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Crime Concentration and Hot Spot Dynamics in Latin America

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Abstract*

Latin America and the Caribbean is the most violent region in the world, with an annual homicide rate of more than 20 per 100,000 population and with an increasing trend. Yet most evidence of crime concentration, geo-temporal patterns, and event dependence comes from cities in high-income countries. Understanding crime patterns in the region and how they compare to those in high-income countries is of first-order importance to formulate crime reduction policies. This paper is the first to analyze crime patterns of cities in five Latin American countries. Using micro-geographic units of analysis, the paper finds, first, that crime in Latin America is highly concentrated in a small proportion of blocks: 50 percent of crimes are concentrated in 3 to 7.5 percent of street segments, and 25 percent of crimes are concentrated in 0.5 to 2.9 percent of street segments. This validates Weisburd's "law of crime concentration at place" (Weisburd, 2105). These figures are fairly constant over time but sensitive to major police reforms. The second finding is that hot spots of crime are not always persistent. Crime is constantly prevalent in certain areas, but in other areas hot spots either appear or disappear, suggesting a possible rational adaptation from criminals to police actions that cause crime displacement in the medium run to other areas. Finally, the paper finds a significant pattern of repeated crime victimization in location and time for property crimes. There are striking similarities with the developed world in crime concentration, although crime levels are much higher and usually increasing. There are also some differences in terms of the persistence of hot spots that pose interesting policy implications and avenues for future research.

JEL Codes: K00, K42, R12

Keywords: crime concentration, crime and place, developing countries, displacement, hot spots, Latin America

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1. Introduction

Crime and violence are of major concern in Latin America. One in four citizens in the region states that insecurity is the main problem in their lives, even worse than unemployment or the state of the economy. While the region is home to fewer than 9 percent of the world's population, it accounts for 33 percent of the world's homicides. Its annual homicide rate of more than 20 per 100,000 population—more than three times the world average, six times that of the United States, and 20 times that of the United Kingdom—makes the region one of the most dangerous places on the planet. On average, six out of 10 robberies in Latin America are violent. While levels of violence are very low or at least decreasing in many parts of the world, Latin America remains the only region where, on average, levels of violence not only continue to be high, but where violence has actually been intensifying since 2005 (Jaitman and Guerrero Compean, 2015a).

Crime leads to costly behavioral responses to mitigate the risk of victimization and to cope with the resulting pain and suffering. Overall, crime imposes significant costs on the Latin American economies, absorbing at least 3 percent of the region's economic output. This conservative estimate is comparable to the amount the region spends annually on infrastructure, or to the income share of the poorest 20 percent of the people in the region (Jaitman, 2015).

Despite the seriousness of the problem, crime has been an understudied issue in the region. There are several challenges for conducting rigorous research on public safety programs. One challenge is political: security in the developing world is a sensitive topic closely related to public opinion and political concerns. Public safety interventions are often driven by politics, dogma, and emotions (Jaitman and Guerrero Compean, 2015b). The constant rotation of public officials in this field also precludes longer-term research projects; however, perhaps the most evident problem is deficient information systems, which result in scarce and unreliable data. Crime statistics in the region are fragmented, inconsistent, and aggregated only to the most macro levels. The lack of information and weak national statistics systems on crime thwart accurate diagnosis, monitoring, and evaluation of crime and the interventions to counter crime.

This paper is the first to conduct a systematic analysis in different countries of the region to identify cities where there have been improvements in crime records that allow for rigorous analysis of crime and place. The main objective is to understand recent crime concentration and hot spot dynamics in the selected cities to better inform crime prevention and reduction strategies in the region and thus promote evidence-based public safety policies. It is of particular interest to see if the patterns are comparable with those of other developed cities and thus if their policing strategies could be adopted.

In his 2014 Sutherland Address to the American Society of Criminology, Professor David Weisburd highlighted the recent trend in criminology to study “where” crime occurs rather than only

analyzing the criminological profile of “who” commits the crimes, as in traditional criminology papers (Weisburd, 2015). Along these lines, the present study conducts geo-temporal analysis of crime in cities in Latin America. Using data from geo-coded police crime records from cities in Brazil, Colombia, Mexico, Uruguay, and Venezuela, we study crime patterns and compare them to those found in the developed world literature on crime and place. These countries have low, medium, and high crime rates, and thus represent a heterogeneous sample of the region. The homicide rates of the urban areas studied ranges from 7 to 100 per 100,000 population.

In developed-country cities and suburban areas crime tends to cluster geographically (Eck and Weisburd, 1995; Evans and Herbert, 1989; Felson, 1987; Gill et al., 2016; Pierce, Spaar, and Briggs, 1988; Sherman, Gartin, and Buerger, 1989; Weisburd, Maher, and Sherman, 1992; Weisburd and Green, 1994), and crime indeed tends to be repeated in time and space (Johnson et al., 2007). A main finding on crime and place is what Weisburd (2015) posits as a general “law of crime concentration at place.” He shows that for some urban and suburban areas in developed countries crime tends to disproportionately cluster in just a few blocks. More precisely, less than 5 percent of “street segments¹” tend to generate more than 50 percent of crime events in a given year. His findings for eight urban and suburban cities in developed countries (primarily the United States) are relatively stable over time. This law (and, more generally, the micro-geographic analysis of crime) has important policy implications, and it is important to test the universality of these findings.

If crime is clustered and exhibits identifiable patterns, understanding its geographical characteristics is fundamental to determining the most efficient way to address this problem. Knowing where crime tends to disproportionately occur, how these clustered units evolve, and whether they are stable or sensitive to specific policing interventions are extremely relevant issues to better target policing and, more broadly, crime prevention and control strategies. These are even more relevant in countries with very high crime rates.

Along these lines, this paper uses the street segment (a micro-place) as the unit of analysis to examine crime patterns and the geographical clustering of crime in cities in developing countries. To the best of our knowledge this paper represents the first large scale data collection and data analysis effort to test the law of crime concentration at place and geo-temporal crime patterns in several developing countries, in our case in Latin America.

The paper answers three relevant questions regarding this issue. First, we test the validity of Weisburd’s law for a subset of countries in Latin America. Second, we analyze the persistence of the geographic concentration over time (i.e., how stable is the proportion of total crime that is explained by a small proportion of street segments). Third, we analyze how identified hot spots evolve over time, that is,

¹ A street segment is defined as the two block faces on either side of a street between two intersections.

whether they persist in time and space in the long run (i.e., how likely it is that a given block will be part of a hot spot for a certain number of years). Finally, we analyze the short-term persistence of crime at the street segment level (i.e., how likely it is that a block that has recently generated a crime will generate another one shortly thereafter, and if that depends on the type of crime).

To test these hypotheses and establish urban crime patterns we use event-level, geo-coded crime data from police administrative records. We analyze Bogota, Colombia, Montevideo, Uruguay, Belo Horizonte, Brazil, and Zapopan, Mexico throughout the paper,² and we perform partial analysis for Sucre, Venezuela. For the main analysis we use aggregated measures of total crimes (all crime types). When disaggregation by crime type is available, we perform further analysis. The temporal coverage goes from 2006 to 2015, with some variations according to the city.

The cities covered have different sizes and geographies. Belo Horizonte is the capital of the State of Minas Gerais (in the Central/South-East of the country) in Brazil. The urban area (“Great Belo Horizonte”) represents the 3rd biggest city in Brazil, and the 14th in Latin America. Montevideo is the capital of Uruguay, and its biggest city (concentrates around 45 percent of its population). It is thus the 32nd biggest city in Latin America. Bogota is the capital and biggest city in Colombia and ranks 4th in Latin America. Finally, Zapopan—located in the State of Jalisco, in the center-west of the country—is the 8th biggest city in Mexico and the 37th in Latin America, with a population of 1.1 Million. Sucre is one of the main municipalities within Caracas department in Venezuela. The Map in Figure 1 shows their location in Latin America. The cities were first selected according to their data quality and availability and within those cities that fulfill that criteria, cities with different levels and types of violence were chosen to get a heterogeneous sample of cities and countries of the region.

We employed different methods to answer the aforementioned relevant research questions: (1) descriptive concentration statistics (proportion of blocks that explain 25 percent, 50 percent, and 100 percent of the crime of a city in a given year); (2) hot spot detection using kernel analysis; (3) hot spot detection using hierarchical nearest neighbor analysis; (4) street segment transition from hot to cold and cold to hot analysis; and (5) analysis of the repetition of crime in time (weeks) and space (radius). We complemented the quantitative research with fieldwork in most of the cities where some hot spots were visited, and conducted interviews with government authorities in charge of public safety, chiefs of police departments, and commanders and officers in charge of police deployment strategies.

The main findings are consistent with the literature on developed countries. Crime in Latin America is geographically concentrated: 50 percent of crimes are concentrated in 3 to 7.5 percent of street segments and 25 percent of crimes are concentrated in 0.5 to 2.9 percent of street segments. This validates

² The choice of cities/years was determined to the access to geo-localized data. We only included cities for which we have enough updated data (more than one year, geo-localized).

Weisburd's law of crime concentration at place. The degree of concentration is stable over time but sensitive to specific policing strategies. The main hot spots for each city are identified, and it is shown that while some of them remain persistent over time, others disappear and possibly appear in other places. These may suggest that some hot spots could have been displaced in the medium run (one to four years) possibly due to the rational adaptation of criminals to some police strategies. Finally, a significant pattern of repeated crime victimization time and place is observed.

The paper is structured as follows. Section 2 reviews the literature on crime concentration and micro-place crime analysis, while Section 3 shows the results on crime concentration and hot spot dynamics in the cities included in this study. The section first describes the data employed, and then turns to the test of the law of crime concentration at place, identification and dynamics analysis of hot spots, and repeat and near-repeat victimization. Finally, Section 4 concludes with discussions on the interpretation of the results and outlines policy implications as well as avenues for future research on crime patterns in Latin America.

2. Crime Distribution in Space and Time

The rise of a new wave of studies focused on "micro-places" gained momentum in the late 1970s and the beginning of the 1980s (Brantingham and Brantingham, 1975; Duffala, 1976; Rengert and Wasilchick, 1985). These studies became more sophisticated in terms of the scope of the unit of analysis by the late 1980s. As noted by Sherman, Gartin, and Buerger (1989), the advent of new technologies and the availability of high-speed computing and its widespread use by many police departments enabled analysts to deepen their research in areas that were previously unavailable. Over the past few years, this trend has become even more pronounced, with highly accurate geographic precision, to the point of using points (i.e., GPS-coded addresses) as the unit of analysis.

As a result of technological advances, the literature on detection and analysis of crime hot spots has grown steadily (Weisburd and Braga, 2003). Many relevant studies focus on crime displacement (Wyckoff, et al., 2004), crime trajectories, the stability of hot spots (Weisburd et al., 2004), and evidence for data-based crime policy (Gottfredson et al., 1997; Sherman and Weisburd, 1995; Veigas and Lum, 2013). Weisburd and Amram (2014) and Weisburd (2015) also offer more evidence of what seems to be a fairly stylized principle in the crime and violence literature: the law of crime concentration at place. According to this law, a very large portion of crime is concentrated on a very small proportion of streets. In past decades, just a few studies used street-level data to test this hypothesis. Sherman, Gartin, and Buerger (1989) found that only 3.5 percent of the addresses in Minneapolis produced 50 percent of all crime emergency calls to the police in a given year. Pierce, Spaar, and Briggs (1988) found that 3.6

percent of street addresses in Boston produced 50 percent of calls to the police. Eck, Gersh, and Taylor (2000) reached a similar conclusion, finding that the 10 percent of locations where the amount of crime was highest in the Bronx (New York) and Baltimore accounted for 32 percent of robberies, assaults, burglaries, grand larcenies, and auto thefts. Weisburd et al. (2004) found that 50 percent of crime incidents in Seattle over a 14-year period occurred on only 4.5 percent of the street segments. Curman, Andresen, and Brantingham (2015) examined crime incidents in Vancouver, Canada, and found that 7.8 percent of street segments produced 60 percent of crime. Weisburd (2015) reviews all the findings to date that support the existence of a law of crime concentration at place that holds for urban and suburban areas in a sample of high-income countries.

In the case of Latin America, CAF (2014) analyses descriptive statistics for the period 2011–2012 for Sucre (Venezuela) and for four Colombian cities (Barranquilla, Bogota, Cali and Medellin) with information from Mejia, Ortega and Ortiz (2014). CAF (2014) concludes that in 2011/2012, 50 percent of homicides take place in 1.6 percent of the blocks of the cities, and 50 percent of thefts and robberies take place in approximately 7 percent of the blocks of the cities. The authors explore the day of the weeks and hours of the day in which crime tends to occur, but do not study any temporal dimension of concentration or hot spots.

Finally, there is some evidence of a geographically temporal concentration of crime (or “event dependence”), for developed countries. For the United Kingdom, for example, Ericsson (1995) shows evidence of repeat victimization of residential burglaries, explained by the idea that known blocks/houses (because they were already attacked) tend to be less risky, more familiar, and therefore easily accessible for criminals. These patterns have also been found for many cities in the United States,³ as well as in other cities in high-income countries (Bowers, Hirschfield, and Johnson, 1998).

Recent research has provided robust evidence in support of crime concentration and repeat victimization (in a lesser extent) in developed cities. However, to the best of our knowledge there is no systematic study of the law of crime concentration at place and crime patterns in Latin America. Our paper makes the first large-scale contribution to the analysis of crime concentration in developing countries, comparing the results for several cities in five Latin American countries. Moreover, we exploit the time dimension of our data to show not only how crime is concentrated at the street-level in many cities of Latin America but also how this concentration evolves over time. To conduct this analysis, this paper employs various techniques that have not been applied to the region before, such as near repeat victimization analysis.

³ See Ratcliffe and Rengert (2008), for Philadelphia; see also Clarke, Perkins, and Smith, Jr. (2001).

3. Crime Patterns in Latin America

3.1. Data Coverage and Sources

This study employs administrative geo-coded police records for every incident, including day and time of occurrence for the following cities.⁴

- Belo Horizonte: Daily data from 2009 to 2013 include all types of crime
- Bogota: Daily data from 2007 to 2013 include all types of crime
- Montevideo: Daily data from 2006 to 2015 include all types of crime
- Sucre: Daily data from January to October 2014 include homicides only
- Zapopan: Daily data from 2009 to 2014 include all types of crime

Figure 2 presents the descriptive statistics for the sample. The figure shows the annual average for street segments (for the years for which we have information, according to the description above). As can be seen, although all the cities are in Latin America, they show very different patterns in terms of crime. Montevideo and Belo Horizonte show higher crime rates (in this case, measured in “per street segment”) but also a high standard deviation. The descriptive statistics already give an idea of concentration. In Montevideo, for example, the maximum number of crimes that took place in a street segment on average per year is 378, whereas in Belo Horizonte it is 460, even though the crime rate per street segment is lower in the latter city. The sections that follow will address this idea more formally.

3.2. Crime Distribution in Latin America

As Weisburd (2015) indicates, the study of criminology focusing on the place (particularly, micro-regions) as the unit of study has expanded since the 1980s. The criminology of place (Weisburd, Groff, and Yang, 2012) examines crime events using very small areas as the unit of analysis: blocks, streets, or even street segments. Rather than focusing on the causes that motivate the person (*who*) to commit a crime, this approach focuses on the characteristics of the specific places *where* the crime was committed. The necessity of understanding the characteristics of the *where* instead of the *who* derives from the simple fact that crime tends to show repetitive patterns, so a better understanding of these facts is vital to the design of effective policies to reduce violence. If crime does not occur randomly across space, then information related to the geography of crime is worthy of being studied. Even if we find relevant and reliable evidence to explain why an offender displays criminal behavior, we would still need to

⁴ The sample was determined but the availability of data, that comes from official sources. The minimum criterion to include a city is that we have data for more than one year, geo-localized and that is recent (i.e., that at least overlaps with the rest of the cities, in order to make reasonable comparisons).

understand the criminal events themselves: why some targets are more appealing than others, what makes a street/block/cluster a hot spot, etc.

What do the data say about crime concentration in Latin America? An initial exploration of the data shows that total crime is far from being evenly distributed. To provide a first impression of crime spatial distribution, we estimate kernel functions to detect hot spots. The kernel density estimation is a point-pattern technique (instead of an aggregated crime method) widely used to produce a “risk map” that is derived from the interpolation of specific crime incidents (the points) in a particular geographic area. Therefore, the kernel density estimation smoothens patterns of data points to generate a continuous surface of different levels of crime. As explained by Hart and Zandbergen (2014), the method basically consists of overlying a grid of equally sized “cells” (defined by the researcher as a parameter) on top of the original map and then calculating a nonparametric estimation of the density based on the distance to the center of each cell.⁵

Figure 3 shows the results of a kernel estimation of hot spots for the cities covered in this paper. For each of the cities, crime seems to be concentrated in a few areas. Naturally, crime tends to be more present in denser urban areas (in the case of Zapopan, Mexico, for instance, it is clear that there are some areas that are not populated). Even in urban densely populated areas, kernel estimations show different intensities of crime events across space. In Montevideo, for example, we see a very concentrated area in the south (in red) with some particular hot spots in the southwest where the downtown area is located. In Sucre, although there is a relatively large hot spot in the center/northwest area of the city, there are also some particularly dangerous spots in the south and some others in the center-east. Even more interestingly, Bogota shows a relatively large and continuous red strip in the east side of the city with many other smaller clusters of crime distributed across the map. A similar pattern of relatively small but widespread dangerous areas can be seen in Belo Horizonte.

This first look at the data is particularly useful for two reasons: first, it shows that geography matters. Crime is not randomly distributed, and therefore we observe particularly dangerous areas that are worth studying in depth. Second, because this first look opens a new set of questions. In particular, which

⁵ An interpolation function is chosen to weight the distance between each crime data point and the center of the cell. This way, the estimator will go through all the center points and will calculate the weighted average distance of the point with all the crime data points included in a radius within a particular set distance. Naturally, the “hot areas” correspond to points where the weighted average distance is relatively small. More formally, the general kernel density estimator (for spatial and nonspatial estimations) could generally be expressed as it follows:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^n k\left(\frac{X_i - x}{h}\right),$$

where x represents the location of the central point of each cell, X_i where x represents the location of the central point of each cell, X_i is the location each crime data point, h is the smoothing parameter (or “bandwidth”) and n is the number of data points. The function K is the kernel function, which is used to define the weighting of each point – typically defined as Normal, Uniform, Spherical, or Triangular. This papers presents estimations with the following parameters: 250 cells for each case, a fixed-interval per crime radius of 400 meters (the “bandwidth”), and a Normal function of interpolation. Results are robust to other parameters and function of interpolation.

blocks or cluster of blocks mostly explain the existence of such hot spots? How concentrated is crime within those particular blocks/clusters of blocks? Finally, are those “hot blocks” or “hot clusters” stable in time? In the sections that follow we provide evidence that crime in Latin America is indeed highly concentrated in a few street segments.

3.3. The Law of Crime Concentration at Place in Latin America

As discussed in the previous section, hot spot kernel estimations show that crime is clustered in particular areas of the city. The next step to better understand geographic concentration is to analyze the problem at the smallest level of disaggregation possible. Following Weisburd (2015), street blocks or segments are employed. This geographic unit is defined as “the two block faces on both sides of a street between two intersections” (Weisburd et al., 2004). The underlying rationale for this unit of analysis is that a lot of economic and social activities usually happen within this space, which makes it a relevant reference geography. As stated above, the law of crime concentration at place indicates that a big portion of crime takes place in a small proportion of street segments. The validity of this law has been widely proven in many cities of developed countries such as Sacramento, Seattle, New York, Tel Aviv, Cincinnati, Vancouver, Brooklyn Park, Redlands, and Ventura, mostly in urban but also in some suburban settings (Andresen and Malleson, 2011; Braga et al, 2014; Gill et al., 2016; Weisburd, 2015; Gill et al., 2016; Weisburd and Amram, 2014; Weisburd and Green, 1994; Weisburd et al., 2004; Weisburd et al., 2012). According to this growing body of literature, approximately 3 to 7.5 percent of small places concentrate 50 percent of crimes and 1.5 percent of small places concentrate 25 percent of crimes.

To add more evidence and test the generality of this law, this paper replicates the exercise using the cities in the Latin American sample. It is important to emphasize that our contribution is not only in terms of providing additional evidence in support of the validity of the law, but also in terms of the type of context that we analyze. This is because developing and developed countries are different in many dimensions, and also because crime levels tend to be much higher in the developing world and, in particular, in Latin America. One fact worth noting about the law of crime concentration at place is that in cities where the number of crimes committed in a given year is low (presumably, cities in high-income countries), there will only be a group of street segments that concentrate most of the crime. It is thus expected that there will be a higher proportion of blocks explaining crime in the most dangerous cities, which runs against the prediction of the law of crime concentration at place. Therefore testing the validity of the law in these cities is especially relevant. In addition to this, the fact that in many Latin American cities crime is not only high but also increasing makes it interesting to test the law (the only city with increasing crime incidents where the law was tested over time is Tel Aviv [Weisburd, 2015]).

Figure 4 provides an answer to this first question: how concentrated is crime in Latin America in terms of street segments? For each country we take the last available year and show the concentration for 25 and 50 percent of crime and compare it to the cities included in Weisburd (2015). Crime in Latin America is highly concentrated in a small proportion of blocks: 50 percent of crimes are concentrated in 3 percent to 7.5 percent of street segments and 25 percent of crimes are concentrated in 0.5 percent to 2.9 percent of street segments thus validating Weisburd’s law of crime concentration at place. If total crime is analyzed, there are heterogeneous results. 100 percent of crime is concentrated in between 9 percent of street segments in Bogota and 48 percent in Montevideo.

Is this pattern constant over time? Figure 5 shows that these numbers tend to be fairly constant over time, with variations of no more than +/-2 percentage points over a 3 to 10-year period. This is consistent with the literature in developed-country cities, though the time series’ available in Latin America are much shorter and further tracking is necessary to obtain more robust results to back up this theory in the future. Also, the context is very different because in many cities in the region crime is not only much higher but also increasing, unlike the locations examined in other papers (except for Tel Aviv). Previous studies show that 50 percent of crime is concentrated in 4.6 to 5.8 percent of street segments over a 16-year period in Seattle, 4.7 to 6 percent of street segments over a nine-year period in New York, and 3.9 to 6.5 percent of street segments over a 10-year period in Tel Aviv (Weisburd et al., 2004; Weisburd and Amram, 2014; Weisburd, 2015).

For the four cities in Figure 5 (Belo Horizonte, Bogota, Montevideo and Zapopan), we also performed a concentration test, known as a Nearest Neighbor Index analysis, suitable for the type of data available. This technique calculates the average expected distance between data points given a normal random distribution and then calculates the actual average distance of the sample to build an index (actual/expected). This is then used to estimate if both distances are significantly different. If they are, then crime is significantly concentrated.⁶ Figure 6 shows the estimations of the Nearest Neighbor Index.

⁶ More formally,

$$d_{NN(random)} = 0.5 \sqrt{\frac{A}{N}}; d_{NN} = \sum_{i=1}^n \frac{Min(d_{ij})}{N}; NNI = \frac{d_{NN}}{d_{NN(random)}}$$

where $d_{NN(random)}$ is the average expected distance between a pair of data-points, A is the area of the map, N is the total number of incidents, d_{NN} is the actual minimum distance a point (i) and its closest pair (j). NNI is the Nearest Neighbor Index. The test is thus performed between NNI and the expected from a random distribution, given by:

$$Z = \frac{d_{NN} - d_{NN(random)}}{SE(d_{NN(random)})}$$

where $SE(d_{NN(random)})$ represents the standard error of the average random distance. Figure 6 shows that, for every city, the crime is significantly more concentrated than what would be expected if the distribution was random. In every case, the hypothesis of randomness is rejected with a confidence of +99%.

In all the cases, the hypothesis of crime randomly distributed was rejected at the 1 percent significance level.⁷

3.4. Hot Spot Persistence in Latin America

Crime in Latin America is not evenly distributed, and certain areas are more prone to suffer criminal offenses. More specifically, there are specific street segments that are notably more prone to produce crimes than others and they constitute a small proportion of the total number of street segments of each city. This is true for every point in time and for time periods of 3 to 10 years. We still do not know, however, if the same areas concentrate crime incidents over time, or if it is in a few areas that vary every year. So the next question is where these hot spots are located and, in particular, how likely it is that they will stay in the same place for a long time.

To answer these questions we employ the graphic illustration of the kernel estimator for hot spot detection (already shown in Figure 2) with the estimation using the hierarchical nearest neighbor clustering method. The aim of this method—which is explained in detail by Gelbard, Goldman, and Spiegler (2007)—is to identify the clustering of crime events that are statistically significant (i.e., groups of incidents that are improbably close to each other) at different levels. The hierarchical nearest neighbor algorithm is a nonparametric technique that is performed in the steps described here. First, each crime data point is taken as a unit. An average distance between data points is calculated (assuming that the points were randomly distributed in the map), and the algorithm calculates all the possible distances between pairs of crime data points and clusters together the crime data points that fulfill two criteria: (1) they are located at a distance lower than the average expected for a random assignment of crime, and (2) taken together, they do a cluster that has at least a minimum set number of observations.⁸ Once the first

⁷ The tests for the other years are available upon request, with the same conclusion.

⁸ More formally, the algorithm that is processed in each step is the following:

$$d_{NN(random)} = 0.5 \sqrt{\frac{A}{N}}$$

$$d_{ij} = \sqrt{(d_{i1} - d_{j1})^2 + (d_{i2} - d_{j2})^2}$$

$$d_{NN(random)} > d_{ij} \rightarrow d_{ij} \in C_k \leftrightarrow |C_k| \geq Min \quad \forall_{ij},$$

where $d_{NN(random)}$ is the average random distance between pairs of points, with A and N the total area of the map and the total number of crime incidents for a given period, respectively; d_{ij} is the Euclidean distance between each pair of points; and C_k represents each of the k clusters identified by the algorithm. Min is the minimum number of points needed to form a cluster. The random distance is calculated following the recommendations of Levine (2004) using the formula $d_{NN(random)} = 0.5 \sqrt{\frac{A}{N}}$. A relevant parameter for this analysis is the minimum number of crime events that is required to form a cluster. Because not all the cities have the same level of crime and grid size, we have to use different parameters for each case. For “Total Crimes” we use a minimum of 30 crimes in Montevideo, 5 in Zapopan and 10 in the rest, holding approximately constant the proportion

group of clusters is created, the algorithm is repeated but now using the clusters as the unit of analysis (instead of the data-points). That is: instead of comparing the distance of pairs of data-points, the process now compares the distances between pairs of clusters. We repeat the process twice.

Why using Nearest Neighbor Hierarchical Clustering instead of other method? One of the advantages is that it provides a relatively more objective measure of clustering since the distance of each pair is compared to an average theoretical distance, not a parameter. Second, the hierarchy provides different levels of clustering which makes easier the analysis: “small” clusters can be identified but if there are too many, then a higher level can also be identified and analyzed.

Figures 7 show the results of the estimations using the method explained above, comparing the first and the last year of the sample, which varies by city. The small colored dots represent the “first-order” clusters, whereas the polygons (small clusters of street segments) represent the “second-order” clusters (clusters of clusters). The small dots therefore tend to be more volatile and the polygons are supposed to be more stable. The figure also shows the street maps to give an idea of the geography of the location (i.e., which areas have more streets and which do not). The maps provide a visual approximation to the question. By comparing the first and last years of the sample, it can be seen that while some clusters of crime remain constant, others disappear and new ones appear.

In Bogota, one can see in 2007 a few relatively big clusters of crime (polygons), especially in the center-east part of the city, with a particularly big polygon at the beginning of the “corridor” of polygons. We also observe some minor clusters (colored points) across the city. In 2012, the largest polygon persists, but we observe some changes with regard to the rest of the clusters. First, the polygons seem like they have been broken apart and displaced to the south, now surrounding the large cluster. Second, there is a new polygon of crime isolated in the northeast part of the city. Third, there are now many more minor clusters (colored dots) all across the city.

For Zapopan, the time span available is shorter, from 2009 to 2012. However, in just three years, there is a notable movement of the identified hot spots. In 2009, there were many “first-order” clusters spread across the map, but only a few polygons, mostly located in the center/northeast side of the city, plus a few isolated polygons in the center/west. In 2012, crime seemed to be heavily displaced: most polygons were located in the south/east side (in locations that were not identified as having hot spots in 2009). Only a few polygons that were in the center/northeast remained.

“minimum/crime.” The literature is not clear about this: it basically depends on the number of clusters that one prefers to identify. A minimum number that is too low would imply the identification of too many clusters, which would render the analysis not very informative. On the other hand, if the minimum is too large, then only a few clusters will be identified and therefore relevant clusters would be omitted.

For Belo Horizonte, crime patterns are analyzed from 2009 to 2014. There is a particular region in the geographic center of the city where hot spots persist throughout the years. Apart from that area, there are several smaller hot spots (polygons) that started to appear in the last years of our sample and tend to localize close to the center and to the north (except one that is located in the south of the city). The additional polygons that were present in 2009—and those were relatively close to the main hot spot—disappeared and seem likely to have been displaced by 2014.

In Montevideo, we compare the clusters identified in 2006 versus those of 2015. Notably, this case shows a combination of stability and displacement of hot spots. There is a clearly hot area in the south of the city (close to downtown) that was present in 2006, with an evident reduction of the number and size of the polygons. In other words, the area became safer but there are still some particular clusters that could not be eradicated. Some of the polygons that were located in the center/northwest part of the city in 2006 disappeared. Some new polygons were created (or displaced) in many areas of the city.

Figure 8 presents an alternative analysis of concentration dynamics using three simple indicators in a transition matrix: the probability of passing from one state to another, total crime per street segment, and the number of hot street segments.⁹ There is an interesting characteristic of the dynamics of “hot street segments” over time. In Montevideo, interestingly, around 52 percent of the segments that were hot became cold, the remaining 48 percent remained hot, and around a fifth of those blocks that were cold became hot. As a consequence, the number of hot segments grew significantly (from 21 to 27 percent of the total number of blocks). However, the crime per segment in the hot segments decreased by a proportion of around 24 percent. To sum up, in 2015 there were more hot segments spread across the city, but each of these segments exhibited a lower crime count. This spreading of crime in more street segments is consistent with the widespread perception of insecurity in Montevideo.

In Bogota, 60 percent of the hot blocks became cold, whereas around 9 percent of those that were cold became hot. This means that only 40 percent of the hot blocks remained hot, but also that, in all, there were more hot blocks in 2013 than in 2009. In fact, there was an increase in the number of hot segments of close to 25 percent (from 9.9 to 12.7 percent of the streets). Contrary to what happened in Montevideo, the average crime per hot block in the street segments increased by approximately 8 percent. All in all, the dynamic analysis shows that there was an increase in both the number of hot street segments and the number of crime per street segments.

Belo Horizonte shows a different picture. First, there is considerable stability of hot spots: around two-thirds of hot streets in 2003 remained hot in 2009 (versus 40 percent in Bogota and 48 percent in Montevideo). The proportion of initially cold blocks that became hot was around 15 percent. Unlike

⁹ A street segment is defined as “hot” if it had more than the mean number of crimes per street segment of a particular city in a given year. The mean number of crimes per segment is shown in Figure 1. In every case we consider the first and last entire year of each city according to the description of data and sources in Section 3.1 of this paper.

Montevideo and Bogota, the crime rate per segment in Belo Horizonte remained fairly constant and the location of hot spots also remained constant. To sum up, there is clear stability in intensity and place in every measure of crime.

Finally, Zapopan shows a pattern relatively similar to Bogota. Only 39 percent of the hot blocks remained hot, and around 10 percent of the cold blocks became hot. As a result, there was a net creation of hot blocks of around 47 percent. As in Bogota, crime also intensified in per-hot-block terms: crime rates per hot segment were 15 percent higher in 2013 than in 2009. This is consistent with the results of Figure 7: few hot spots remained as hot and a lot of new hot spots appeared. Overall there was a combination of crime intensification and crime generation: more hot blocks over time, usually in new places and on average with a higher level of crime in each of those hot blocks.

3.5. Repeat Victimization: Identifying Geo-temporal Patterns of Crime

It has already been established that crime is not evenly distributed in space in the medium and long terms. Yet another characteristic to analyze is how crime shows geographic-temporal repetition patterns. As previously explained, there are theoretical and empirical reasons to believe that a house or a block that was victimized exhibits a higher probability of being victimized again in the short run. We formally test this idea for Latin America.

To analyze how crime is concentrated in space and time, a “repeat/near repeat” method is used. This method compares the likelihood of repetition of the crimes in the data with a random distribution of crimes across time (days) and space (blocks). To perform this analysis we determine four geographical levels and five temporal levels. In terms of time, we use periods of 15 days; in terms of space we use five radii with variable size by city (average length of the street segments). In all the cases, the estimations use 20 iterations, enabling us to identify a statistical significance level of 5 percent.¹⁰

Figure 9 shows the results for thefts and robberies (together).¹¹ There is a significant repeat victimization pattern for many of the cities. In Bogota, there is a 25 percent higher chance than average of

¹⁰ The calculations were performed using the Near Repeats software (Ratcliffe, 2009). The program expands the concept originally presented by Knox (1964) to the case of NxN dimensions. The method measures the distance between all pairs of crime events in two dimensions: date and location. Then, a Monte Carlo permutation is employed to randomize the event dates so that the permutation is done separately for each unit (interval) of time and space separately. Repeating the process N times, the program is able to generate an expected distribution of crime in time/space which is then used to compare the crime count per time-space intervals of the sample with that derived from the Monte Carlos process and identify which cells significantly exceeds the expected value according to simulation.

¹¹ Running the algorithm with more than 10,000 observations becomes increasingly complicated. Therefore, we had to trim the samples and include only a few months of analysis. The number of months included varies in each case (three months for Montevideo and Belo Horizonte, five months for Bogota, the whole year for Zapopan) because the total number of crimes is different. This should not make a difference, since we are only interested in knowing how crime is repeated in periods of 15 days. Adding more observations would make the estimation more precise but does not make a difference in terms of bias. We test the results taking different months and find similar results, which can be provided upon request. We present the results of the last available year.

being a victim of a robbery in the same place within the two weeks following the first attack. In Montevideo, there are significantly higher chances of suffering a robbery within the next two weeks after the first attack for the same location (+5 percent) but also for nearby locations (+1 percent). The conclusion is similar for Belo Horizonte (+11 percent in the same location, +4 /5 percent in nearby areas). In Zapopan, the results point in the same direction, although in this case the extremely high estimation for the “same location/within two weeks” may have to do with coding. In particular, if an incident that involves multiple crimes or multiple victims is recorded as many incidents (i.e., as multiple subsequent entries in the database) then we would find an unusual repetition pattern when it is actually one incident that is recorded as multiple ones. Although this possibility is minimized given that we made a thorough examination of the data, we cannot rule it out. All in all, our results provide additional evidence of “event dependence” in Latin America.

4. Discussion

Recent trends in the study of crime have shown that it is relevant to focus on the geography of crime and, more specifically, its micro-geography. Crime tends to show not only time patterns but also geographic clustering, it is thus important to better understand how crime mechanisms operate to identify the best ways to reduce violence. This is especially relevant in Latin America, which is the most violent region in the world.

Moreover, given that crime data are becoming increasingly available and precise worldwide, there is a unique opportunity to develop general propositions about crime and test their universal validity. Following this idea, this paper represents the first large scale data collection and data analysis effort to test the law of crime concentration at place and geo-temporal crime patterns in several developing countries in Latin America. The paper analyses a sample of cities in five countries (Belo Horizonte, Brazil; Montevideo, Uruguay; Zapopan, Mexico; Sucre, Venezuela, and Bogota, Colombia) over a period of time ranging from three to ten years.

This paper provides additional evidence of the idea that geography matters when understanding crimes. Most papers to date have focused on crime patterns in developed countries. This study shows that their conclusions are generally valid for cities in Latin America that are structurally different from those cities in high-income countries. The homicide rates of the urban areas studied in this paper ranges from 7 to 100 per 100,000 population, which makes these cities much more violent than the ones studied before for other continents. Furthermore, in most of these cities (as in Latin American and Caribbean cities in general) crime has been increasing.

Therefore, it is very interesting that the law of crime concentration at place holds in such a different setting. Indeed in the cities studied in this paper, 50 percent of crimes are concentrated in 3 to 7.5 percent of street segments and 25 percent of crimes are concentrated in 0.5 to 2.9 percent of street segments, thus validating Weisburd's law of crime concentration at place. This compares to the finding in developed countries (mostly US cities) where approximately 3 to 7.5 percent of street segments concentrate 50 percent of crimes and 1.5 percent of street segments concentrate 25 percent of crimes.¹²

Once established that crime is concentrated in few small places in Latin America, the paper studies the evolution of its concentration over time, which has never been assessed in the region. Indeed, the degree of concentration tends to be fairly constant and with variations of no more than +/-2 percentage points over a 3 to 10-year period. This is consistent with the literature in developed-country cities, though the time series' available in Latin America are much shorter and further tracking is necessary to obtain more robust results to back up this theory in the future. It is also striking that in settings where crime increases, as in most of these cities, crime is still very concentrated over time, consistent with the findings in previous work on developed cities where crime was decreasing (except for Tel Aviv). Previous studies show that 50 percent of crime is concentrated in 4.6 to 5.8 percent of street segments over a 16-year period in Seattle, 4.7 to 6 percent of street segments over a nine-year period in New York, and 3.9 to 6.5 percent of street segments over a 10-year period in Tel Aviv (Weisburd et al., 2004; Weisburd and Amram, 2014; Weisburd, 2015).

The paper then analyses if this concentration takes place in the same places over time. Combining hot spot detection using hierarchical hot spots mapping, nearest neighbor analysis, and the transition of blocks from hot to cold and cold to hot, the study concludes that there are areas of the city that chronically concentrate hot spots and hot street segments, which account for 40 to 66 percent of the original hot segments detected. Overall, the results are interpreted as a high concentration of crime that is persistent over time. However, there is some variation in crime concentration that in some cities could be related to specific police strategies. In Bogota, the changes in crime concentration are consistent with the timing of implementation of *Plan Cuadrantes*, a policing strategy based on information that included focused deterrence activities. In Montevideo, the decrease in crime concentration coincides with a change in the policing strategy of the Montevideo Police Department since 2013, which started applying focused deterrence strategies in hot spots which were not the common practice before. As a result, more resources were deployed to hot blocks, especially in the old city (*Ciudad Vieja*) in the downtown area, where a new emergency service was put in place only for that high-crime area of the city, together with many other interventions such as CCTV's installation. The results show a decrease of crime in that area that can be

¹² The cities include Sacramento, Seattle, New York, Tel Aviv, Cincinnati, Vancouver, Brooklyn Park, Redlands, and Ventura (see Andresen and Malleson, 2011; Braga et al, 2014; Gill et al., 2016; Weisburd, 2015; Gill et al., 2016; Weisburd and Amram, 2014; Weisburd and Green, 1994; Weisburd et al., 2004; Weisburd et al., 2012).

seen in figures of hierarchical hot spots in the southern part of the city, but also the result of targeting patrols was an increase in crime in areas and in street segments that before were not considered hot. This is consistent with the increase in the population's perception of insecurity in a context where total crime was relatively stable. In the analysis of cold and hot blocks, more blocks are now considered hot (having more than average crime counts per year) but the number of incidents in the hot blocks decreased.

Fieldwork conducted in Montevideo help understand how police strategies affect crime concentration and crime patterns in the city. In the case of Montevideo the evolution of crime and the responses to the new evidence-based approach of the Police Department was studied extensively. The main target of the police was to reduce robberies, so hot spots were chosen according to the concentration of this type of crime (locations that are highly correlated with the concentration of most of the other crimes). When the evolution of robberies concentration is analyzed it is very evident that the focused activities in the areas of larger concentration of robberies led to the displacement of robberies to other street segments in other areas. In Figure 10a the evolution of crime concentration for robberies in Montevideo is provided. Since 2013, when the new strategy started taking place there is an increase in the number of robberies and a decrease in their concentration (from 2 percent to 3.5 percent of street segments concentrating 50 percent of robberies). At the same time robberies were increasing. To identify those areas where robberies got displaced, Figure 10b shows the hierarchical hot spots maps for robberies before and after the intervention. Before the intervention (this pattern holds until 2012), there was a high concentration in the southern part of the city (which drives the concentration of total crime there stated before). After the police action, in 2014 this hot spot of robberies disappeared, which shows that the police was effective in decreasing robberies substantially there. However, there are some places of the city where robberies increased and new hot spots were formed. This is especially the case of the other area signaled in the map, in the northwest of the previous hot spot. This is not surprising, as this area is closer to where aggressors usually live in Montevideo.

Therefore, as a result of the police targeting Ciudad Vieja (the most touristic area with high value potential robberies), the aggressors showed a rational response by choosing other targets and displacing crime closer to their awareness spaces that is consistent with criminology literature. Furthermore, the value of the stolen goods is much lower after the police change of strategy, which can be also consistent with the fact that the count of robberies might have increased in spite of police efforts. This observed form of displacement of crime in the medium run does not refer to the immediate spatial displacement that did not seem to occur, but rather to a rational response from criminals to police patrol in their preferred area.

Returning to the overall findings of the paper, we also focus on a question that is especially relevant in terms of policy: how concentrated is crime in time and space in the short run? We know that

prior victimization is a good predictor of future risk. This is especially true for certain types of crimes: if the burglar maximizes profit and there is a cost of understanding when and how to commit a burglary, then from the burglar's point of view it makes sense to repeat the theft in places where he or she already has some information (from a previous theft) that is relatively up to date (Bowers and Johnson, 2005). This reasoning would normally be different in the case of a homicide. We provide new evidence of event dependence patterns in time/space (block/weeks) in Latin America. In the region, revictimization tends to occur within 2 or 3 blocks from the first location up to 15 days after for the case of property crimes.

The fact that crime is as concentrated in Latin American cities as it is in developed-country cities has policy implications in terms of the strategies that could be applied to prevent and reduce crime. Police presence can deter crime and disorder through various mechanisms, including influencing the probability of apprehension of active offenders, which is a necessary step for their subsequent conviction; proactively targeting places and people that are "hot" with crime; speeding up the response to calls for services; and contributing to successful post-crime investigation (Lum and Nagin, 2015). Studies of changes in police presence, whether achieved by changes in the strategic deployment of officers or some other method, consistently find positive effects in reducing crime (Nagin, 2013). There appears to be a consensus that random patrols and unfocused enforcement efforts have not been effective in preventing crime (Lum et al., 2010; Sherman and Eck, 2002). Over the last two decades, policing strategies have been more place-based and directed toward very small units (smaller than neighborhoods, blocks, or block segments). These tactics are usually known as "hot spot policing."

Various rigorous evaluations of such types of interventions suggest that the police can be more effective in addressing crime and disorder when they focus on small, high-crime-rate geographic units (Braga, Papachristos, and Hureau, 2014; National Research Council, 2004; Weisburd and Eck, 2004). Those strategies that proved to be successful in other settings, such as hot spot policing, focused deterrence interventions, and problem-oriented policing, could also be promising in Latin America. However, the possibility of crime displacement to other areas in the medium run seems likely to occur in the region.

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Figures

Figure 1. Selected Cities



Figure 2. Descriptive Statistics

	Total Crime	Min # of Crimes (per S.S.)	Max # of Crimes (per S.S.)	Mean (Crime per S.S.)	S.D. (Crime per SS)	# Street Segments	Population	Area	Available years
Montevideo	101,016	0	378	2.97	9.01	33,935	1.3 M (2011)	74.9 Sq Miles	2006-2015
Bogota	23,129	0	26	0.17	0.64	136,159	7.8 M (2005)	613 Sq Miles	2007-2012
Zapopan	6,482	0	35	0.14	0.60	46,919	1.1 M (2010)	344.8 Sq Miles	2009-2012
Belo Horizonte	32,805	0	460	1.81	5.92	18,067	2.4 M (2010)	127.9 Sq Miles	2009-2014
Sucre*	223	0	33	0.23	1.32	1,064	0.6 M (2012)	63 Sq Miles	2014

*Includes only homicides

Source: Authors' estimation with data from police administrative records.

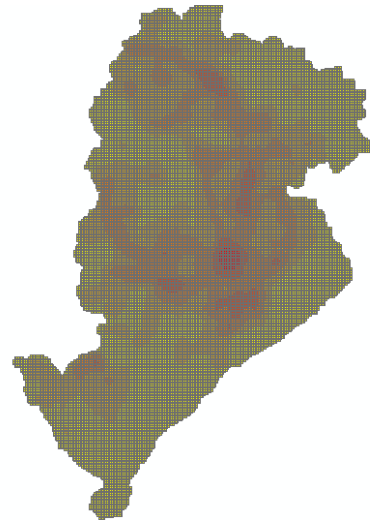
Note: Yearly average for the years available.

Figure 3. Crime Concentration in Latin America, Kernel Estimation

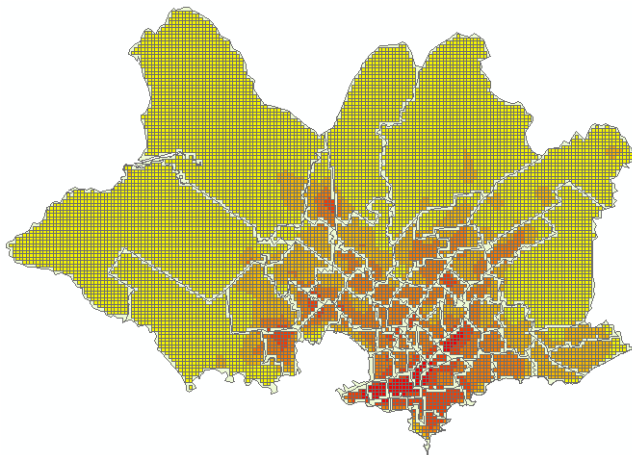
a. Bogota - Total Crime, 2012



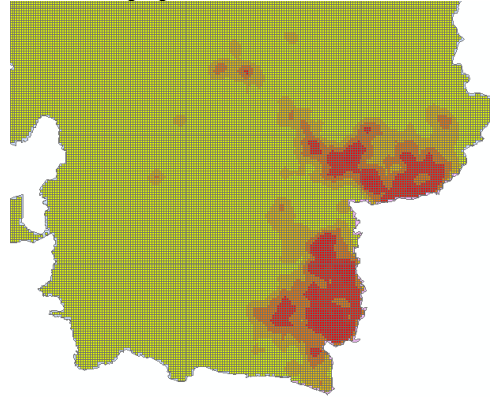
b. Belo Horizonte - Total Crime, 2014



c. Montevideo - Total Crime, 2015



d. Zapopan - Total Crime, 2014

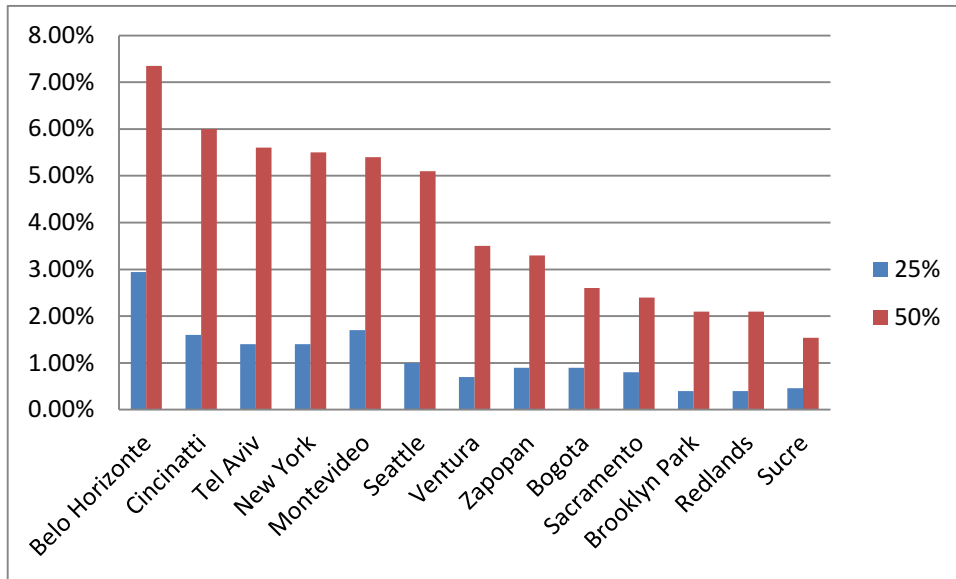


e. Sucre - Homicides, 2014



Source: Authors' estimation with data from police administrative records.

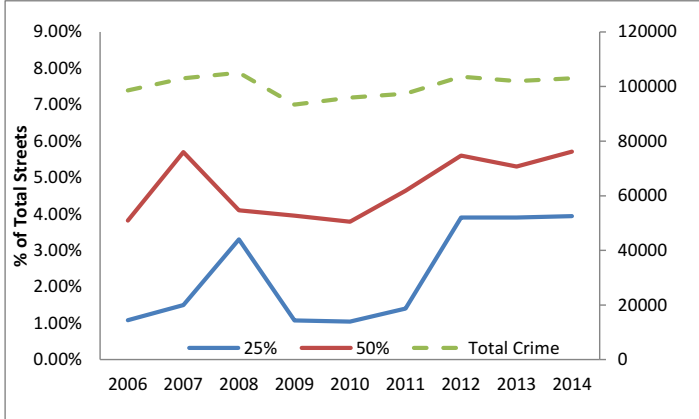
Figure 4. Crime Concentration by Street Segment (total crime)



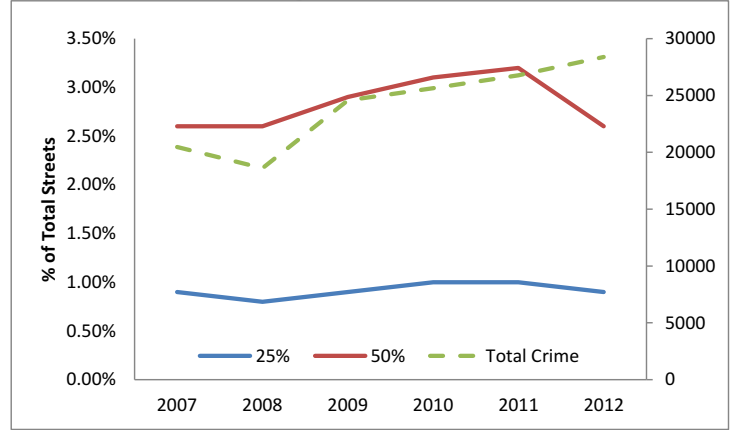
Source: Weisburd (2015) for Cincinnati: 2009, Seattle: 2004, Tel Aviv: 2010, New York: 2012, Sacramento: 2012, Brooklyn Park: 2013, Redlands: 2013, Ventura: 2011 and own estimation with data from police administrative records for Belo Horizonte: 2014; Montevideo: 2015; Zapopan: 2012, Bogota: 2012, and Sucre: 2014.

Figure 5. Crime Concentration by Street Segment in Latin America

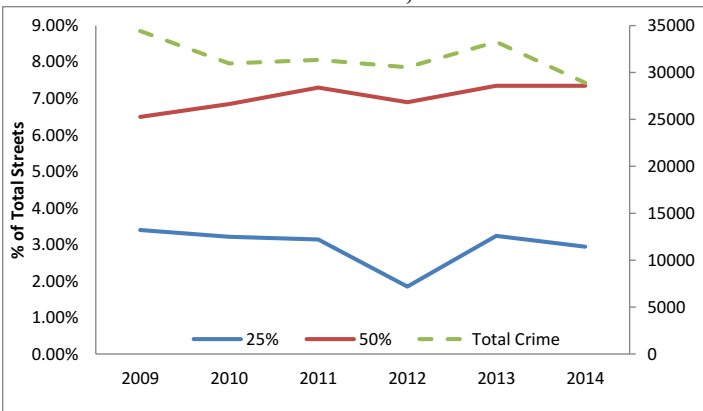
Montevideo, Uruguay



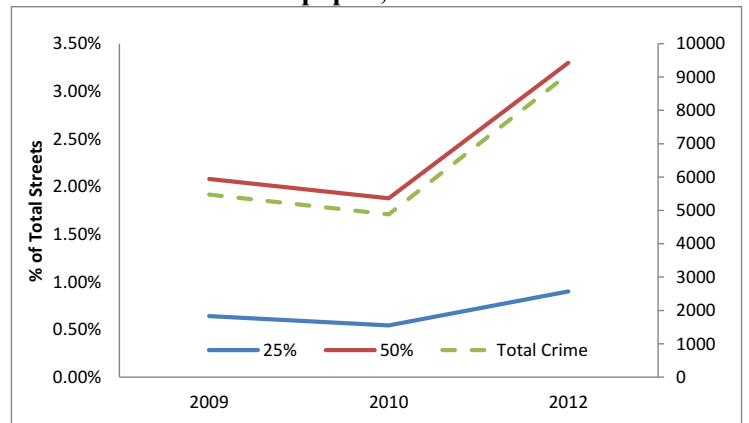
Bogota, Colombia



Belo Horizonte, Brazil



Zapopan, Mexico



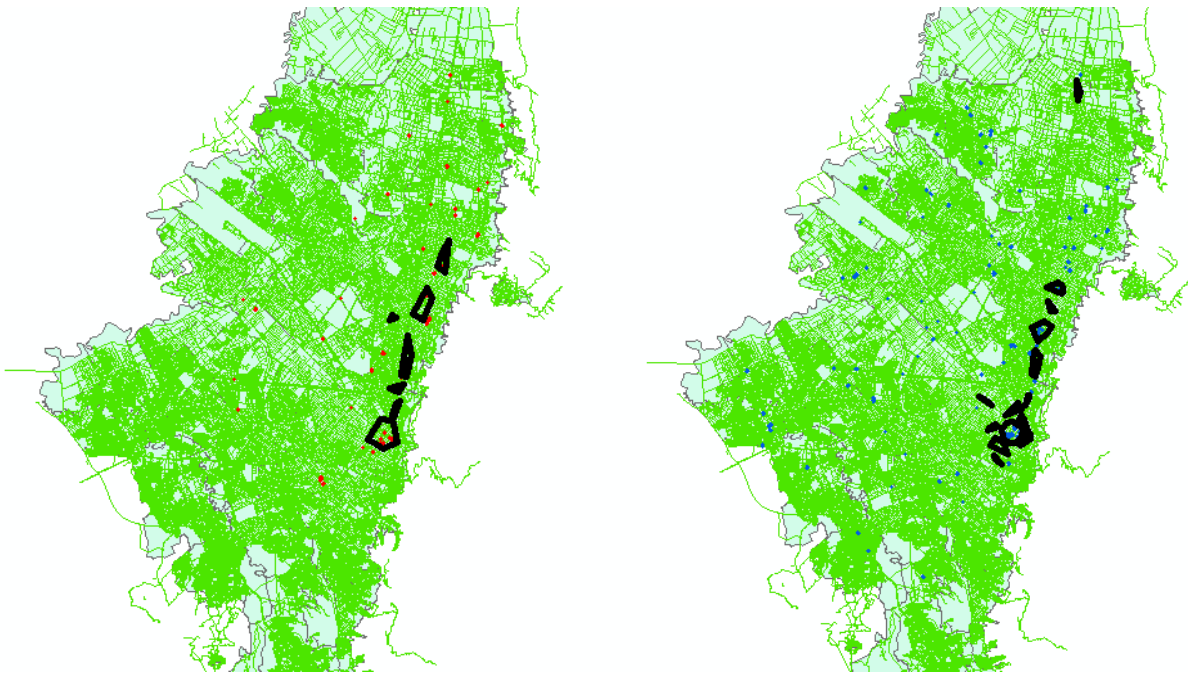
Source: Authors' estimation with data from police administrative records.

Figure 6. Test of Global Concentration, by City (total crime, last available year)

	Montevideo	Bogota	Zapopan	Belo Horizonte
Observed Mean Distance (meters)	17.25	31.25	151	57
P-Value	0	0	0	0
Z-Score	-609	-197	-177	-277
H0: Random Distribution of Crime	Rejected (1%)	Rejected (1%)	Rejected (1%)	Rejected (1%)

Source: Authors' estimation with data from police administrative records.

Figure 7a. Hierarchical Clustering in Bogota, 2007–2012 (total crime)



Note: We present a zoomed-in version to focus on the most populated areas just to have a more clear visual idea of the most relevant regions within each city.

Figure 7b. Hierarchical Clustering in Montevideo, 2006-2015 (total crime)

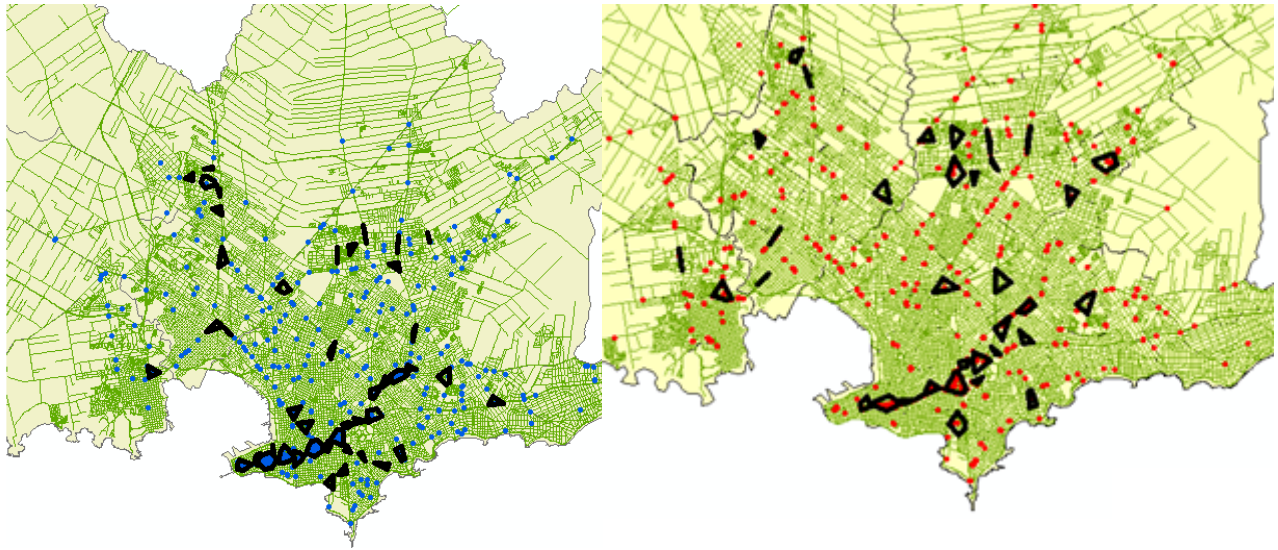


Figure 7c. Hierarchical Clustering in Belo Horizonte, 2009-2014 (total crime)

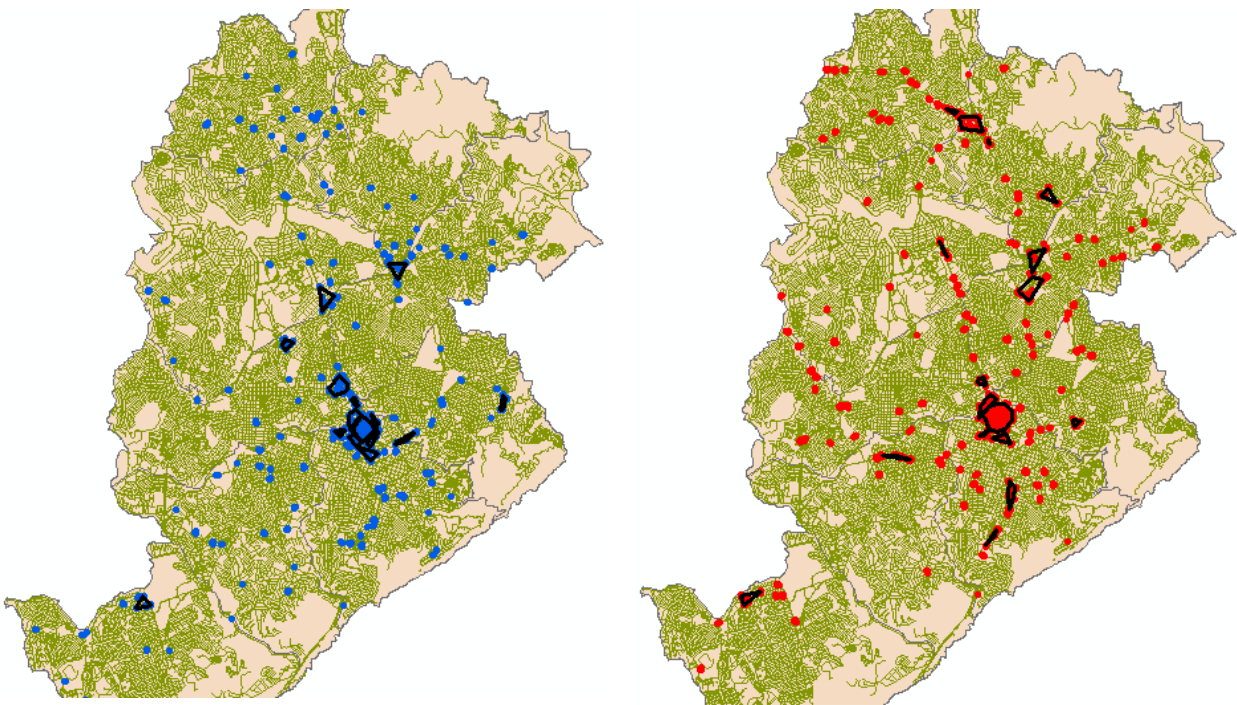
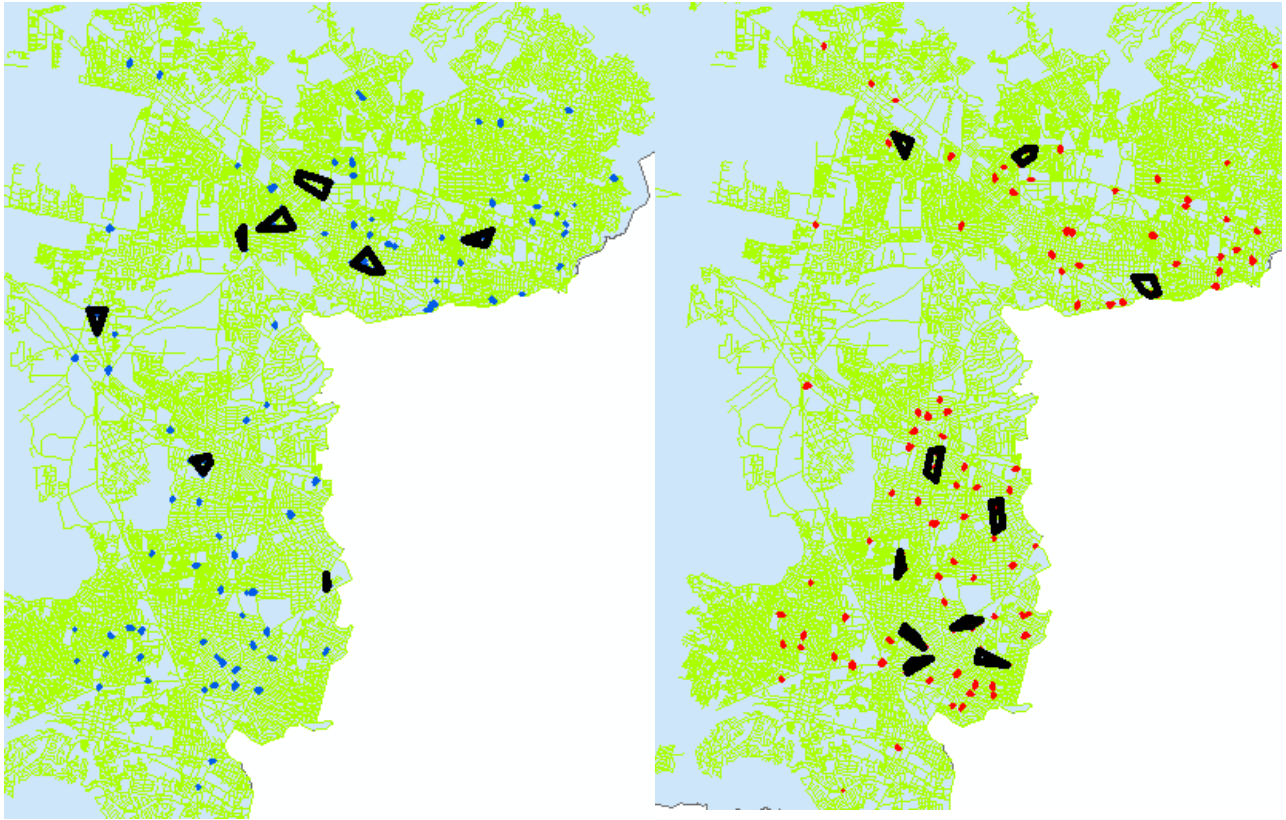


Figure 7d. Hierarchical Clustering in Zapopan, 2009–2012 (total crime)



Source: Authors' estimation with data from police administrative records.

Figure 8a.1. Hot Blocks (Street Segments) in Montevideo, Transition Matrix 2006–2015

	Hot (t=1)	Cold (t=1)
Hot (t=0)	48.3%	51.7%
Cold (t=0)	21.2%	78.8%

Figure 8a.2. Hot Blocks (Street Segments) in Montevideo

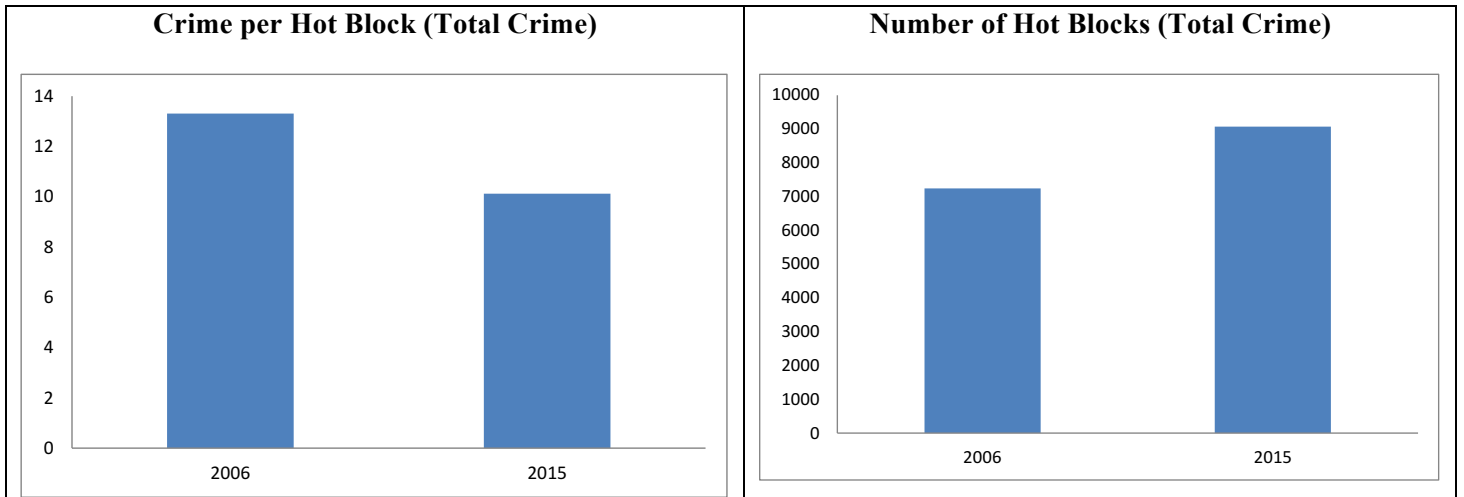


Figure 8b.1. Hot Blocks (Street Segments) in Bogota, Transition Matrix 2009–2013

	Hot (t=1)	Cold (t=1)
Hot (t=0)	40.1%	59.9%
Cold (t=0)	9.7%	90.3%

Figure 8b.2. Hot Blocks (Street Segments) in Bogota

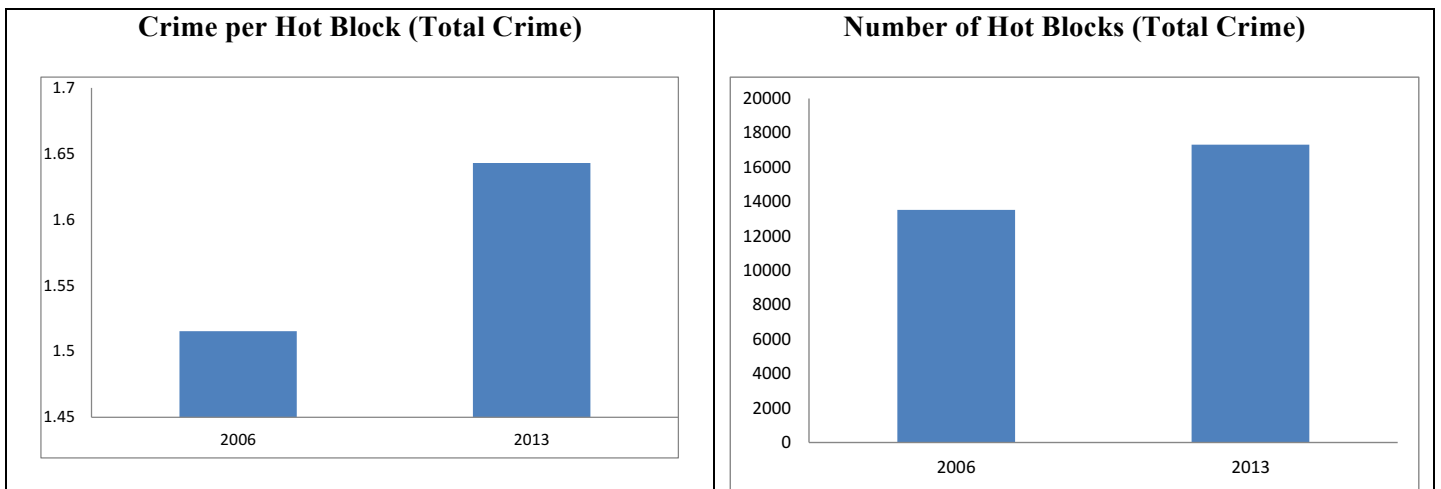


Figure 8c.1. Hot Blocks (Street Segments) in Belo Horizonte, Transition Matrix 2009–2013

	Hot (t=1)	Cold (t=1)
Hot (t=0)	66.3%	33.7%
Cold (t=0)	15.0%	85.0%

Figure 8c.2. Hot Blocks (Street Segments) in Belo Horizonte

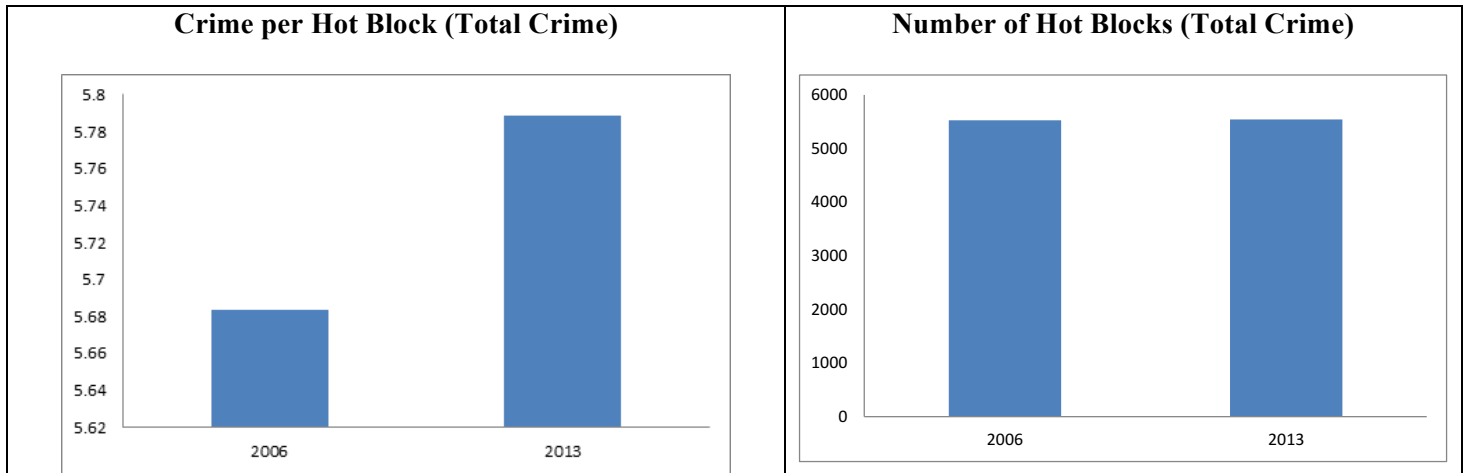
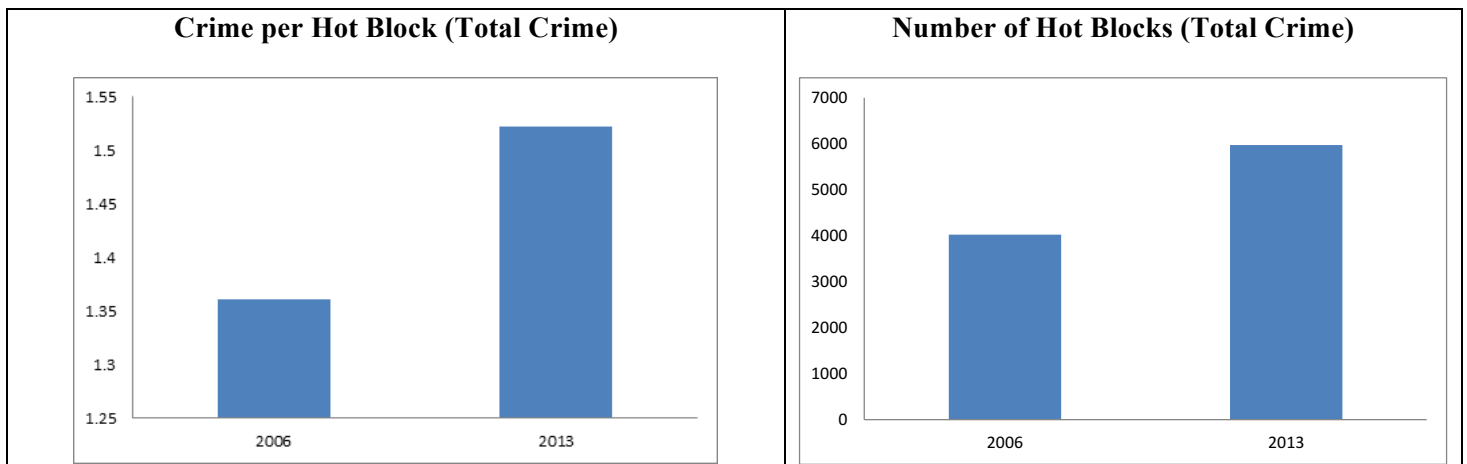


Figure 8d.1. Hot Blocks (Street Segments) in Zapopan, Transition Matrix 2009–2013

	Hot (t=1)	Cold (t=1)
Hot (t=0)	38.9%	61.1%
Cold (t=0)	10.3%	89.7%

Figure 8d.2. Hot Blocks (Street Segments) in Zapopan



Source: Authors' estimation with data from police administrative records.

Figure 9a. Repeat/Near Repeat Crime, Bogota (total thefts and robberies)

	0 to 15 days	16 to 30 days	31 to 45 days	46 to 60 days	More than 60 days
Same location	1.25	1.03	0.98	0.86	0.92
1 to 65	1.05	0.95	0.97	0.99	1.02
66 to 130	1.00	0.95	1.03	0.97	1.03
131 to 195	1.00	0.97	1.02	1.00	1.01
196 to 260	1.01	1.00	0.99	1.00	1.00
261 to 325	1.01	0.97	0.98	1.04	1.00
More than 325	1.00	1.00	1.00	1.00	1.00

Figure 9b. Repeat/Near Repeat Crime, Montevideo (total thefts)

	0 to 15 days	16 to 30 days	31 to 45 days	46 to 60 days	More than 60 days
Same location	5.70	2.38	0.95	0.00	0.62
1 to 115	2.04	1.90	0.00	0.00	0.92
116 to 230	0.56	3.46	1.52	2.48	0.69
231 to 345	0.59	1.43		1.50	1.02
346 to 460	1.96	1.94	0.37	1.39	0.75
461 to 575	1.09	1.10	1.10	0.33	1.02
More than 575	1.00	1.00	1.00	1.00	1.00

Figure 9c. Repeat/Near Repeat Crime, Belo Horizonte (total thefts and robberies)

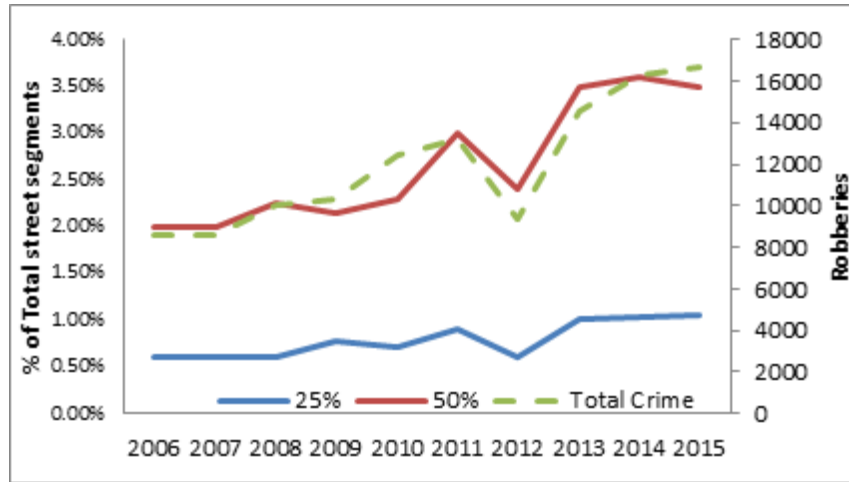
	0 to 15 days	16 to 30 days	31 to 45 days	46 to 60 days	More than 60 days
Same location	1.11	0.96	0.96	1.04	0.81
1 to 200	1.05	1.02	0.95	0.98	0.93
201 to 400	1.04	0.99	0.98	1.01	0.93
401 to 600	1.01	1.01	0.99	1.03	0.95
601 to 800	1.01	1.01	0.99	1.00	0.95
801 to 1000	1.02	1.00	1.00	1.00	0.95
More than 1000	1.00	1.00	1.00	1.00	1.00

Figure 9d. Repeat/Near Repeat Crime, Zapopan (total thefts and robberies)

	0 to 15 days	16 to 30 days	31 to 45 days	46 to 60 days	More than 60 days
Same location	9.69	0.88	0.00	0.00	0.23
1 to 80 meters	1.19	0.97	1.07	1.10	0.96
81 to 160 meters	1.01	0.93	1.02	1.01	1.00
161 to 240 meters	1.00	1.02	1.08	1.02	0.99
241 to 320 meters	1.05	1.07	1.06	1.06	0.97
321 to 400 meters	1.04	1.00	1.03	0.97	1.00
More than 400	1.00	1.00	1.00	1.00	1.00

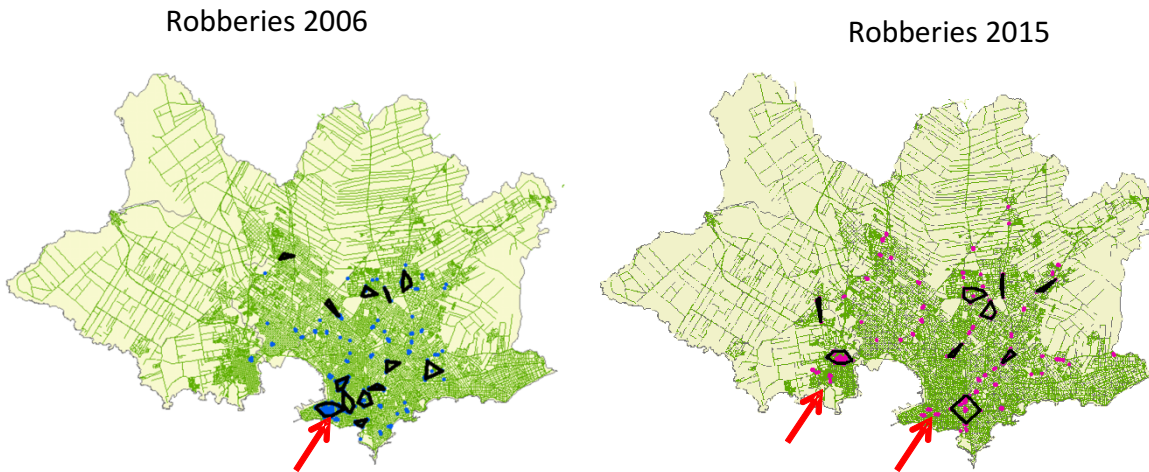
Source: Authors' estimations with data from local police departments.

Figure 10a. Robberies Concentration at Street Segments in Montevideo



Source: Authors' estimation with data from Montevideo Police Department administrative records.

Figure 10b. Robberies Distribution in Montevideo



Source: Authors' estimation with data from Montevideo Police Department administrative records.