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The spatial dynamics and socioeconomic correlates of drug arrests in Mexico city☆

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A B S T R A C T

The two objectives of this study were to determine the spatial patterns of arrests for drug possession and to identify the socioeconomic correlates of drug hotspots in Mexico City. Spatial statistics allowed detection of four Marijuana and three Cocaine hotspots. Statistical correlation and difference tests showed Marijuana hotspots to have better housing conditions and more female-headed households. No socioeconomic correlates could be established for Cocaine hotspots. These spatial patterns are worth further causal studies on this important issue. To this point, results make more convincing the argument that crime solutions can be found in a combination of urban planning, social development, and policing strategies.

Introduction

We have a war on crime, on drugs, and Mexico City is one of the most unsafe cities in Latin America. Drug violence has been increasing and some murders have been attributed to drug dealers fighting for territories (Fernandez & Salazar, 2008).

It is theoretically expected that drug crimes are neither uniform nor spatially random (Lum, 2008; Vilalta, 2009b). Indeed, a quick view of the Mexico City media news[1] reveals where drugs can be bought. Why is drug activity concentrated in some areas? There are at least two theoretical explanations: First, modern formulations of social disorganization theory (Haining & Ceccato, 2005; Haining, Ceccato, & Kahn, 2007; Sampson, 1993; Weisburd & Mazerolle, 2000) explain that deviant social conditions (e.g. children from single-parent families, inadequate supervision, working women) and/or public disinterest (lack of self-policing, poorly policed, etc.) lead to local delinquent behavior. These are modern formulations of social disorganization theory because incorporate newer and contemporary aspects of social diversity: newer family structures, durability of social interactions, and responsible police work. Second, broken windows theory (Corman & Mocan, 2005; Jang & Johnson, 2001; Silverman & Della-Giustina, 2001; Wilson & Kelling, 1982) explains that vacant run-down housing, graffiti covered walls, and/or dirty sidewalks encourage delinquent behavior because it indicates community indifference to deviant behavior. These theories have been subjected to empirical testing in many North American and European cities, but not in Mexico City. In fact, extremely few mapping and/or spatial studies on crime activity can be found in Mexico (Vilalta, 2009a). None has focused on drug crimes and its socioeconomic correlates.

Understanding the socioeconomic correlates of drug hotspots is an important urban public safety and planning issue. The results of this study can help local authorities to better spot troubled areas, plan according to needs of the community, and

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[1] And informal talks with police officers and college students.

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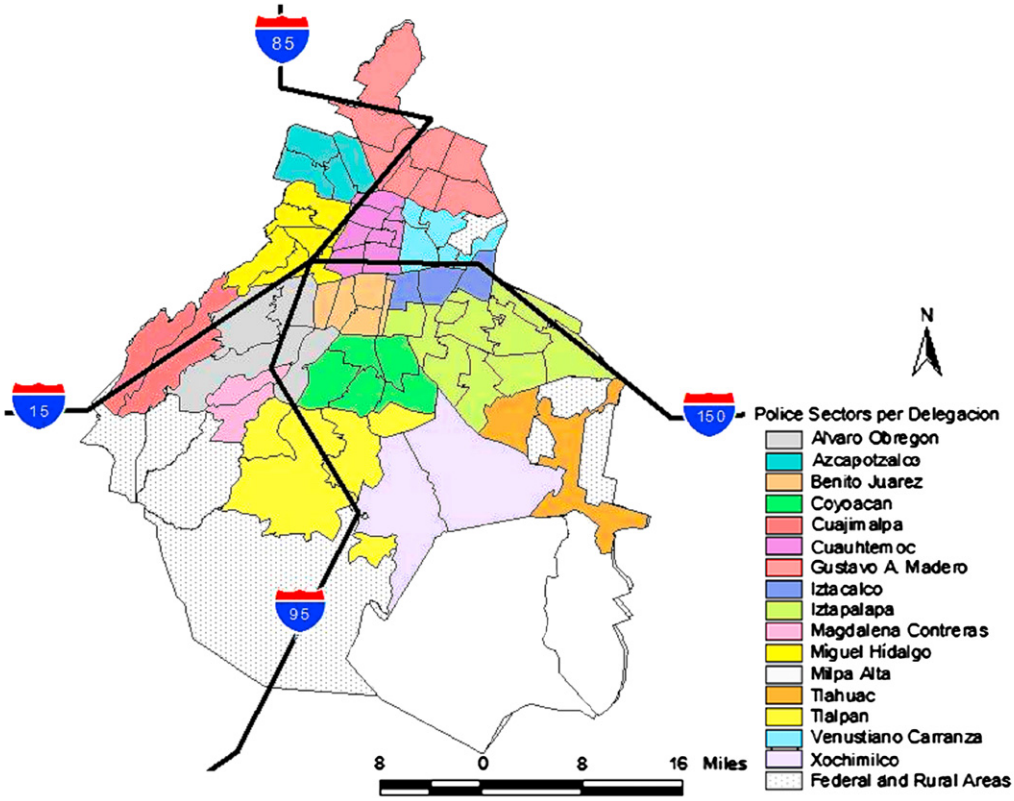


Map 1. Total number of arrests for Cocaine, Marijuana and other substances, January 2007–February 2008 goes here. Source: Secretary of Public Security in Mexico City.

involve delinquency issues into the planning process. Results can also help federal police as well to target more accurately their resources in the battle against drug crimes and organized crime in general.

The objectives of this study were to test the spatial concentration hypothesis of drug arrest activity, to statistically detect the corresponding hotspots, and to identify socioeconomic variable correlates. This study focused on Marijuana and Cocaine possession arrests since these two accounted for 97% of the total drug possession arrests.[2] In all, empirical evidence shows several spatial clusters and spatial outliers of drug hotspots within the city.

Previous studies

As previously said, crime is neither spatially uniform nor random. It has intrinsic spatial conditions (Chainey & Ratcliffe, 2005), principally a tendency to concentrate.

Crime has social correlates as well. These correlates (measurements of area risk factors) are demonstrative of social disorganization and broken windows theories. Measurements summarize area social dynamics (Craglia, Haining, & Signoretta, 2005). Some examples are the proportions of single people, young males, female-headed families, unemployed, literacy, low income households, vacant properties, social housing, commercial land uses, bar densities, single family residential zoning, and measures of access to urban services (Craglia et al., 2005; Sampson & Morenoff, 2004; Savoie, 2008; Schulenberg, Jacob, & Carrington, 2007; Tremblay & Ouimet, 2001; Vilalta, 2009a). Previous correlates apply to other behaviors such as electoral preferences and shopping habits.

Both theories explain criminal spatial variation as responses to environmental conditions. The causal mechanism underlying both theories is that individuals make decisions based on the aggregated behavior around them. Individuals are constantly exposed to social stimuli, and they make use of the information derived from the environment (e.g. behavioral contagion). This information may be understood as "social networks, sources of information and reference to groups rooted in places" (Sauerzopf & Swanstrom, 1999, p. 87).

This connection of crime occurrence to neighborhood social networks, social composition, and physical conditions is not new in urban studies (Shaw & McKay, 1942). An extensive review of previous studies showed no empirically derived evidence

[2] Arrests for pills possession are also available but its frequency is very low.

Table 1
Dependent and independent variables.

Variables under study	Definition and year
Dependent variables	
Arrests for possession of Marijuana	Total number of arrests, January 2007–February 2008
Arrests for possession of Cocaine	Total number of arrests, January 2007–February 2008
Police force	Total police force, 2008
Independent variables	
Income	Percentage of working population earning <2 minimum wages a day, 2000
Schooling	Average years of schooling, 2000
College education	Percentage of population 18+ with some college education, 2000
Social security coverage	Percentage of population with no social security coverage, 2000
Housing conditions	Percentage of private homes with precarious materials in roof (i.e. anything but concrete or brick), 2000
Female-headed households	Percentage of households headed by women, 2000

suggesting that the environment was not positively correlated to criminal behavior. Thus, maybe it would be an anomaly to find some study reporting criminal random behaviors and conclude based on that crime areas do not exist or do not matter.

Quite the opposite, it is empirically argued that some crime areas (in Mexico City) are prevalent to the extent of being endemic in time and space (Vilalta, 2009b). Furthermore, drug dealers do not seem to move or diffuse across Mexico City neighborhoods (Vilalta, 2009b). Drug markets have also identifiable correlates. The best two predictors of drug crime so far, are other crimes (Vilalta, 2009b) and poor police surveillance (Weisburd & Mazerolle, 2000). Thus, the common risk factors apply. In particular, other crimes such as assaults and homicides are frequent in drug crime areas. This is due to the fatal combination of drugs, fights, and firearms (Martinez, Mares, & Stowell, 2005).

Spatial analysis is fundamental in crime research. The most common techniques are location quotients, point mapping, thematic mapping of administrative units, grid thematic mapping, and kernel density maps (Chainey & Ratcliffe, 2005; Savoie, 2008). A spatial statistical technique that has been overlooked in the literature is the local Moran autocorrelation coefficient. However, there are some studies that have applied this technique in crime analysis and conclude that it is an effective tool for hotspot detection (Anselin, Cohen, Cook, Gorr, & Tita, 2000; Vilalta, 2009b).

Crime mapping is also fundamental for crime control. Police must detect and quickly interfere in problematic areas. In this sense, a great deal of strategic information can be derived from spatial analyses. Many studies insist on the necessity of setting aside and go beyond standard police procedures such as scheduled patrolling and static street corner policing, and incorporate intelligent data and mapping.

Data set and methodology

Arrests for drug possession were analyzed for 2007 and part of 2008.[3] Data were collected at the police sector level ($N = 69$).[4] Police sectors are distributed among the 16 city's administrative *delegaciones* (Map 1). Data are presented by the local police agency "Secretary of Public Security" and it is available via Internet.[5]

The choice of independent variables was based on both social disorganization and broken windows theories. The socio-economic variables available were level of income, level of education, social security coverage, housing conditions, and female-headed households (Table 1). Data were collected and analyzed at the neighborhood level (*colonia*). Socioeconomic data are provided by the Mexico City GIS information office which is part of the local "Secretary of Economic Development".[6] The original source of socioeconomic data is the Population and Housing Census of 2000.[7]

Spatial analysis was conducted using police sector centroids given by its geographic coordinates. Global and local Moran *I* autocorrelation coefficients were calculated. The global Moran *I* coefficients were calculated for four different buffer zones: 5, 10, 15 and 20 miles. Coefficients were calculated for different buffer zones so that the effect of different area definitions of nearby police sectors could be observed. A buffer zone is a zone of contact within which the effects of several places on one place is measured. An increase in the buffer zone size implies an increase in the number of neighboring police sectors. It is expected that the strength of the association will decrease for the dependent variables as the radius of the buffer zone increases. Again, this finding would validate Tobler's first law of geography. As applied to this research, the law states that as we expand the geographical area within which the levels of spatial dependence are calculated, the level of clustering in our variable of interest will tend to decrease since its spatial variation will tend to increase (distant things are less related). The local Moran *I* coefficients were calculated only for the 20 miles buffer. Local coefficients allowed us to detect drug hotspots in

[3] There are no other measures available for these variables.
[4] The total number of police sectors is 70, yet police does not report any data on arrests for one sector in both years.
[5] Webpage: http://portal.ssp.df.gob.mx/portal.
[6] Webpage: http://www.siege.df.gob.mx/.
[7] There are no more recent measures available for these variables.

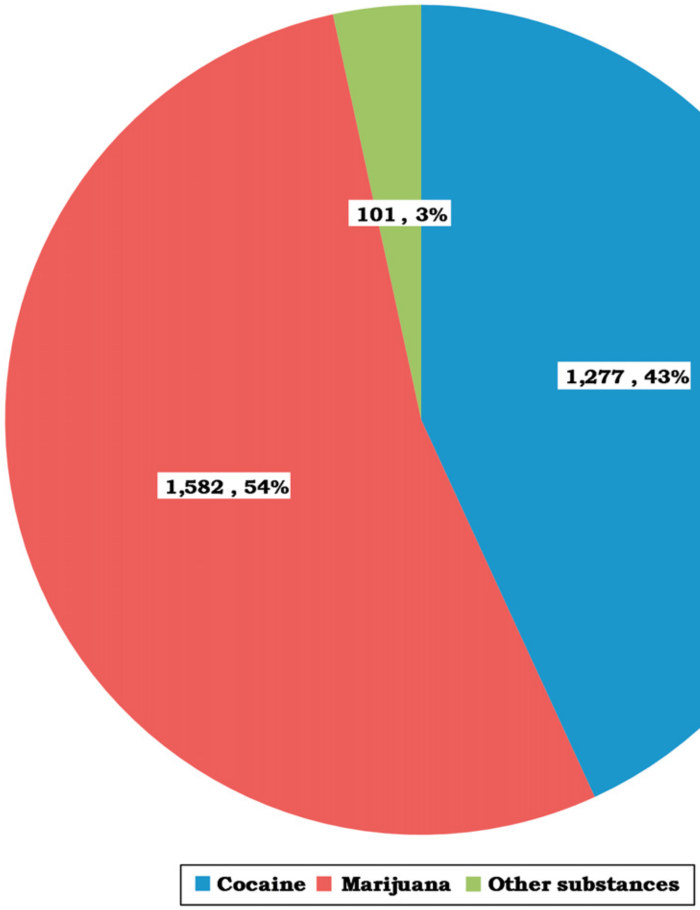


Chart 1. Mexico City: Police sectors goes here.

the form of spatial outliers. The significances of global and local Moran coefficients were tested within a normal (Z) probabilities curve. All analyses were done using SPSS and S-Plus spatial statistics extension for ArcView.

Moran's I coefficient is given by the following formula (Holt, 2007):

$$I = \left(\frac{1}{S^2}\right)\frac{\sum_{i=1}^{N}\sum_{j=i}^{N} w_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}}$$

where N is the number of police sectors, y_i and y_j are the values of the variable (i.e. drug arrests) in the sectors i and j, S^2 is the sample variance, and w_{ij} is the neighboring matrix. Values cannot exceed 1 or -1. Positive values suggest positive spatial autocorrelation, in which similar values are spatially clustered. Negative values suggest negative spatial autocorrelation, in which neighboring values are unalike.

The local Moran coefficient is given by the following formula

$$I_i = \frac{x_i - \overline{x}}{S^2}\sum_{j=1}^{N} w_{ij}(x_j - \overline{x})$$

Coefficient values may be above 1 or below -1. Local Moran coefficients show the specific location and type of spatial hotspots. Positive values indicate spatial clusters and negative values indicate spatial outliers. Spatial clusters are statistically significant groups of similar spatial units, whereas spatial outliers are statistically significant groupings of dissimilar spatial units. In this study, a drug hotspot in the form of a spatial cluster is a police sector which is significantly similar to its neighboring sectors, whereas a drug hotspot in the form of a spatial outlier is a sector significantly different from its neighboring sectors.

Parametric and non-parametric tests were also conducted. Pearson's r linear correlation tests and Kolmogorov–Smirnov tests on normality were applied. Based on that, either independent samples Student-t or Mann–Whitney's Z tests of difference were conducted among police sectors. For all tests the significance cutoff was $p \leq 0.05$.

Table 2
Descriptive statistics on arrests for Marijuana and Cocaine and police force per sector, January 2007–February 2008.

Statistic	Arrests for Marijuana	Arrests for Cocaine	Arrests for other substances	Police force
Mean	19	15	1	279
Median	13	8	0	272
Std. Dev.	13	22	0	101
Total	1582	1277	101	19,534

Source: Own calculations using data from the Secretary of Public Security in Mexico City.

Table 3
Pearson correlation coefficients*.

Variables	Arrests for Marijuana	Arrests for Cocaine	Police force	Income	Years of schooling	College education	Social security coverage	Housing conditions
Arrests for Cocaine	0.430**							
Police force	−0.033	−0.124						
Income	−0.125	0.167	0.027					
Years of schooling	0.218	−0.068	−0.040	−0.977**				
College education	0.250*	−0.008	−0.079	−0.948**	0.989**			
Social security coverage	−0.090	0.133	−0.036	0.845**	−0.775**	−0.711**		
Housing conditions	−0.301*	0.151	−0.230	0.664**	−0.685**	−0.626**	0.636**	
Female-headed households	0.303*	−0.113	0.140	−0.699**	0.728**	0.682**	−0.637**	−0.917**

*$p < 0.05$; **$p < 0.01$.
Note: Significance values were not included for lack of space.

Results

According to the Secretary of Public Security in Mexico City, the number of arrests for drug possession between January 2007 and February 2008 was 2960 in total. Most of the arrests were for the possession of Marijuana (1582, 53%) and Cocaine (1277, 43.1%). The total number of arrests for other substances was not as important (Chart 1, Table 2). We have no equivalent time series data, thus we do not know if the number of drug arrests in the city are increasing or decreasing.

Police force is uniform across police sectors. Police force was neither associated with Marijuana nor Cocaine arrests. Marijuana arrests were statistically correlated with college education, poor housing conditions, and female-headed households. No socioeconomic correlates could be established for Cocaine arrests (Table 3).

Interestingly, arrests for Marijuana and Cocaine were not spatially concentrated for the city as a whole (Table 4, Map 2). This is so because arrests for drug possession were evenly distributed across police sectors. In this sense, one limitation of the global Moran coefficient is that it cannot detect specific crime locations. Conversely, local Moran coefficients allowed the detection of seven drug hotspots; four Marijuana hotspots and three Cocaine hotspots (Table 5). These hotspots have the form of spatial outliers. In this case, a spatial outlier (hotspots) is a police sector with significantly different and higher numbers of arrests than its neighboring sectors. These hotspots are spread out throughout the city. These are located in the center, west and south areas of the city (Map 2).

Since some variables were not normally distributed (Table 6), both parametric and non-parametric tests were conducted to detect differences in the socioeconomic composition of Marijuana and Cocaine hotspots.

In this respect, difference tests detected lower percentages of homes with precarious materials and more female-headed households in Marijuana hotspots (Table 7). Difference tests failed to detect any socioeconomic variable associated with Cocaine hotspots (Table 8).

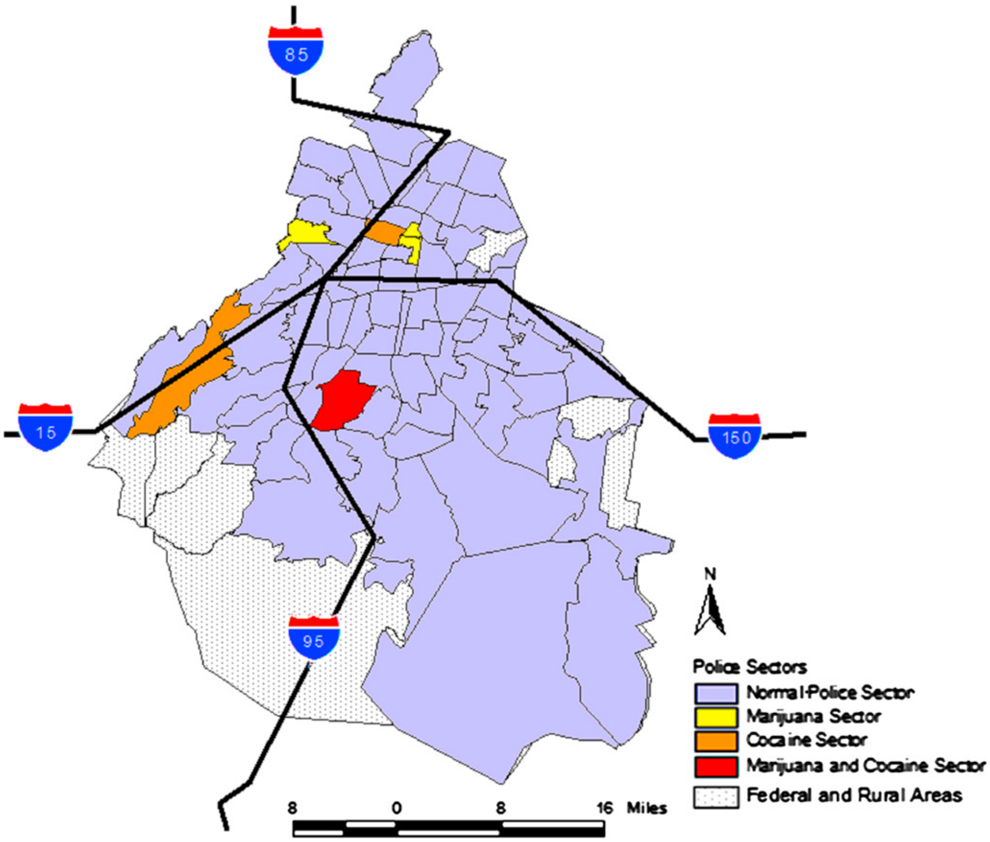
Discussion

This study focused on arrests for possession of Marijuana and Cocaine in Mexico City. Three null hypotheses were tested: (1) drug arrests were randomly distributed across the city's police sectors, (2) drug hotspots cannot be statistically detected,

Table 4
Global autocorrelation coefficients of arrests for possession of Marijuana and Cocaine in four different buffer zones[a].

Global coefficients	5 miles	10 miles	15 miles	20 miles
Coefficients for Marijuana possession	−0.077 (0.100)	−0.003 (0.418)	−0.013 (0.806)	−0.011 (0.297)
Coefficients for Cocaine possession	−0.014 (0.991)	−0.005 (0.497)	−0.006 (0.250)	−0.008 (0.039)

[a] These values represent the global Moran *I* coefficients. Significance values in parentheses.



Map 2. Mexico City: Marijuana and Cocaine hotspots and normal police sectors goes here.

and because there was no sufficient evidence to reject the latter, we proceeded hypothesizing that (3) drug hotspots have no specific socioeconomic correlates. These hypotheses were tested by applying spatial autocorrelation techniques, Pearson linear correlation tests, and tests of difference of means and ranked means. Statistical evidence suggests not to reject hypothesis one and to reject null hypotheses two and three.

Although social disorganization and broken window theorists maintain that criminal activity concentrates, global Moran statistics show the opposite at least for drug possession crimes in Mexico City. This happened because most police sectors in Mexico City had similar numbers of arrests for these crimes. However, although most police sectors had similar numbers of arrests for drug crimes, this did not disprove that there were drug hotspots in the form of spatial outliers. A spatial outlier is a spatial unit that is significantly different from its neighbor units. Doing things this way, local Moran statistics detected four Marijuana and three for Cocaine hotspots; i.e. police sectors that had significantly higher number of arrests for Marijuana and/or Cocaine than its neighbor units.

Drug hotspots are scattered throughout the city. These are located in center ($n = 3$), west ($n = 2$), and south ($n = 1$) of the city.[8] The southern sector (i.e. *Universidad*), is both a Marijuana and Cocaine sector. This sector includes the National University campus and has quick access to commercial and leisure places. For that reason, it is visited by young individuals throughout the day and night. Except for the *Sotelo* sector, the other sectors are a mixture of residential and commercial areas. In both *Centro* and *Morelos* areas (Marijuana sectors), informal street vendors, pirated products, and illegally imported products can be found without difficulty. These two police sectors have a reputation for property crimes and violent crimes. Finally, the *Cuajimalpa* police sector (a Cocaine hotspot) is surrounded by some of the wealthiest neighborhoods and most expensive universities. This area is not considered dangerous or violent.

Social disorganization and broken windows theories were proposed in this study to portray drug hotspots. Lower proportions of homes with precarious materials and higher proportions of female-headed households were found in Marijuana hotspots. No socioeconomic correlate was associated with Cocaine hotspots. Naturally, for the case of Mexico City (as in many other cities) socioeconomic composition variables are associated with neighborhood age structure. Lower proportions of homes with precarious materials and more female-headed households are actually found in older than average

[8] If all sectors were spatially closer, global Moran statistics would have detected a concentration pattern.

Table 5
Local autocorrelation coefficients of arrests for possession of Marijuana and Cocaine[a].

Local coefficients	Police sector	Local Moran I coefficient[a]	Spatial feature	Location within the city
Coefficients for Marijuana possession	Universidad	−0.308 (0.000)	Outlier	South
	Morelos	−0.128 (0.002)	Outlier	Center
	Centro	−0.116 (0.002)	Outlier	Center
	Sotelo	−0.071 (0.014)	Outlier	West
Coefficients for Cocaine possession	Buenavista	−0.354 (0.000)	Outlier	Center
	Universidad	−0.205 (0.000)	Outlier	South
	Cuajimalpa	−0.106 (0.001)	Outlier	West

[a] These values represent the local Moran I coefficients for each police sector. The coefficients were calculated for the 20 miles buffer area. Significance values in parentheses.

Table 6
Results of the normality tests for each of the dependent and independent variables in the data set.

Variables	Kolmogorov–Smirnov test results[a]
Crime and police measures	
Arrests for possession of Marijuana	1.793 (0.003)
Arrests for possession of cocaine	2.015 (0.001)
Police force	1.419 (0.036)
Socioeconomic measures	
Lower salaries	1.166 (0.132)
Years of education	1.327 (0.059)
Some college education	1.765 (0.004)
Social security coverage	1.186 (0.120)
Housing conditions	0.783 (0.572)
Female-headed households	1.380 (0.044)

[a] These values represent the Z statistic for the Kolmogorov–Smirnov test. Significance values in parentheses.

Table 7
Results for the tests of difference in the socioeconomic composition of the Marijuana hotspots.

Variables	Mean for each type of police sector	Test results[a]
Income	Not-a-hotspot ($n = 65$) = 39.7%	$t = 0.348$ (0.751)
(percentage of working population earning <2 minimum wages a day)	Hotspot ($n = 4$) = 36.7%	
Schooling	Not-a-hotspot ($n = 65$) = 9.7	$t = -0.711$ (0.527)
(average years of schooling)	Hotspot ($n = 4$) = 10.6	
College education	Not-a-hotspot ($n = 65$) = 22.1%	ZMW = −0.258 (0.797)
(percentage of population 18+ with some college education)	Hotspot ($n = 4$) = 31.3%	
Social security coverage	Not-a-hotspot (n = 65) = 45.4%	$t = 0.140$ (0.898)
(percentage of population with no social security coverage)	Hotspot ($n = 4$) = 44.4%	
Housing conditions	Not-a-hotspot ($n = 65$) = 12.8%	$t = 2.429$ (0.018)
(percentage of private homes with precarious materials in roof)	Hotspot ($n = 4$) = 4.5%	
Female-headed households	Not-a-hotspot ($n = 65$) = 26.0%	ZMW = −2.524 (0.012)
(percentage of households headed by women)	Hotspot ($n = 4$) = 35.1%	

[a] These values represent either the Mann–Whitney's Z or t-test statistics. Significance values in parentheses.

Table 8
Results for the tests of difference in the socioeconomic composition of the Cocaine hotspots.

Variables	Mean for each type of police sector	Test results[a]
Income	Not-a-hotspot ($n = 66$) = 39.4%	$t = -0.175$ (0.877)
(percentage of working population earning <2 minimum wages a day)	Hotspot ($n = 3$) = 41.9%	
Schooling	Not-a-hotspot ($n = 66$) = 9.7	$t = -0.159$ (0.888)
(average years of schooling)	Hotspot ($n = 3$) = 10.0	
College education	Not-a-hotspot ($n = 66$) = 22.3%	ZMW = −0.236 (0.813)
(percentage of population 18+ with some college education)	Hotspot ($n = 3$) = 28.5%	
Social security coverage	Not-a-hotspot ($n = 66$) = 45.1%	$t = -0.516$ (0.657)
(percentage of population with no social security coverage)	Hotspot ($n = 3$) = 49.9%	
Housing conditions	Not-a-hotspot ($n = 66$) = 12.0%	$t = -0.779$ (0.516)
(percentage of private homes with precarious materials in roof)	Hotspot ($n = 3$) = 18.6%	
Female-headed households	Not-a-hotspot ($n = 66$) = 26.6%	ZMW = −1.210 (0.226)
(percentage of households headed by women)	Hotspot ($n = 3$) = 23.8%	

[a] These values represent either the Mann–Whitney's Z or t-test statistics. Significance values in parentheses.

neighborhoods around the center of the city. Hence, more research in Latin American cities is needed to further test these two theories.

In spite of data limitations, results still provide consequential findings for urban planning and social development policies. Statistically, drug arrests took place in certain areas that include or are in the vicinity to colleges, parks, night clubs, and have access to metro stations. Thus, there is place for land use solutions to have a role in assisting with drug crime issues. Hotspot intervention should be a core priority for the police as well. It was found that police sector force is neither associated with Marijuana nor Cocaine arrests. This statistical finding may conjecture that increasing or decreasing police force would not bring any benefit in terms of arrests for possession of drugs. However, this finding neither proves nor insinuates that sector police is inefficient. Rather it suggests the need for better policing.

More data and comparative research are needed of course. Nevertheless, results show that the war on drugs might be wan if local authorities connect urban planning and social development policies with police strategies. Local authorities can force out drug dealers who locate in criminally strategic but also predictable locations.

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