of intentional homicides is highly dynamic. Indeed, there have been years of spatial concentration followed by years with no recognisable spatial pattern of intentional homicide rates across Mexican states. However, it should be noted that spatial dependency has significantly increased in the past couple of years. Over the past decade, intentional homicide rates have increased and clustered in northern states such as Chihuahua, Baja California Norte, Sinaloa and Sonora (Figure 2.5). Intentional homicide rates in other states such as Tlaxcala, in the centre, and Yucatán, on the peninsula, have remained well below the national average for the last decade.

In the case of the United States, murder rates have always been clustered; yet this concentration has been constantly increasing since 1990. It must be said that the national intentional homicide rate in 2010 was half of what it was in 1990. However, regional differences remain. States like North Dakota and Iowa have been historically among the safest regions of the 180 analysed in this set of 7 countries, similar to some Canadian regions (*e.g.* New Brunswick or Prince Edward Island). However, neighbouring states like Louisiana and Mississippi, in the south, or the District of Columbia and Maryland in the mid-Atlantic, have kept very high intentional homicide rates over time (the values of these rates are similar to the ones in Mexican states like Baja California Sur or Coahuila).

Figure 2.5. **Intentional homicide rates in Mexico (2009)**



Note: This map is for illustrative purposes only and is without prejudice to the status of or sovereignty over any territory covered by this map.

Source: OECD Regional Database (2009).

Countries like Canada and France show relatively stable geographical patterns of intentional homicide rates. Both countries are characterised by one region suffering from a particularly high intentional homicide rate compared to the rest of the regions in the country; this is the case of Northwestern Territories in Canada and Corsica in France.

Italy shows the opposite pattern from Canada and France. While Canada and France show a pattern of spatial concentration of intentional homicide rates in a small group of regions, Italy presents a pattern suggestive of (decreasing) spatial dispersion between 2006 and 2009; meaning that neighbouring regions are dissimilar from each other. Calabria, in the south, and Emilia-Romagna in the north-centre of the country present the highest intentional homicide rates: about twice the national average.

Turkey, like Italy, is another case of constant spatial dispersion. Although intentional homicide rates have decreased over time, one region consistently reports much higher rates than the national average. This is the Kastamonu, Çankiri, Sinop region in the north-centre of the country, bordering the Black Sea. Istanbul has also reported high numbers of intentional homicides over the period; however, intentional homicide rates have notably decreased since 2007.

Poland is the most spatially unstable of the seven countries for this type of crime. Still, although highly variable from one year to another, Poland has shifted from geography of concentration in the late 1990s towards a geography of dispersion by the end of the period. Specifically in 2009, the regions with the highest intentional homicide rates were located on its borders and farthest away from each other, particularly Lubelskie in the eastern border: Dolnoslaskie, Lubuskie and Zachodniopomorskie in the western border; and Warminsko-Mazurskie in the north.

Spatial heterogeneity of intentional homicide rates

If the relationship of intentional homicide rates with another socio-economic factor varies depending on the geographic location, we consider this relationship to be spatially heterogeneous. In other words, in the presence of spatial heterogeneity, the effect of a socio-economic variable on the number of intentional homicides is not the same in different regions of the same country. In some cases, it is even possible to find countries where this effect is positive for some regions and negative for others. This is also known as an inverse relationship. The results of the analysis show that three socio-economic factors have the strongest relationship with intentional homicide rates among the countries in the sample: the youth unemployment rate, GDP *per capita* and the share of working age population (population aged 15-64).[2] The socio-economic factors having the strongest relationships on intentional homicide rates for each country are shown in Table 2.1.

Both Canada and the United States showed an inverse relationship between the socio-economic variable and the intentional homicide rate. In Canada, regional youth unemployment rates were statistically associated with regional intentional homicide rates for the year 2010. This relationship was positive for the northern, western and central regions of the country; it was negative for the eastern and Atlantic regions. This implies that youth unemployment rates are positively related to intentional homicide rates in British Columbia and Alberta, while negatively related in Ontario or Quebec. In the case of the United States, the socio-economic factor showing the strongest relationship with intentional homicide rates in 2010 was GDP *per capita*. In this case, the relationship between the two variables is negative in the west and positive in the east and Alaska. Higher levels of GDP in western states are associated with lower levels of intentional homicide rates; the opposite is true in the eastern states. It is important to highlight that these results are preliminary; they should be validated by a complementary analysis on their robustness and to better assess the underlying mechanisms between crime and various socio-economic variables.

Table 2.1. **Socio-economic variables with the strongest relationship to intentional homicide rates**

Country	Strongest covariate	Pearson's coefficient
Canada	Youth unemployment rate	-0.782[2]
France	Youth unemployment rate	-0.282
Italy	Population 15-64 years old (%)	0.342
Mexico	Youth unemployment rate	-0.138
Poland	GDP *per capita*	0.160
Turkey	Youth unemployment rate	0.788[2]
United States	GDP *per capita*	0.632[2]

Note: Based on Pearson's linear correlation analysis. 1. 0.05 level

Although other countries did not show inverse relationships between regional intentional homicide rates and socio-economic factors, all countries did show varying degrees in the strength of the relationships. For instance, in France the relationship between youth unemployment rates and intentional homicide rates was stronger in the western regions and weakened progressively towards the east. In Italy, the relationship between the percentage of the population 15-64 years old and intentional homicide rates was stronger in the centre, particularly in the regions of Marche and Umbria, while becoming progressively weaker towards the south and north. In Mexico, the relationship between youth unemployment rates and intentional homicide rates was stronger in the central-southern states. In the case of Poland, GDP *per capita* was strongly correlated with intentional homicide rates in the southern regions, particularly in Slaskie, and began to weaken towards the north.

The empirical literature is inconclusive regarding the link between unemployment and some crime activities, for example homicides. While many studies point out the correlation between these two variables, the direction of this correlation has been found to be positive in some cases and negative in others, depending on the territory and the types of crime under study. In the present analysis, this correlation is negative in the case of Mexico from 2005 to 2008, though its significance should be tested at lower territorial scales. Other evidence suggests that while crime is a youth activity in Mexico, homicide is not so much. Murders can be linked to illegitimate sources of income/earnings, but may not be significantly influenced by regional economic factors. Indeed, in many instances murders are not fully driven by the situation of the regional economy, but by contextual factors associated with drug trafficking and dealing, family structure and community cohesion instead. The latter suggests that in order to better understand the link between these two variables from a territorial perspective, it may be necessary to focus on more disaggregated data (*e.g.* municipal or city level data).

The geography of crimes against property[3]

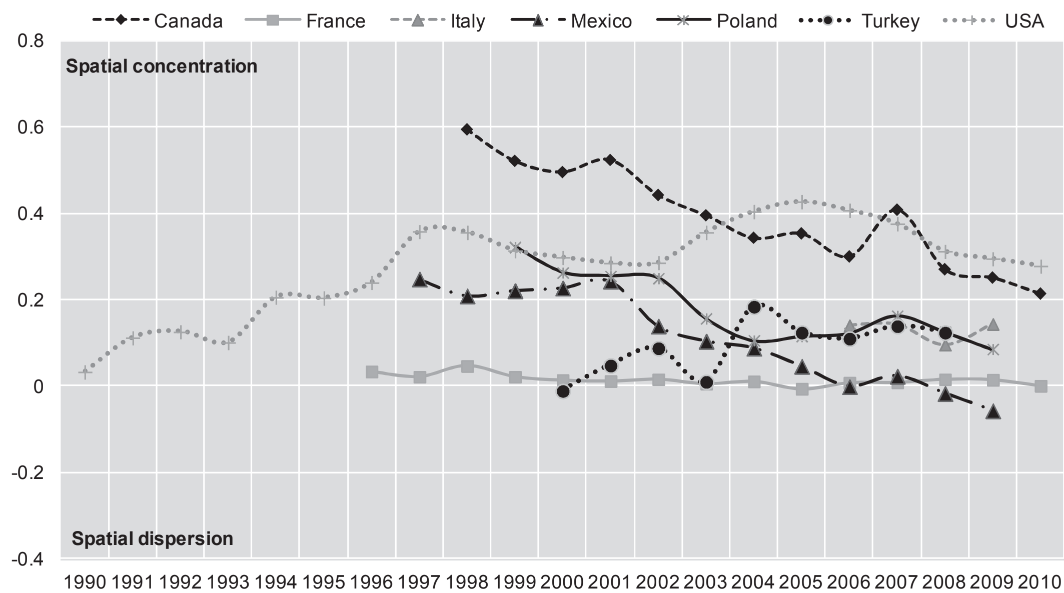
Crimes against property account for those crimes that have a direct impact on material assets. They are an interesting complement to intentional homicide rates as they provide information on a more common type of criminal activity. The same type of spatial analysis used for identifying the geographical patterns of intentional homicide rates has been applied to analyse crimes against property. The spatial analysis of property crimes considers the same set of OECD countries, and it is also composed of analyses of spatial dependence and spatial heterogeneity.

Spatial dependence of crimes against property

Most countries show a pattern of spatial clustering of property crimes at some point between 1990 and 2010. Spatial dispersion is rare and only present in Mexico towards the middle of the last decade. Prior to that, property crime rates in Mexico were spatially clustered (Figure 2.6). Overall, the trend of the six remaining countries is towards decreasing spatial concentration, meaning that property crimes tend to be more dispersed across regions. The exceptions are France and the United States.

Between 1997 and 2004, property crimes in Mexico were concentrated in a set of states, particularly in north-western states like Baja California Norte and Baja California Sur, Sonora and Colima along the Pacific Ocean. Since 2004, property crimes have dispersed and other states have begun to suffer from these crimes. States such as Tabasco in the Gulf of Mexico, Morelos and the Federal District now also have above-average property crime rates (Figure 2.6). Indeed, crime dynamics in geographically separated states have resulted in a shift from spatial concentration to spatial dispersion. In fact, the observable trend for the entire period is towards increasing dispersion – that is, neighbouring states become more and more unalike each other.

Figure 2.6. **Property crimes: Spatial autocorrelation coefficients over time by country**



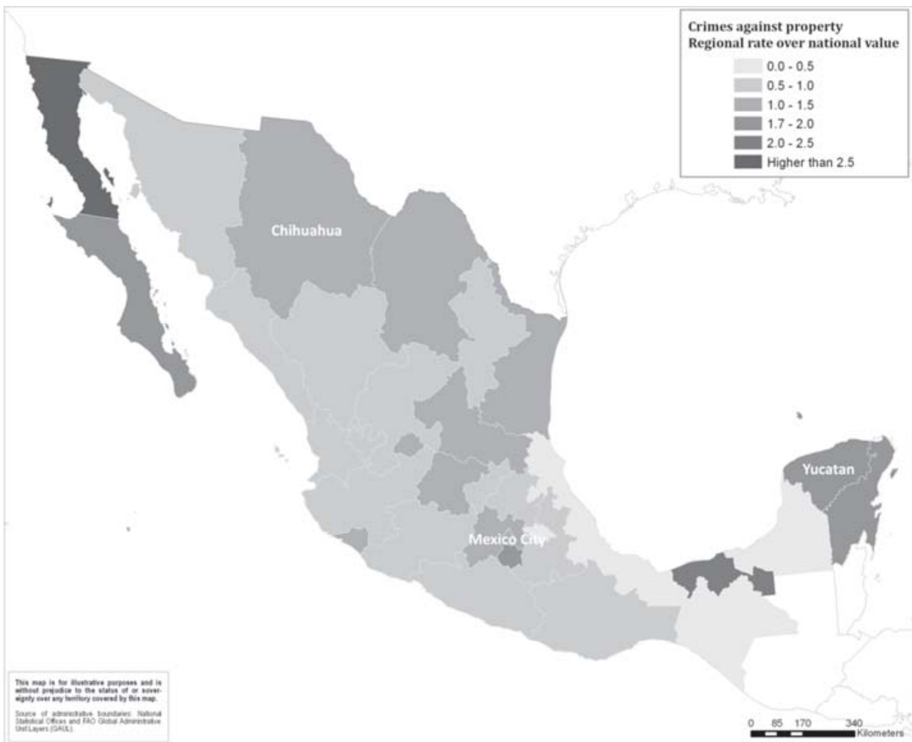
Note: Based on an inverse distance function, with the exception of the United States, for which calculations were based on a squared inverse distance function.

Property crimes in Canada have tended to be highly dependent or concentrated; yet there is a national trend towards a decrease in this spatial concentration. This trend has been very stable over time – meaning not volatile. This implies that provinces have become subtly, yet progressively, closer or similar in terms of their property crime rates since 1998. Contrary to Canada, property crimes in France are not spatially clustered. However, there are some regions that do stand out with property crime rates above the national average: Provence-Alpes-Cote d'Azur, Ile-de-France and Languedoc-Roussillon. Still, overall there has not been a statistically detectable spatial pattern in the activity of this crime (at least not between 1996 and 2010). The spatial trend is the same: random.

The Italian geography of property crime rates shows a pattern opposite that of intentional homicide. In the case of intentional homicides, Italian regions were unalike (*i.e.* spatially dispersed). However, regarding property crimes, Italian regions showed a stable pattern of spatial clustering extending towards the Mediterranean and the northern regions between 2006 and 2009. Regions such as Liguria, Lombardia and Emilia-Romagna have had property crime rates well above the national average, whereas other regions such as Basilicata and Molise in the south have been well below the national average. Still, the incidence of these crimes decreased for most regions in this period.

Poland is somewhat similar to Mexico in its trend towards spatial dispersion of property crimes. While in the late 1990s and early 2000s these kind of crimes were spatially concentrated, particularly in the Zachodniopomorskie and Pomorski regions, for2009 the spatial pattern was random (not dependent) and the trend is towards increasing spatial dispersion. Zachodniopomorskie and Pomorski still possess the highest property crime rates in the country, yet they are less spatially dependent from their neighbouring regions. It must be noted that property crime rates descended nationwide between 1999 and 2009, whereas in Mexico property crimes have increased notably.

Figure 2.7. **Crimes against property (2009)**



Note: This map is for illustrative purposes only and is without prejudice to the status of or sovereignty over any territory covered by this map.

Source: OECD Regional Database (2009).

In the Turkish case, the trend is towards a spatial concentration of property crime activity. Most activity is concentrated in the Antalya-Isparta-Burdur, Izmir and Adana-Mersin regions on the Mediterranean coast. Another region that stands out is Ankara, the capital. It must be noted that rates of property crime rates in the former regions more than tripled in the last decade. After Mexico, Turkey is the country with highest growth in property crime activity.

Finally, the United States presents a spatial clustering of both intentional homicide and property crime rates. With regards to property crimes, the rates have been decreasing since the 1990s. Most of the crime activity has been, and still is, concentrated in southern states, particularly in Arizona, Florida, Texas, Louisiana and South Carolina. Washington and Oregon, in the northwest, also have property crimes rates above the national average.

However, the District of Columbia in the mid-Atlantic, similar to intentional homicide rates, ranks first in the nation in property crime rates.[4] The spatial trend observed between 1990 and 2010 suggests a decrease of spatial clustering in the coming years.

Spatial heterogeneity of crimes against property

With the exception of Mexico, the socio-economic variable showing the strongest relationship with the property crime rate was GDP *per capita* (Table 2.2). Indeed, for Canada, France, Italy, Poland, Turkey and the United States, the relationship between property crimes and GDP *per capita* was positive; in other words, high values of GDP *per capita* are associated with high values of property crime rates. In the case of Mexico, the socio-economic variable showing the strongest relationship with property crime rates was the youth unemployment rate; this relationship is positive, that is, regions facing high youth unemployment rates are characterised by high property crime rates.

The United States was the only country showing evidence of inverse local relationships between property crime rates and GDP *per capita*. This means that there is a negative relationship between property crime rates and GDP *per capita* in all central and western states, while there is a positive relationship in the western states like Alaska and Hawaii.[5]

Table 2.2. **Socio-economic variables with the strongest relationship to property crimes**

Country	Strongest covariate	Pearson's coefficient
Canada	GDP *per capita*	0.592[1]
France	GDP *per capita*	0.577[2]
Italy	GDP *per capita*	0.414[1]
Mexico	Youth unemployment rate	0.221
Poland	GDP *per capita*	0.503[2]
Turkey	GDP *per capita*	0.631[2]
United States	GDP *per capita*	0.243[1]

Note: Based on Pearson's linear correlation analysis. 1. Significant at 0.10 level. 2. 0.05 level

The results from the spatial analysis suggest that every country is characterised by its own geography of crime. Indeed, the geographic patterns of both crimes against property and intentional homicide rates are not only different among countries, but for some of these countries they change over time. As in any other empirical analysis, certain caveats regarding these results should be issued. In the first place, the objective of this analysis was exploratory in nature. Thus, a more complete modelling strategy is needed to actually identify causality links between criminal activities and socio-economic variables. In the second place, certain data limitations should be acknowledged, as a large number of crimes are committed, particularly property crimes, but never reported to the police. Under-reporting not only misguides authorities by undermining the actual magnitude of the problem, but it also creates issues in terms of internal and international comparability.

The differences in the spatial dynamics of criminal activities suggest that place-based policies, which integrate top-down national policies with bottom-up local initiatives, can be necessary for more effective crime prevention and law enforcement, as discussed below.

Improving the metrics of crime in regions for effective policy making

The spatial analysis of the previous paragraphs shows that differences in crime activity can be important within countries. However, it is not only difficult to measure criminal activities in different places, but also to detect and anticipate their changes. This is essentially due to three reasons. The first concerns the identification of the relevant "geography" for economic and social phenomena, which is where society self-organises (live, work and leisure) and where policies are decided and implemented. Often these places do not coincide with administrative boundaries and therefore statistical information is more difficult to produce. Most recently, with the help of information and communication tools, many countries have invested in producing geo-referential information that can be aggregated at different territorial details. National statistical offices and international institutions have started using GIS not only to disseminate data but also to produce more information by integrating administrative, statistical and geographic sources. A recent analysis done by INEGI shows that only by geo-referencing crime activity and a large set of socio-economic conditions, was it possible to provide indications to public authorities on how to reduce property crimes in Aguascalientes City, Mexico. The interpretation of crime factors was difficult before because the offences and the other socio-economic variables were not available at the geographical level required to produce evidence on the causes of crime activity, and not merely on its effects.

Box 2.1. **Spatial analysis of criminal data in selected OECD countries**

The analytical strategy in this analysis began with an examination of the spatial distribution of the intentional homicide rates and property crime rates over the map. Spatial dependence was tested via Moran's I global autocorrelation coefficients for each year of available data in each country. Because of the small sample size in most countries, a "p" value of ≤0.10 was the cut-off level of significance for spatial tests.

Then, the linear correlation of the dependent variables with the following four structural covariates was estimated: population 15-64 years old (%), unemployment rates, youth unemployment rates and GDP *per capita*. This was performed via Pearson's linear correlation analysis. The covariate with the largest magnitude was selected for further examination in the spatial heterogeneity analysis. The purpose was to detect preliminary evidence of divergent spatial relationships between variables across regions, whether substantive or as statistical nuisance. As such, the largest covariate was included in the right side of the geographically weighted regression (GWR) equation. Finally, local coefficients of determination and local slopes (the latter when needed) were estimated.

Second, in the case of crime and security, it is difficult to gather robust data. Crimes reported to the police are sensitive to changes in legislation, may not be informative about the severity of each offence, and may not include detailed information on the victims. All these issues reduce the potential of this information to design preventive policies against crime. Moreover, research demonstrates that official police-based statistics only tell a part of the story, as a large number of crimes are never reported or recorded (the so-called "dark figure"). According to the US Bureau of Justice Statistics (2010) only 40% of property crimes and 49% of violent crimes are reported to the police. Similar estimates of unreported crimes for Mexico are as high as 90% (INEGI, 2010) (see Box 2.2). Reporting by citizens and business is linked to issues of public trust, the efficiency of law enforcement, integrity in the public sector, attitudes towards the police and the perceived cost associated with the criminal process. All these reasons have specific geographic features within countries as well, making it even more difficult to detect the causality links between socio-economic, institutional and cultural conditions and crime activities. As the potential to overcome these constraints is limited, it is important to supplement the information gathered through police statistics with evidence derived by victimisation surveys. Victimisation surveys can provide a more comprehensive picture of the prevalence and incidence of crime, while helping to understand people's perceptions and fear of crime. The way communities perceive themselves is not only critical for citizens' well-being but also to give orientations to public policies. Results from the British Crime Survey show that the most important factor associated with public confidence in local police was whether people perceived the police to be dealing with things that matter to their community (Myhill and Beak, 2008).

Box 2.2. **Cross-country comparability issues in regional crime statistics**

Despite national governments' and international agencies' efforts to standardise and harmonise criminal statistics, some comparability constraints still need to be overcome. Moreover, these comparability issues are not only present at the international level, but concern sub-national crime statistics for some countries as well.

A critical comparability issue affecting a wide set of criminal statistics at different territorial levels is concerned with the multiple definitions of crimes. Indeed, due to the differences in legal procurement systems, the definition of a particular crime can differ from country to country. This issue can also be present within countries, when sub-national governments have their own criminal procedures code, as is the case in Mexico.

The comparability of intentional homicide rates, across and within countries, may be compromised if this indicator is built using different sources of information. Information on the number of intentional homicides committed during the year can be collected through criminal justice or health registries. However, these two sources usually provide different intentional homicide counts. A possible reason explaining this difference is the lack of capacity of law enforcement agencies to identify and record criminal activity. This issue may be more important in developing countries who are still consolidating their institutions. Despite this drawback, homicides tend to be constantly reported or registered (by either source).

Contrary to intentional homicides, crimes against property can be significantly under-reported. In some countries, including Mexico, official registries tend to undermine the actual number crimes against property committed because people do not report them the police. One possible way to estimate the frequency of these crimes is through the use of victimisation surveys. Victimisation surveys ask the population whether they have been the victim of crime. In Mexico, the difference between official registries and estimates provided by victimisation surveys is commonly known as the "dark figure" ("*cifra negra*" in Spanish). Victimisation surveys usually include questions on the perception of criminal activity. Questions regarding the perception of security not only allow authorities to compare objective and subjective measures, but they also show whether the effect of certain security policies is perceived by the population. While in general, the sample used in the victimisation surveys does not provide evidence at the sub-national level, some countries have recently addressed this issue (and notably Mexico) through the victimisation and perception survey (ENVIPE).

Box 2.2. **Cross-country comparability issues in regional crime statistics** (*cont.*)

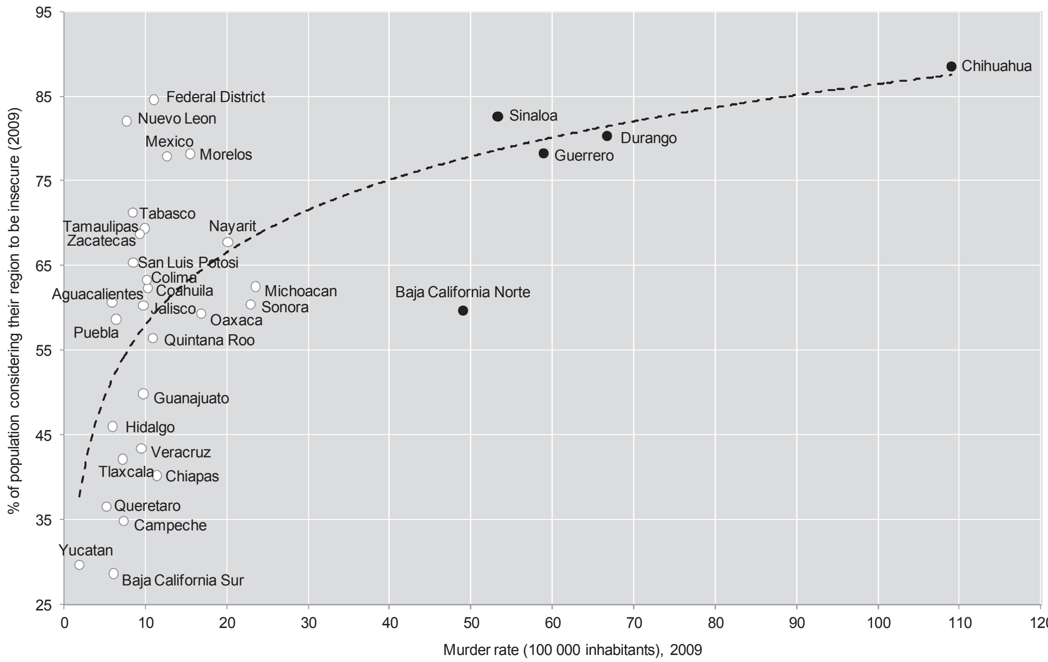
Victimisation surveys provide an interesting solution for overcoming some of the most important national and international comparability issues in the short term. Indeed, the international harmonisation of victimisation surveys is easier to achieve than the harmonisation of national governmental registries. Victimisation surveys do have some limitations though. In the first place, they are based on respondents' perception of crime; this perception can vary across different cultural and socio-economic contexts, which could make international comparisons more difficult. Moreover, the accuracy of responses is influenced by the ability to recall past crimes. Finally, victimisation surveys cannot be a complementary source of information for all types of crimes; they are a good source of information on common crimes affecting citizens, and most recently to business as well.

The increasing demand for well-being measures at the sub-national level has motivated the inclusion of additional indicators on security into the RDB. Indeed, in the following years, the RDB will include a more compelling collection of objective measures of security at the regional level. But more importantly, a significant part of the collection efforts will be directed at identifying internationally comparable indicators on the perception of security. As it has been widely recognised, well-being cannot only be captured through objective outcome indicators. Indeed, to design policies that enhance the population's well-being, it is necessary to account for the perception of the level of security embedded in the society.

In the case of Mexico, where an extensive victimisation survey was recently developed, evidence suggests that an increase in the regional number of intentional homicides initially has a strong effect on the perception of insecurity; yet, as the regional number of intentional homicides increases, the effect on people's perception tends to decrease (Figure 2.8). Moreover, populations in states with similar intentional homicide rates expressed very different perceptions of the security of their region. For example, the Federal District (Mexico City) and Nuevo León have a perception of insecurity similar to states like Sinaloa and Durango, which suffer from the highest intentional homicide rates. It should be noted, though, that the perception of insecurity accounts for crimes other than intentional homicides; in regions like the Federal District and the State of Mexico, the perception of insecurity may be driven by crimes like kidnapping or car theft and not only by intentional homicides. In addition, violent crimes and, in particular, intentional homicides tend to receive more media coverage, thus affecting people's perception (Figure 2.8).

The third issue relates to the fact that better data do not automatically translate into actionable evidence. The availability of comprehensive, high-quality, shared, accessible information about how a society is performing is crucial to ensure that decision making is simultaneously responsive and responsible. However, in some cases, sound evidence may not be enough to provide guidance to policy in the design and implementation of a strategy. This impediment is caused by multiple constraints: the comparative analysis may rely on indicators that are far away from policy intervention; the institutional conditions may not be known or very difficult to evolve; the information on the policy objectives may not be shared or agreed on among the different stakeholders (national, local policy makers, citizens and business); or the causality and correlation links may be difficult to establish.

Figure 2.8. **Perception of security and intentional homicide rates (2009)**



Source: Based on the INEGI (2010), *National Survey of Victimization and Perception of Public Security (ENVIPE)*, INEGI; *OECD Regional Database* (2009).

Specific inputs, then, need to be added to enter more directly in the “policy toolbox”, *i.e.* understand a country’s policy design, its implementation and delivery. To underline the fact that these inputs matter for the design, delivery, monitoring and evaluation of policies, they can be referred to as policy measures. Policy measures are of particular relevance in public policies related to crime and justice for which responsibility is shared among different levels of government and stakeholders. As such, their design and implementation depends on how well information is shared among actors and a common vision of results and changes needed to accomplish them is understood and shared among citizens and institutions at different territorial levels.

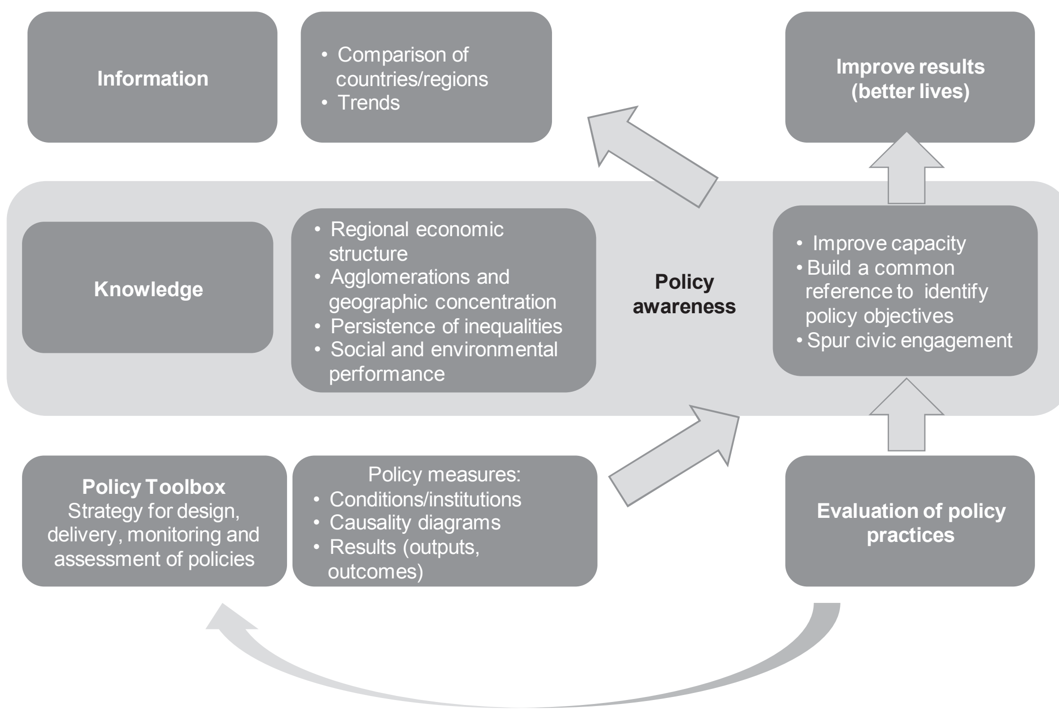
Broadly speaking, three categories of policy measures can be identified. The first measures the conditions in different countries and places (macroeconomic conditions, structural policies, institutional setting) as well as institutional conditions within a country (this includes actors, financial and human resources, different stakeholders’ responsibilities, etc.). The second category of policy measures relates to a better understanding of the causality links among policy objectives and actions, as well as to the policy levers and complementarities among different policies in a territory. This category cannot include only statistical indicators; it must be coupled with qualitative and quantitative evaluations. The third category is outcome indicators aimed at capturing the results on which policy can claim to have an effect. These indicators are relevant for a certain policy/territory, and as such they may differ from region to region.

Policy measures can leverage the information and knowledge to improve policy results, which in turn will demand refined information and knowledge; this “informed regional policy cycle” aims at improving the final outcomes of policy actions, *i.e.* better lives (Figure 2.9). This iterative process will also help to improve capacity in delivering policies, build a common vision on the objectives of policy and the means to achieve them and spur civic engagement.

In the iterative system of decision making, policy evaluation has a decisive role in offering insights on conditions, causalities and bottlenecks for the implementation of regional policy and in suggesting ideas on how to revise objectives, resource allocation and tools to deliver. The value-added of evaluation, among others, comes from its external position in relation to the policy toolbox (design, delivery and monitoring) allowing an **outer vision** on the process and, at the same time, it can enable a learning process for policy makers and strengthen the public accountability of policies.

Finally, the effectiveness of the informed regional policy cycle will depend on the interactions among the different actors, national and local policy makers, business and citizens, who have different information needs, capacities and policy objectives.

Figure 2.9. **Informed regional policy cycle**



Source: OECD (2009), *Regions at a Glance 2009*, OECD Publishing, Paris, doi: *10.1787/reg_glance-2009-en*

The territorial dimension of crime activity, thus, requires coherent policies across levels of government and government bodies. The multi-level governance issue is particularly important not only because states have broad powers in the organisation of police and courts of law, but because given the strong local dimension of crime, the alignment of policy objectives across levels of government is essential to increase the effectiveness of prevention and security policies.

Policy implementation needs a mix of top-down and bottom-up approaches so as to treat the conditions, context, policy levers and learning outcomes as an interconnected system. Conditions, instruments and actors to correctly co-ordinate broad policies with bottom-up practices can be different depending on the capacity of local governments, the transparency and accountability of practices, etc. National and local governments should put in place a process to identify the major co-ordination gaps and adapt instruments to overcome them. In fact, practices in OECD countries show that national policies to reduce crime activities (tax evasion, organised crime, property crimes, etc.) can be more effective if co-ordinated with increased responsibility of local authorities and involvement of the local community. While top-down policies can be ineffective if lower levels of government are not accountable and communities do not perceive the objectives as their own, the devolution of responsibilities to lower levels of government should be accompanied by instruments to integrate national and local objectives and co-ordinate actions to avoid that incentives to local accountability become an obstacle to national or state reforms. Recent news pointed out, for example, that the state correctional system in Louisiana (United States) created a system of financial incentives to local sheriffs that resulted in longer prison sentences than in the rest of the country and worse prison conditions in local prisons than in state-run prisons.

Conclusions

The following key recommendations can be made:

- Develop evidence-based policy making in this area by improving crime and security information at different geographical levels. Mobilise Mexico's statistical and analytical capacity at national and state levels to improve evidence on and the quality of security indicators.
- Build on recent work regarding victimisation surveys in order to improve the integration of objective and perception measures. The complementary use of these two types of measures can help to enhance the effectiveness of the judicial system and law enforcement by states.
- Give security and justice a strong local footing. Incorporate an assessment of the conditions and incentives for states/localities that could help in reforming the justice system.

Notes

1. A detailed description of the concepts used and the statistical output provided by the analysis can be found in Annex 2.A1.
2. The factors were chosen based on a correlation analysis, *i.e.* the factor showing the strongest correlation among the set of all socio-economic factors was chosen for the spatial heterogeneity analysis. The set of socio-economic factors included demographic, labour and economic variables.
3. A detailed description of the concepts used and the statistical output provided by the analysis can be found in Annex 2.A1.
4. Naturally, in the comparison, it must be considered that the District of Columbia is an urban area, whereas the other spatial units are states that include rural and urban areas.
5. It should be highlighted that this type of heterogeneity in the local relationships may be the consequence of an omitted variable in the model. In any event, the reader must be cautious when interpreting these results.

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Annex 2.A1
Methods for spatial analysis

Spatial dependence is present when "the value of the dependent variable in one spatial unit of analysis is partially a function of the value of the same variable in neighbouring units" (Flint *et al.*, 2000). Spatial dependence may be tested via spatial autocorrelation analysis. These techniques measure the degree of likeness of objects or activities across units (Goodchild, 1988). The oldest and most typical technique of spatial autocorrelation is Moran's I global autocorrelation coefficient. Coefficients can be either positive or negative. Significant positive autocorrelation indicates a non-random clustering of values and significant negative autocorrelation indicates a non-random dispersion of values.

In this analysis, spatial dependence was diagnosed via Moran's I spatial autocorrelation coefficients. These can be calculated in the following manner (Rogerson, 2001):

$$I = \frac{n \sum_i^n \sum_j^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_i^n \sum_j^n w_{ij}\right) \sum_i^n (y_i - \bar{y})^2}$$

Where n is the number of spatial units, x_i and x_j are the values of the dependent variable in the neighbouring areas i and j, and W_{ij} is the array of neighbouring units also known as a neighbourhood matrix. Neighbourhood matrices can be based on different metrics; they can be based on the distance among territorial units or on their position (*e.g.* contiguity). Values cannot exceed 1 or -1. Again, positive values suggest a positive spatial autocorrelation, in which spatial units with similar values are spatially clustered, whereas negative values suggest negative spatial autocorrelation, in which neighbouring spatial unities present dissimilar values. A coefficient equal or close to zero is suggestive of a spatial random variable.

Spatial heterogeneity is the variation in relationships across space (O'Loughlin and Anselin, 1992). It may be due to three different reasons (Vilalta, 2012a): two purely methodological and one theoretical.

The first methodological reason is sampling variation. It is unrealistic to expect the same estimates from significantly different samples or subsets of spatial data. In regression analysis this statistical nuisance is characterised by non-constant error variance. The second methodological reason is model misspecification.

The third, and theoretical, reason is substantive spatial variation in relationships. This means that relationships are indeed inherently different across space as a result of a place or a local contextual effect. If spatial heterogeneity is present in the data set, whether it is substantive or not, ordinary least squares (OLS) regressions intercept and slope estimates will be biased. The reason is that different relationships in different locations will cancel each other out in the calculation of the estimates (Vilalta, 2012a).

Spatial heterogeneity can be detected via geographically weighted regression (GWR). The GWR model extends the traditional OLS model by allowing parameters to vary across space (Fotheringham *et al.*, 2002). The GWR model is written as (Vilalta, 2012a):

$$\hat{y}_i = a_i + \sum_{j=1}^{k} b_{ij}x_{ij} + e_i$$

Where $\hat{y}_i$ is the estimated value of the dependent variable, a_i is the intercept, b_{ij} is the parameter estimate for variable j, x_{ij} is the value of the j-th variable for i, and e_i is the error term.

Each spatial unit is given a different weight in the model. Similar to Moran's I coefficients, larger weights are given to closer places and smaller to farther places. In traditional OLS, all places have the same weight as if they all shared the same location. In GWR, this assumption is also avoided in order to conform to Tobler's first Law of Geography that "everything is related to everything else, but near things are more related to each other" (Tobler, 1970).

Typically, weights are calculated with a negative exponential continuous function of the square distance among geographic centroids.[1] This way, closer units are given larger weights for the test of the model. For each place, the data will be weighted differently, so that results will be unique to that place (Fotheringham *et al.*, 2002). The weighting function is written as (Rogerson, 2001):[2]

$$w_{ij} = e^{-\beta d_{ij}^2}$$

Where "wij" are the weights given between units "i" and "j".

Spatial data units have to be determined to calibrate each local equation. In GWR, spatial units neither have the same weight nor the same number of neighbours. Not only are closer areas more important than farther areas, but some are more "central" or closely located than others.[3] Spatial kernels are utilised for this purpose, to define which spatial units will be neighbours.[4] These are necessary in the estimation of each local model. Spatial kernels can be either fixed or adaptive. A fixed spatial kernel implies that neighbours will be all units within a "fixed" distance, and an adaptive spatial kernel implies that neighbours will be defined based on the density of the data units. Where the data is sparse, adaptive spatial kernels will provide wider bandwidths, and where the data is dense, adaptive spatial kernels will provide narrower bandwidths (Fotheringham *et al.*, 2002). As such, it is better to use adaptive spatial kernels as they provide identifiable variable bandwidths for each spatial data unit. This was the criteria for this analysis.[5]

A local linear equation is obtained for each spatial unit, meaning that the descriptive or explanatory model is tested in all areas or regions. Each is given a local intercept coefficient, a local slope coefficient for the covariate variable, and a local coefficient of determination. All these can be mapped in order to visually assess the null hypothesis assumption of no spatial heterogeneity in the results.[6]

Results: Linear correlations

Table 2A.1. **Property crimes: Strongest structural covariate**[1]

	Best covariate	Pearson's coefficient
Canada	GDP *per capita*	0.592[1]
France	GDP *per capita*	0.577[2]
Italy	GDP *per capita*	0.414[1]
Mexico	Unemployment rate	0.221
Poland	GDP *per capita*	0.503[2]
Turkey	GDP *per capita*	0.631[2]
United States	GDP *per capita*	0.243[1]

Note: Based on Pearson's linear correlation analysis. 1. Significant at 0.10 level. 2. 0.05 level.

Table 2A.2. **Intentional homicide: Strongest structural covariate per country**

	Strongest covariate	Pearson's coefficient
Canada	Youth unemployment rate	-0.782[2]
France	Youth unemployment rate	-0.282
Italy	Population 15-64 years old (%)	0.342
Mexico	Youth unemployment rate	-0.138
Poland	GDP *per capita*	0.16
Turkey	Youth unemployment rate	0.788[2]
United States	GDP *per capita*	0.632[2]

Notes: Based on Pearson's linear correlation analysis.1. Significant at 0.10 level. 2. 0.05 level.

Results: Spatial correlation in intentional homicide rates

Table 2A.3. **Intentional homicide: Spatial autocorrelation coefficients over time per country**[1]

	Canada	France	Italy	Mexico	Poland	Turkey	United States
1990	n.a.	n.a.	n.a.	0.123[1]	n.a.	n.a.	0.074
1991	n.a.	n.a.	n.a.	0.087	n.a.	n.a.	0.066
1992	n.a.	n.a.	n.a.	0.076	n.a.	n.a.	0.096[1]
1993	n.a.	n.a.	n.a.	0.114[1]	n.a.	n.a.	0.089[1]
1994	n.a.	n.a.	n.a.	0.073	n.a.	n.a.	0.088
1995	n.a.	n.a.	n.a.	0.123[1]	n.a.	n.a.	0.103[1]
1996	0.666[2]	0.090[2]	n.a.	0.138[2]	n.a.	n.a.	0.093[1]
1997	0.113	0.086[1]	n.a.	0.138[2]	n.a.	n.a.	0.110[2]
1998	0.147	0.091[2]	n.a.	0.092	n.a.	n.a.	0.136[2]
1999	0.243	0.065[2]	n.a.	0.104	0.207	n.a.	0.119[2]
2000	0.149	0.060[2]	n.a.	0.084	0.079	-0.162	0.132[2]
2001	0.628[2]	0.061[2]	n.a.	0.098	0.183	-0.04	0.149[2]
2002	0.673[2]	0.102[2]	n.a.	0.112[1]	0.108	-0.172	0.172[2]
2003	0.429[2]	0.093[2]	n.a.	0.094	0.122	-0.177	0.188[2]
2004	0.255	0.086[2]	n.a.	0.081	-0.182	-0.109	0.269[2]
2005	0.650[2]	0.081[2]	n.a.	0.08	0.036	-0.314	0.362[2]
2006	0.823[2]	0.102	-0.178	0.061	-0.058	-0.274	0.370[2]
2007	0.408[1]	0.013	-0.115	0.077	-0.078	-0.143	0.338[2]
2008	0.405[1]	0.068[2]	-0.165	0.124[2]	-0.238	-0.001	0.339[2]
2009	0.428[2]	0.059[2]	-0.122	0.130[2]	-0.019	n.a.	0.336[2]
2010	0.241	0.097[2]	n.a.	0.154[2]	n.a.	n.a.	0.402[2]
n	15	15	4	21	11	9	21
M	0.417	0.077	-0.145	0.103	0.015	-0.155	0.192
s	0.226	0.023	0.031	0.025	0.144	0.1	0.117
CV[3]	54.20%	30.40%	21.50%	24.90%	990.70%	64.40%	60.90%

Notes: 1. Significant at 0.10 level. 2. 0.05 level. Note that significance depends not only on the magnitude of the coefficient but on the sample size and the expected variation which may vary every year. 3. CV stands for coefficient of variation, which is the standard deviation(s) of the sample (n) coefficients divided by its arithmetic mean (M).

Based on an inverse distance function with the exception of the United States, for which calculations were based on a squared inverse distance function.

Results: Geographically weighted regression results for intentional homicide rates

Table 2A.4. **Intentional homicide: Geographically weighted regression results (GWR)**

	Canada	France	Italy	Mexico	Poland	Turkey	United States
Covariate	Youth unemployment rates	Youth unemployment rates	Population 15-64 years old (%)	Youth unemployment rates	GDP *per capita*	Youth unemployment rates	GDP *per capita*
R2	0.467	0.194	0.141	0.245	0.107	0.470	0.865
AICc	65 160	28 729	70 047	263 604	41 233	69 769	204 734
Global Moran's I on residuals	-0.013 (0.728)	-0.060 (0.942)	-0.110 (0.471)	0.070 (0.464)	-0.066 (0.984)	-0.001 (0.809)	0.015 (0.340)
Spatial heterogeneity	Inverse relationships were detected	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	Inverse relationships were detected

Results: Spatial correlation in crime against property rates

Table 2A.5. **Property crimes: Spatial autocorrelation coefficients over time per country**

	Canada	France	Italy	Mexico	Poland	Turkey	United States
1990	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	0.033
1991	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	0.112
1992	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	0.126
1993	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	0.101
1994	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	0.206[2]
1995	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	0.204[2]
1996	n.a.	0.034	n.a.	n.a.	n.a.	n.a.	0.240[2]
1997	n.a.	0.022	n.a.	0.248[2]	n.a.	n.a.	0.358[2]
1998	0.594[2]	0.047	n.a.	0.209[2]	n.a.	n.a.	0.356[2]
1999	0.521[2]	0.022	n.a.	0.221[2]	0.322[2]	n.a.	0.314[2]
2000	0.495[2]	0.014	n.a.	0.227[2]	0.263[1]	-0.011	0.298[2]
2001	0.523[2]	0.012	n.a.	0.243[2]	0.255[1]	0.048	0.285[2]
2002	0.442[1]	0.016	n.a.	0.139[2]	0.250[1]	0.088	0.286[2]
2003	0.395[1]	0.006	n.a.	0.104[1]	0.157	0.01	0.356[2]
2004	0.343[1]	0.011	n.a.	0.088[1]	0.106	0.184	0.404[2]
2005	0.353[1]	-0.006	n.a.	0.046	0.116	0.124	0.427[2]
2006	0.300[1]	0.008	0.141[2]	-0.001	0.123	0.11	0.407[2]
2007	0.408[1]	0.009	0.143[2]	0.023	0.163	0.139	0.376[2]
2008	0.27	0.016	0.096[1]	-0.017	0.126	0.124	0.312[2]
2009	0.251	0.015	0.144[2]	-0.057	0.086	n.a.	0.295[2]
2010	0.214	0.001	n.a.	n.a.	n.a.	n.a.	0.278[2]
n	13	15	4	13	11	9	21
M	0.393	0.015	0.131	0.113	0.179	0.091	0.275
s	0.118	0.013	0.023	0.109	0.079	0.064	0.11
CV[3]	30.00%	84.90%	17.80%	95.90%	44.40%	70.10%	39.80%

Notes: 1. Significant at 0.10 level. 2. 0.05 level. Note that significance depends not only on the magnitude of the coefficient but on the sample size and the expected variation which may vary every year. 3. CV stands for coefficient of variation, which is the standard deviation(s) of the sample (n) coefficients divided by its arithmetic mean (M).

Based on an inverse distance function with the exception of the United States, for which calculations were based on a squared inverse distance function.

Results: Geographically weighted regression results for crimes against property

Table 2A.6. **Property crimes: Geographically weighted regression results (GWR)**

	Canada	France	Italy	Mexico	Poland	Turkey	United States
Covariate	GDP *per capita*	GDP *per capita*	GDP *per capita*	Unemployment rate	GDP *per capita*	GDP *per capita*	GDP *per capita*
R2	0.693	0.304	0.272	0.102	0.561	0.570	0.614
AICc	235 166	357 109	347 822	533 911	234 884	340 186	783 244
Global Moran's I on residuals	0.074 (0.565)	0.051 (0.264)	-0.015 (0.694)	-0.070 (0.600)	-0.203 (0.436)	-0.023 (0.919)	0.029 (0.632)
Spatial heterogeneity	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	No inverse relationships (local slopes) were detected[1]	Inverse relationships (local slopes) were detected

Notes

1. Under a discrete or dichotomous definition of location, places within each local space are given a weight of “1” and places outside the space are given a weight of “0” (Fotheringham *et al*, 2002).
2. Note that a traditional OLS model is given when distance is 0 ($d = 0$) or $\beta = 0$.
3. Spatial data units or places are not uniformly distributed across space.
4. A spatial kernel is both a measure of density and a method for density analysis. The kernel density function calculates the density of a variable within a radius. A spatial kernel has shape and width (*i.e.* kurtosis and variance).
5. In spatial analysis, the bandwidth is a measure of the kernel.
6. Before that, it is always convenient to run OLS or GWR on a one-by-one key independent variable basis and constantly examine the resulting coefficients (*i.e.* exhaust all possible alternative hypotheses in spatiality).

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