Victimization and spillover effects in Mexico

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- **Abstract:** Using several rounds of nationally representative victimization survey data, this study examines the determinants of municipality level property crime rates in Mexico and the potential effects of spatial dependence. Baseline results suggest that population size, self-protection rates, and prior victimization rates are the strongest predictors of municipality level property crime. Spatial model results present statistical evidence of spatial dependence in municipality property crime rates. Different specifications suggest that property crime rates are significantly and positively related to crime rates in neighboring municipalities. These effects appear to be growing stronger in more recent years, suggesting increasing spillover effects for property crime in Mexico.

- **Key words:** Victimization, crime, Mexico, spillover effects, spatial dependence.

- **JEL Classification:** C33, 054, y P48.

- **Resumen:** Este artículo examina los determinantes de las tasas de criminalidad contra la propiedad a nivel minicipal, así como sus efectos de espaciales. Se utilizan varias rondas de encuestas nacionales de victimización. Los resultados principales sugieren que el tamaño de la población, las tasas de auto-protección y las tasas de criminalidad previas son las variables explicativas más significativas de los crimenes contra la propiedad. Los resultados de las especificaciones espaciales presentan evidencia estadística significativa de dependencia. Diferentes especificaciones espaciales sugieren dependencia positiva de los municipios vecinos. Dicho efecto parece creciente en años recientes lo que sugiere efectos de contagio creciente.

- **Palabras clave:** Victimización, delincuencia, México, los efectos secundarios, la dependencia espacial.

- **Clasificación JEL:** C33, 054, y P48.

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■ *Introduction*

Crime and violence have been two of the most pressing problems Mexico has faced in the last decades. Unfortunately, the problem has dramatically worsened in recent years mainly due to the ongoing war on drugs. A significant part of President Calderon's government's efforts to fight drug violence was focused on the persecution and removal of some notorious drug lords, but this has been typically followed by unprecedented levels of violence amongst cartel leaders fighting for control of territories, supply chains, and distribution networks. After federal elections in 2012, the then new administration of President Peña Nieto announced a new strategy to deter drug-trafficking violence.[2] However, the new enforcement policies have proved so far to be incomplete and the overall deterrence capacity continues to be very limited and unable to deter the escalation of violence (Felbab-Brown, 2014). Consequently, crime and violence in the country have proven to be sturdily persistent. Official statistics indicate that between 2003 and 2010 federal crimes, including drug-related crimes and homicides, grew at an 8 percent annual rate. Other types of crime, usually referred to as common crimes, have continued rising. However, common crime rates, which refer mainly to property theft, tend to be grossly underreported. Household surveys in Mexico indicate that the percentage of unreported property crime can be as high as 85 percent, implying that the magnitude of the problem is significantly larger than what the official statistics would indicate.

The study of crime is important for the human, social, and economic costs associated with it, but these costs are difficult to assess for it involves different dimensions (Soares and Naritomi, 2010). Nonetheless, there have been some real efforts to estimate these costs. Aside from the incalculable human costs, Bourguignon (1999a) estimates that the economic costs of crime could be as high as 7.5% of GDP for Latin American countries, compared to 3.5% for the U.S. and 2% for Asian countries. The higher costs of crime for Latin American countries, among the highest in the world, compared to developed countries are mainly due to higher crime rates (Bourguignon, 1999a; Soares and Naritomi, 2010). Within Latin America, countries like Colombia, Brazil, and Mexico have the highest crime rates (Fajnzylber *et al.,* 2000, 2002; Bourguignon, 1999a, 1999b).

Given its importance, numerous empirical studies have been conducted in order to identify and understand the determinants of victimization and crime at the individual, family, city, and country level. This effort has produced a large array of variables used to predict the probability of victimization and crime rates. However, this array can be summarized into a relatively standard set of covariates typically used in applied studies of crime (Deane *et al.,* 2008). Most studies consider measures of population socio-economic disadvantage, region indicators and population size, measures of household composition and family disruption, population instability indicators, and measures of policing activity, including proactive measures.

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2 The new "National Security Strategy" consists of six points; planning, prevention, protection and respect to human rights, institutional coordination, and evaluation

Aside from the identification of the determinants of crime, some researchers have concluded that crime is not a random activity; there tends to be important spatial and temporal concentrations. Tobler's first law of geography states that everything depends on everything else, but closer things more so. In the context of crime, the crime rate in a municipality might depend in part on the rates of all other municipalities but especially on the rates of its closest neighbors. Empirically, it has been shown that crime and poverty are correlated with each other and tend to exhibit strong spatial clustering (Peterson and Krivo, 2010). Consequently, most neighborhood crime rates tend to be similar for neighborhoods that are proximate to each other, even when crime rates vary from one section of the city to another (Graif and Sampson, 2009). The spatial dependence of crime and victimization rates among municipalities might be due in part to the mobile nature of crime and criminals; research has found that up to 70% of crimes are committed by individuals outside their neighborhoods of residence (Bernasco, 2010(a)). It might also be due in part to the arbitrary nature of neighborhood assignment, which might lead to common characteristics shared by the neighbors in an area. This arises from the definition of neighborhood that only considers the place of residence, and it has led to a call for a definition of neighborhood context that takes into account individual's daily activity patterns (Cagney *et al.,* 2013; Matthews and Yang, 2013). In either case, ignoring spatial dependence effects might result in a misspecified model, biased estimates, and misleading conclusions about the determinants of property crime in Mexico (Anselin, 2002).

Taking into account the clustering nature of crime and victimization, the main mechanisms in the study of crime and victimization have been summarized under four categories: Social ties and local interactions, norms and collective efficacy, institutional resources, and routine activities (Sampson *et al.,* 2002).

This study utilizes data from several rounds of a nationally representative victimization survey in Mexico to consider the determinants of municipality level property crime rates. Not all municipalities are included in the samples, but this study represents an alternative to the use of government victimization statistics, which might be unreliable. This study considers several of the determinants of crime previously used in the literature, test for the presence of spatial dependence effects, and try to account for these effects explicitly in different econometric model specifications. Regression analysis is conducted for each survey year separately to account for changing characteristics and to consider variation across time in spatial dependence effects among municipalities in Mexico.

Having employed different weighting matrices, the main results indicate that population size, self-protection rates, and prior victimization rates are the strongest predictors of property crime rates in Mexico. We also find evidence that spatial dependence effects are statistically significant and are becoming stronger in more recent years, suggesting growing diffusion effects of property crime in Mexico.

The next section briefly reviews some of the existing literature on victimization and crime, including some of the literature that considers spatial dependency effects of crime. The section "Methodology" describes briefly the modeling of spatial dependence effects of crime, followed by a data description and summary statistics section. The results from the baseline and other models that consider spatial dependence effects are presented in section “Results”. Finally, the conclusions and observations about the political implications of the main results of this study are presented.

■ *Literature review*

Crime can be analyzed from the perspective of potential criminals and from the perspective of victims. From the perspective of potential criminals and starting with Becker (1968), researchers typically consider a rational individual’s decision of whether or not to commit a crime. It is assumed then that the individual would opt to commit the crime if the expected payoffs from committing the crime exceed the expected costs. The former depends mainly on the economic gains, while the latter depends mainly on the probability of apprehension and the severity of punishment.

From the perspective of victims and using aggregate units of observation, many studies have considered the determinants of victimization across neighborhoods (Smith *et al.,* 2000), cities (Stretesky *et al.,* 2004), and countries (Worrall, 2005). Among the most common covariates used, measures of socio-economic disadvantage have been found to be positively correlated with crime rates (Kubrin *et al.,* 2006; Andresen, 2006). Low opportunity costs for socially and economically disadvantaged individuals have been cited as one of the main drivers of crime. Higher population size and density are also positively correlated with crime rates (MacDonald, 2002), which are determined by low apprehension probabilities and higher pecuniary gains from crime in larger areas (Glaeser and Sacerdote, 1999). Indicators of region (Stretesky *et al.,* 2004) have also been employed to address significant differences among communities within a large area. In terms of population instability, the literature has found the areas with high migration and low social cohesion tend to have more crime (Miethe *et al.,* 1991). Another important covariate used in the study of crime is the amount and extend of policing activities (Kubrin *et al.,* 2006). The net effect of this covariate on crime is not clear. On one side, the amount of policing resources might reflect the amount of deterrence to crime applied in the community, but on the other side, it might be a reflection of the extend of illegal activities prevalent in the community. Another concern related to this covariate is the potential endogeneity of policing resources, which might lead to biased estimates of their effect on crime. Some studies have also considered the likelihood of repeat victimization (Sagovsky and Johnson, 2007). This literature has proposed two explanations for how prior victimization can be correlated with current victimization probabilities. The first one suggests that criminals might return to the victim to exploit good opportunities further, while the second one suggests that repeat victimization might be a result of different offenders, at different times, choosing the same victim independently (Johnson, 2008).

Social scientists have also acknowledged the importance of considering the role of spatial effects in criminology and sociological studies (Weisburd *et al.,* 2009). It’s believed that a place does not stand alone as an island, but rather as a part of the main

(Dean *et al.,* 2008). With regards to crime and victimization, two of the main reasons attributed for the existence of spatial dependence effects are the potential for diffusion effects and the use of arbitrary geographic boundaries that do not necessarily are the same for the unit of observation and the social process being described. The potential for diffusion effects in criminal activities in general can be best understood by considering that criminals are mobile and their behavior would not necessarily be constrained by geographical boundaries, especially across smaller aggregate units like neighborhoods and municipalities (Bernasco and Block, 2011; Bernasco, 2010(b)). Altogether, these studies propose that not controlling explicitly for spatial dependence effects while modeling victimization and crime rates might lead to serious identification problems.

■ *Methodology*

The municipality level property crime rate, the dependent variable, is modeled as dependent on a set of predetermined covariates commonly used in the crime literature. The baseline model has the following form:

(1) $$y = X\beta + \varepsilon,$$

where X contains municipality level characteristics correlated with victimization rates, including border and rural condition indicators, internal and international migration rates, self-protection and past victimization rates, homicide and unemployment rates, and the percentage of households headed by females, among others.[3] As a start, the error term in model (1) is assumed to have ideal standard properties, so OLS gives appropriate coefficient estimates. Throughout the remainder of the paper, model (1) is referred to as the baseline model.

The baseline model is commonly used in the literature but ignores the potential effects of spatial dependence in municipality level property crimes, which might result in estimation problems. This could then lead to wrong interpretations about the effects of different explanatory variables used in the model on the incidence of property crime. More importantly, misspecification in the analysis of property crime or other more general forms of crime might lead to the implementation of erroneously directed public policies that might not have the desperately needed results and even result in the exacerbation of the problem.

The use of maps depicting Mexican states or municipalities and their corresponding crime rates has been suggested as a way to assess whether or not victimization rates in Mexico suffer from spatial dependency. This approach might be informative and valuable. Maps might show that crime rates in some areas are significantly correlated with the rates of neighboring communities. However, it has been argued that relying on

[3] Municipality level homicide and domestic and international migration rates are based on 2005 data. The idea is that this might lessen the contemporaneous simultaneity effects of victimization rates on these variables. An instrumental variables approach is definitely recommended in this case, but the lack of appropriate relevant and exogenous variables preclude us from following this approach

visual inspection to identify data clusters and patterns might be problematic. Human perception is typically not adequately rigorous and tends to be biased towards finding patterns and clusters, even in spatially random data (Messner *et al.,* 1999).

Instead of relying on visual considerations to decide whether or not victimization rates across municipalities in Mexico exhibit spatial dependency, this study relies on simple econometric tests. These tests are applied to the outcome of interest, the municipality victimization rate, and to the residuals from the baseline model (1) to help in deciding whether or not spatial dependence effects are present and significant.

Generally, these tests require the computation of statistics followed by hypothesis testing based on the statistics' expected value. This study uses Moran's "I" and Geary's "C" statistics to test the null hypothesis of no spatial correlation.[4] Failure to reject the null hypothesis would suggest that OLS estimates based on the baseline model would be econometrically appropriate and that spatial dependence in the errors is not significant. Rejecting the null hypothesis, on the other hand, implies that running the baseline model (1) using OLS might lead to biased, inefficient estimates, or wrong interpretations about the parameters of interest and/or their significance level, depending on the type of spatial dependency. In this case, Maximum Likelihood Estimation (MLE) will provide unbiased and efficient estimates and remove the spatial dependence in the errors, provided that the model is correctly specified. For different specifications considered in this study, the null hypothesis of spatial independence is rejected, so the appropriate spatial econometric model to be applied needs to be selected next.

The choices considered to model spatial dependence effects are the spatial error model (2) and the spatial lag model (3), sometimes referred to as the mixed spatial lag model.

$$y = X\beta + \varepsilon, \qquad \varepsilon = \lambda W\varepsilon + \xi \tag{2}$$

$$y = \rho Wy + X\beta + \varepsilon, \tag{3}$$

where X is as explained before and W represents an NxN symmetric weighting matrix. Each cell in the W matrix represents a pair of municipalities, and the matrix can take on different forms. One form of this matrix contains zeros in the diagonal and only zeros

4 Under the null hypothesis, Moran's I statistics has an expected value equal to -1/N-1 and Geary's C statistic has an expected value equal to 1. The null hypothesis is for the absence of spatial dependence.

Year	2007	2008	2010
Observations	698	883	851
Moran's I	7.8	9.3	12.0
p-value	0	0	0
Geary's C	-5.5	-6.9	-6.8
p-value	0	0	0

or ones in the off-diagonal. The values off the diagonal are ones if the municipalities are located within a predetermined distance, the cutoff distance, and zeros otherwise. This matrix can be easily standardized by dividing the ones in each row by the number of neighbors, so that the sum equals to one for each row.[5]

However, not all municipalities in Mexico are in each year sample, so there are plenty of "islands" in the data. That is, many municipalities do not have any neighbors within the cutoff distance. This creates computational problems, so they must be excluded from the analysis.[6] To reduce the number of islands in the data, one could increase the cutoff distance. However, if spatial dependence in property crime among close neighbors really exists, this might effectively lower the probability of finding statistical evidence in the results.

Another way to construct the W matrix is having the off-diagonal values of the matrix to be the inverse of the distance between units. This approach considers the effects of all other units in determining the municipality's crime rate, while allowing for larger effects from closer neighboring units.[7] Yet another way considered for the W matrix is to identify an arbitrary number of closest neighbors, different numbers were considered, and have ones for those units and zeros for the rest. Regardless of the form of the W matrix, one must first choose the appropriate way to model the spatial dependency.

The spatial error model (2) suggests that the errors are not spatially independent. In other words, there are unobserved variables that are associated with victimization rates at the municipality level and they are significantly correlated among neighbors. Trying to correct for it with standard procedures might prove ineffective (Almeida, 2003). As with omitted variables, running the baseline model when the true model is as in model (2) might lead to biased estimates of the regression coefficients. The covariance estimates will be biased and might lead to incorrect inferences. If instead the true model is the spatial lag model (3), running the baseline model will result in biased and inefficient estimates of the regression coefficients.

The decision rule between models is based on goodness of fit criteria by comparing the baseline model to each of the alternative models. Having a significant test statistic for the spatial lag or the spatial error model suggests that considering spatial dependence effects improves the model's fit. A way to choose which spatial dependence model is more appropriate requires the use of a robust version of the tests (Anselin and Florax 1995). The rule to follow then is that if the robust version of the test is significant for model (2) but not for model (3), the appropriate model is the spatial error model, and vice versa. For most specifications of the weighting matrix and years, the appropriate model suggested by the criteria is the spatial lag model.

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5 This type of weighting matrix requires the use of a cutoff distance to define neighbors; municipalities are considered neighbors if the distance between them is smaller than the cutoff distance. Larger cutoff distances typically result in having more neighbors, but it might also decrease the likelihood of observing significant spatial dependence effects if present

6 This could also be due to the size of the municipalities. For example, some municipalities in the states of Baja California and Baja California Sur have no neighbors within one hundred kilometers due to their size

7 Using the inverse of distance squared has the effect of decreasing the effect of farther units more rapidly

■ *Data and statistics*

This study utilizes 2007, 2008, and 2010 data from Mexico's National Survey about Insecurity (ENSI: Encuesta Nacional Sobre Inseguridad). This survey was conducted by the Citizen's Institute for the Study of Insecurity (ICESI), and it contains individual and family demographic and socio-economic characteristics, as well as information on crime and victimization.[8] This is not a panel data, so one cannot identify the households that have participated in previous rounds, but one can identify which municipalities have been surveyed in previous rounds. Not all municipalities are included in the survey rounds, and the result is having a significantly smaller sample size compared with the total number of municipalities in Mexico. However, the use of this victimization survey data allows us not to rely on official crime statistics, which might suffer from serious reliability issues.

The unit of observation in this study is the municipality, so individual and family characteristics were aggregated at this level and were complemented with measures of total population and internal and international migration rates computed from the 2000 and 2005 population census.[9] A municipality index of marginalization computed in 2000 by Mexico's CONAPO (National Population Council) and annual homicide rates in 2005 from INEGI are also included.

The municipality property crime victimization rate, the models' dependent variable, was computed by counting all households that report any household member as victim of a property crime in their community of residence and dividing it by the total number of households surveyed in the municipality.[10] Regression analysis is conducted for each year separately to account for changing characteristics and to consider variation in the potential spatial dependence effects among municipalities.

Table 1 presents summary statistics for each of the three rounds considered. The sample size shows that only about one third of all municipalities in Mexico are present in our sample, but these municipalities represent more than two thirds of the country's total population. Statistics show that the victimization rates increased slightly in later rounds, but it must be noted that only about half of all municipalities surveyed are present in all rounds, so some variation is expected. Also, statistics in the latter two rounds seem more similar than the first round.

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8 The ICESI was a non-profit organization founded by several civil society institutions in Mexico with the goal of providing reliable information on victimization and crime in Mexico. The last survey conducted by the ICESI was in 2010. After that, Mexico's INEGI (National Institute of Statistics, Geography, and Information) got in charge of the survey, but the information is not easily matched with previous rounds

9 Using previous years' values for some of these variables is preferred to avoid potential simultaneity problems

10 This rate does not include crimes occurring outside the municipality of residence

Table 1
Summary Statistics

ENSI Surveys			
	2007	2008	2010
Victimization Rate	5.173	5.926	5.685
	(6.373)	(6.794)	(6.388)
Border	0.123	0.152	0.140
	(0.328)	(0.358)	(0.347)
Rural	0.225	0.458	0.443
	(0.417)	(0.498)	(0.497)
Population	106.877	89.960	77.210
	(207.159)	(187.584)	(125.871)
Marginalization	-0.529	-0.530	-0.521
	(0.970)	(0.920)	(0.935)
Internal Migration	9.798	9.478	11.199
	(12.090)	(11.718)	(11.322)
Int'l Migration	7.717	7.297	6.981
	(8.122)	(7.814)	(7.020)
Self-Protection	30.728	38.641	27.950
	(19.656)	(20.872)	(17.658)
Past Victimization	7.705	8.714	9.296
	(7.703)	(8.368)	(9.375)
Male-Female Ratio	0.916	0.943	0.910
	(0.794)	(0.578)	(0.521)
College	9.019	8.640	10.203
	(10.124)	(9.975)	(11.268)
Unemployment	5.781	8.717	7.034
	(6.951)	(7.498)	(6.620)
Homicide Rate	9.226	8.940	10.274
	(12.345)	(11.685)	(17.079)
Female Head	17.802	17.559	17.584
	(4.440)	(4.480)	(4.475)
Low Education Head	40.584	40.272	40.546
	(16.975)	(16.314)	(16.636)
Observations	698	883	851

*Standard of deviation in parenthesis.
Source: Own elaboration.

Average total population and rural condition show that later rounds tend to include smaller municipalities. Based on the literature, it is expected that total population has a positive effect on victimization, greater economic gains and lower probability of apprehension, but a negative effect from rural condition, higher probability of apprehension and larger social costs. The marginalization index, a composite measure of economic disadvantage, shows that the average municipality is not marginalized.[11] The expected effect on victimization is not easy to assert, for it represents the low opportunity cost of committing a crime, but it also represents the low economic rewards from property crime. As measures of population instability and social cohesion, internal and international migration rates are included. These measures represent the percentage of adults born in another municipality and the percentage of households with at least one migrant to the U.S. in 2000, respectively. It is expected that municipalities with high domestic and international migration might have lower social cohesion among its citizens, therefore, higher victimization rates.

Self-protection rates measure the percentage of households reporting taking a protective measure in the survey year. It's suggested that this measure represents the level of awareness about insecurity and the general perception of crime in the community. Consequently, this variable is expected to have on net a positive effect on victimization. Prior victimization rate represents the percentage of households reporting at least one member has been a victim of a crime the year prior to the survey. Similar to self-protection rates, it is expected to have a positive effect on victimization. The main idea is that this variable captures the prevalence of crime in the municipality and serves as an identifier of prevalent lucrative economic opportunities to criminals.

Homicide rates are computed as per 100,000 inhabitants in 2005. We believe this variable captures in part the amount of policing resources employed in the municipality and the extent of criminal enterprises.[12] This rate is smaller for our sample than for the country as a whole. According to INEGI, the rate per 100,000 for the country in 2011 was 24. In states like Chihuahua, Guerrero, and Sinaloa, homicide rates were around 100 on average. Overall, municipalities in our sample tend to be larger compared to the country and have lower victimization and homicide rates. It is expected that homicide rates have a positive effect on victimization mainly because they reflect the extent of criminal activities prevalent in the municipality. However, and as mentioned before, this variable might also have a negative effect because it might also capture the amount of policing resources allocated to the municipality.

The rest of the covariates refer to household composition and to the socioeconomic conditions present in the community. They include the percentage of residents with college education, the unemployment rate, the percentage of households headed by a female, the municipality average age, the average family size, the average number of children in the household, and the percentage of households headed by a low-education adult.

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[11] The composite marginalization index is constructed as a weighted average of 9 measures, including illiteracy rates, dwelling conditions, and workers' earnings. Positive values refer to municipalities considered marginalized, and vice versa

[12] As mentioned previously in the crime literature, the amount of policing resources might be endogenously determined and therefore give biased estimates of its effect on crime. Potential solutions to this problem are to find instrumental variables for the amount of policing resources (Levitt, 1997) or truly exogenous sources for the variation of the covariates (Di Tella and Schargrodsky, 2004). However, due to data availability, these approaches are not feasible. In order to lessen, at least partially, the contemporaneous simultaneity effects of crime on the covariates, this variable is measured as of 2005

■ *Results*

This section presents the regression results of the municipality level victimization rates for 2007, 2008, and 2010 separately. To illustrate the potential problems of ignoring spatial correlation in victimization across municipalities, it begins with typical OLS estimations based on the baseline model. Then, the results for different tests for spatial dependence are discussed, followed by the decision on the appropriate spatial dependence model and presentation of the main estimation results using MLE.[13]

Baseline regression estimates are presented in Table 2. This table shows that coefficient estimates differ to a certain extent from year to year. However, the coefficient estimates for population, self-protection rates, and prior victimization rates are consistent and statistically significant across years. The former is consistent with the existing crime literature that has found that larger municipalities tend to have more crime, while the latter two might be considered as evidence that property crime in Mexico is a familiar, widespread, and persistent problem.

Table 2
OLS Regressions

Dependent Variable: Victimization Rate			
	2007	2008	2010
Border	2.004***	0.116	-0.019
	(0.733)	(0.603)	(0.642)
Rural	-0.793	-1.175***	-0.876**
	(0.546)	(0.423)	(0.444)
Population	0.005***	0.004***	0.007***
	(0.001)	(0.001)	(0.001)
Marginalization	-0.283	-0.517	0.072
	(0.599)	(0.516)	(0.548)
Internal Migration	0.001	0.030**	0.027*
	(0.016)	(0.015)	(0.015)
Int'l Migration	-0.053**	-0.035	-0.018
	(0.025)	(0.022)	(0.033)
Self-Protection	0.040 ***	0.030 ***	0.077***
	(0.011)	(0.009)	(0.012)
Past Victimization	0.303***	0.258***	0.113***
	(0.031)	(0.025)	(0.023)
Male-Female Ratio	-0.099	-0.755**	-0.694
	(0.283)	(0.373)	(0.430)

[13] In the presence of spatial correlation in victimization across municipalities, OLS beta estimates will be biased. Alternatively, if the model is correctly specified, MLE will provide consistent estimates of the betas and the spatial correlation in the errors will be removed

	2007	2008	2010
College	-0.053	-0.030	0.079**
	(0.034)	(0.030)	(0.032)
Unemployment	-0.056*	-0.009	-0.051*
	(0.032)	(0.024)	(0.028)
Homicide Rate	-0.014	0.050***	0.029***
	(0.017)	(0.015)	(0.010)
Female Head	0.040	0.008	0.156***
	(0.055)	(0.047)	(0.051)
Low Education Head	-0.005	-0.003	0.036
	(0.032)	(0.026)	(0.030)
Constant	1.526	10.501**	-9.369*
	(5.875)	(4.724)	(5.661)
Observations	698	883	851

Notes: Robust standard errors in parenthesis. ***, **, * represent statistical significance at the 1%, 5%, and 10% respectively.

Source: Own elaboration.

Similar to summary statistics, the regression results for the last two rounds seem more similar than those for the first round. In terms of statistical significance, similar results for these years are found for rural condition, internal migration, and the homicide rate. Border condition, international migration, and unemployment rate are only statistically significant for 2007. Again, this might be due in part to sampling issues or to changing conditions related to property crime in Mexico. Nonetheless, most estimates are consistent with the existing literature on victimization.

As mentioned before, the existence of spatial dependence in municipality level victimization rates might result in reaching wrong conclusions using the baseline model's results. The approach is then to test for the presence of spatial dependence in municipality level victimization rates and, if necessary, decide on the appropriate spatial dependence model.

To test for spatial dependence, we obtain Moran's I and Geary's C statistics based on the dependent variable and the residuals from baseline model (1). The null hypothesis of no spatial autocorrelation is rejected for each year separately, suggesting there is statistically significant correlation among neighboring property crime rates and the baseline residuals. The choice is then between the spatial error model (2) and the spatial lag model (3). Lagrange multiplier and modified Lagrange multiplier statistics were used to decide which model gave a more appropriate fit. The results are now presented based on different specification of the W weighting matrix.

As mentioned before, one option for the W matrix contains only zeros and ones. All diagonal elements are zeros and off-diagonal elements are ones if the municipalities are located within a predetermined distance and zero otherwise. For illustration purposes only, Table 3 presents the results using weighting matrix and a cutoff distance of 10 kilometers for each year separately. The null hypothesis of spatial independence is rejected for each year, and based on specification criteria, model (2) was used for 2008 and model (3) for 2007 and 2010. However, this approach resulted in having plenty of municipalities without neighbors, so a large proportion of municipalities were excluded and the sample size was reduced significantly. Other larger cutoff distances were used to construct the W weighting matrix, and the results vary significantly. Furthermore, spatial dependence statistics based on the longest distances suggest that the null hypothesis of spatial independence cannot be rejected.

Table 3
Spatial dependence model (10 Km)

Dependent Variable: Victimization Rate			
	2007	2008	2010
Border	3.570**	-0.444	-1.585
	(1.725)	(1.872)	(1.620)
Rural	-1.697	-2.066**	-0.921
	(1.538)	(0.889)	(0.884)
Population	0.004***	0.00316**	0.008***
	(0.001)	(0.001)	(0.002)
Marginalization	-1.361	-0.793	1.330
	(1.495)	(1.269)	(1.151)
Internal Migration	-0.019	0.020	0.028
	(0.037)	(0.031)	(0.028)
Int’l Migration	-0.042	-0.039	0.055
	(0.052)	(0.045)	(0.078)
Self-Protection	0.057 **	0.007	0.056 **
	(0.026)	(0.018)	(0.023)
Past Victimization	0.324***	0.266***	0.104***
	(0.057)	(0.042)	(0.037)
Male-Female Ratio	1.328	-1.217	-0.896
	(1.114)	(0.793)	(0.782)
College	-0.083	-0.142**	0.043
	(0.068)	(0.061)	(0.056)
Unemployment	-0.001	0.060	0.001
	(0.068)	(0.047)	(0.047)
Homicide Rate	-0.131*	0.121***	0.057***
	(0.067)	(0.044)	(0.019)
Female Head	0.079	0.024	0.137
	(0.104)	(0.095)	(0.100)
Low Education Head	0.078	-0.017	-0.032
	(0.081)	(0.065)	(0.060)
Constant	-0.841	25.152***	1.236
	(2.978)	(9.755)	(1.051)

	2007	2008	2010
Observations	189	267	270
Rho	-	0.024**	
		(0.011)	
Lambda	-0.124**		0.073***
	(0.061)		(0.019)

Notes: MLE Estimates. Robust standard errors in parenthesis. ***, **, * represent statistical significance at the 1%, 5%, and 10% respectively.

Source: Own elaboration.

Having the small sample size in mind, results in Table 3 show that municipality population, self-protection rates, and previous victimization rates are positively correlated with property crime rates and continue to be statistically significant. The homicide rate variable is statistically significant for all years, but it has a negative sign for 2007. Finally, the specification for each year shows there is evidence of spatial dependence in property crime rates among municipalities in Mexico. However, and given the significantly reduced sample size, these results should be taken cautiously.

As alternative forms of the W matrix and to avoid significant sample size reductions, the inverse of distance and the nearest five neighbors approach were also considered.[14] These results are adjusted for the potential clustering effects of the standard errors at the state level. The results are presented in Tables 4 and 5. For the most part, the results from these two approaches are similar, except for the statistical significance level of some covariates. Population size, self-protection rates, and previous victimization rates continue to be statistically significant for all rounds. However, and as shown in Table 2, the results for 2008 and 2010 are more similar than those for 2007. Selection criteria suggest that the best model for each year separately is the spatial lag model. However, the spatial lag variable results for Table 5 are somewhat different for 2007 and 2008 data.

Table 4
Spatial dependence model (Inverse distance)

Dependent Variable: Victimization Rate			
	2007	2008	2010
Border	1.887**	0.888	0.721
	(0.781)	(0.680)	(0.615)
Rural	-0.794	-1.165***	-0.845*
	(0.614)	(0.371)	(0.404)
Population	0.005***	0.004***	0.007***
	(0.001)	(0.001)	(0.001)

14 Results using a smaller number of closest neighbors show stronger evidence of spatial dependence. Other coefficient estimates do not vary significantly. Municipalities in all rounds do not necessarily include the same households. Results in tables 4-6 present errors adjusted for clustering at the state level

	2007	2008	2010
Marginalization	-0.264	-0.687	-0.266
	(0.590)	(0.489)	(0.503)
Internal Migration	0.001	0.029**	0.025*
	(0.017)	(0.015)	(0.013)
Int'l Migration	-0.051**	-0.039*	-0.033
	(0.027)	(0.021)	(0.032)
Self-Protection	0.040***	0.030***	0.071***
	(0.010)	(0.010)	(0.013)
Past Victimization	0.306***	0.245***	0.093***
	(0.031)	(0.034)	(0.025)
Male-Female Ratio	-0.096	-0.737**	-0.687
	(0.284)	(0.373)	(0.430)
College	-0.053	-0.026	0.083***
	(0.034)	(0.040)	(0.039)
Unemployment	0.056*	0.008	0.049
	(0.031)	(0.030)	(0.037)
Homicide Rate	-0.014	0.046***	0.028**
	(0.015)	(0.015)	(0.009)
Female Head	0.042	0.004	0.151***
	(0.054)	(0.044)	(0.051)
Low Education Head	-0.009	0.031	0.079**
	(0.033)	(0.027)	(0.030)
Constant	1.612	8.410*	-11.443**
	(6.172)	(4.814)	(6.098)
Observations	698	883	851
Rho	-0.013	0.051***	0.063***
	(0.032)	(0.016)	(0.016)

Notes: MLE Estimates. Robust standard errors in parenthesis. ***, **, * represent statistical significance at the 1%, 5%, and 10% respectively.
Source: Own elaboration.

Table 5
Spatial dependence model (nearest 5 neighbors)

Dependent Variable: Victimization Rate			
	2007	2008	2010
Border	1.911**	0.121	0.111
	(0.739)	(0.649)	(0.579)
Rural	-0.770*	-1.157***	-0.859**
	(0.477)	(0.372)	(0.398)
Population	0.004***	0.004***	0.006***
	(0.001)	(0.001)	(0.001)

	2007	2008	2010
Marginalization	-0.252	-0.513	0.220
	(0.592)	(0.471)	(0.499)
Internal Migration	-0.001	0.029	0.024
	(0.016)	(0.018)	(0.014)
Int'l Migration	-0.055**	-0.037*	-0.018
	(0.022)	(0.021)	(0.032)
Self-Protection	0.038***	0.031***	0.074***
	(0.011)	(0.010)	(0.014)
Past Victimization	0.294***	0.252***	0.093***
	(0.046)	(0.042)	(0.032)
Male-Female Ratio	-0.099	-0.761**	-0.655
	(0.206)	(0.384)	(0.438)
College	-0.048	-0.025	0.085*
	(0.039)	(0.039)	(0.047)
Unemployment	-0.057	-0.009	0.049*
	(0.038)	(0.027)	(0.027)
Homicide Rate	-0.014	0.049***	0.025***
	(0.014)	(0.015)	(0.008)
Female Head	0.042	0.006	0.152***
	(0.053)	(0.046)	(0.049)
Low Education Head	-0.002	0.003	0.041
	(0.033)	(0.026)	(0.029)
Constant	0.788	9.725**	-11.851*
	(6.282)	(4.821)	(6.233)
Observations	698	883	851
Rho	0.016*	0.016*	0.050***
	(0.009)	(0.009)	(0.010)

Notes: MLE Estimates. Robust standard errors in parenthesis. ***, **, * represent statistical significance at the 1%, 5%, and 10% respectively.
Source: Own elaboration.

Some results are expected to vary between years in part because the sample for each year does not necessarily include the same households or municipalities. To account partially for this, the spatial dependence model using the inverse of distance and the nearest five neighbors approach is applied using only municipalities surveyed in all 3 rounds. Table A1 in the appendix lists the municipalities included in this restricted sample. This intentional truncation renders the working sample no longer representative and the sample size is reduced significantly, but the results might be used to discuss whether or not the spillover effects of crime are intensifying, constant, or disappearing.[15]

15 Larger municipalities are more likely to be in all rounds, so the restricted sample, which accounts for around 1/6 of the municipalities, accounts for around 40 percent of the population. Solutions to the sample selection

As before, the inverse of distance and the nearest five neighbors approach result in similar results, so we present only the results using the inverse of distance.

Table 6 shows that the estimates for population size, self-protection rates, and previous victimization rates continue to be statistically significant and very consistent across years. The main differences in results are for the latest round, 2010. Table 6 shows significant differences with respect to rural condition, internal and international migration, male-female ratio, college rate, homicide rate, and the female head rate. Again, the restricted sample includes only municipalities surveyed in all rounds, so these differences might be due to different households being surveyed in different years or to changing conditions related to property crime in Mexico. As mentioned before, self-protection rate measures the level of awareness about insecurity and the general perception of crime in the community. Prior victimization rate, on the other hand, represents the percentage of households reporting at least one member has been a victim of a crime the year prior to the survey and represents in part the presence of good crime opportunities for criminals. Taken together, the policy implications of the results might be that crime fighting resources are allocated more efficiently when directed toward large communities and to communities with high percentage of prior victims and to communities with large incidence of self-protection measures.

Table 6
Spatial dependence model (Inverse distance, restricted sample)

Dependent Variable: Victimization Rate			
	2007	2008	2010
Border	2.773***	0.357	1.036
	(0.981)	(1.049)	(0.954)
Rural	-0.734	-0.685	-1.803***
	(0.700)	(0.602)	(0.643)
Population	0.004***	0.002*	0.005**
	(0.001)	(0.001)	(0.001)
Marginalization	-1.040	-0.337	1.690*
	(0.957)	(1.039)	(1.009)
Internal Migration	-0.003	0.017	0.035*
	(0.026)	(0.023)	(0.020)
Int'l Migration	-0.060*	-0.113***	0.005
	(0.031)	(0.030)	(0.060)
Self-Protection	0.057***	0.041**	0.086***
	(0.017)	(0.017)	(0.021)

are proposed in Flores-Lagunes and Schnier (2008) in the form of a type II Tobit model with a sample selection model, estimates of the inverse Mills ratio, and its inclusion in the outcome model. However, and given the main goal of the paper, the working sample is used to assess whether or not the spillover effects of crime are intensifying, constant, or disappearing

Past Victimization	0.295***	0.287***	0.132***
	(0.048)	(0.045)	(0.038)

	2007	2008	2010
Male-Female Ratio	1.329**	-0.935	-1.595**
	(0.681)	(0.654)	(0.812)
College	-0.033	-0.042	0.152***
	(0.049)	(0.054)	(0.060)
Unemployment	0.058	0.014	-0.061
	(0.049)	(0.047)	(0.054)
Homicide Rate	-0.013	0.032	0.024**
	(0.018)	(0.023)	(0.012)
Female Head	0.080	-0.023	0.215***
	(0.072)	(0.079)	(0.084)
Low Education Head	0.020	0.043	0.035
	(0.059)	(0.052)	(0.057)
Constant	-3.597	9.857	-0.989
	(8.232)	(8.056)	(10.721)
Observations	411	411	411
Rho	-0.030	0.066**	0.100***
	(0.041)	(0.030)	(0.028)

Notes: MLE Estimates. Robust standard errors in parenthesis. ***, **, * represent statistical significance at the 1%, 5%, and 10% respectively.
Source: Own elaboration.

Finally, the estimate for the spatial dependence coefficient estimate is not statistically significant for 2007. The coefficient estimate is only statistically significant for 2008 and 2010, but it's significantly larger for 2010. It should be noted here that, for the most part, the decision rule for the presence of spatial dependence effects in municipality level property crime in Mexico do not depend on the choice of the weighting matrix or the set of covariates used. Taken together, these results can be interpreted as evidence that property crime in Mexico is becoming more prevalent and there is a diffusion mechanism that appears to be growing stronger in more recent years. Furthermore, the coefficient for the homicide rate is statistically significant only for 2010, suggesting that the changing conditions in Mexico regarding property crime rates is also significantly correlated with increasing levels of more serious types of crime.

■ *Conclusions*

Using nationally representative victimization data for several years, this study considers the determinants of municipality level property crime rates in Mexico. Baseline results show that population size, self-protection rates, and prior victimization rates are the stronger predictors of victimization rates. These covariates are consistently, positively, and statistically correlated with property crime rates for all years and specifications.

Different tests are applied for each round to consider the presence of spatial dependency in crime rates. All tests for each year reject the null hypothesis of spatial independence.

We explore different ways to define the weighting matrix W, but the hypothesis testing rule for spatial dependency for the most part does not depend on the form of the weighting matrix or the set of covariates used. Having rejected the null hypothesis of spatial independence for each year, we consider the appropriate way to model municipality level property crime in Mexico, while controlling explicitly for the presence of spatial dependence effects. In most cases and based on model selection criteria, the spatial lag model is preferred over the spatial error model for each year separately.

The main spatial lag model results show that population size, self-protection rates, and prior victimization rates continue to be positively and statistically correlated with municipality level property crime rates. In terms of spatial dependency, the results suggest that spatial dependence effects are present and are becoming stronger, suggesting growing spillover effects in property crime in Mexico.

The results from this study might help policy makers to develop and implement more efficient measures to fight property crime and other forms of crime in Mexico. The main specification results suggest that areas with high homicide rates and prior victimization rates are significantly more likely to continue suffering from high property crime rates. Moreover, the evidence suggests that spillover effects are getting stronger, which gives a special sense of urgency to the need to address the problem of crime and victimization in Mexico. Failing to act effectively and promptly will result most likely in significant economic and social losses for Mexico.

■ *Appendix*

Table A1

- *Aguascalientes*

Aguascalientes
Asientos
Calvillo
Jesús María
Rincón de Romos
Llano, El
San Francisco de los Romo

- *Baja California*

Ensenada
Mexicali
Tecate
Tijuana
Comondú
Mulegé
Paz, La
Cabos, Los

- *Campeche*

Calkiní
Campeche
Carmen
Champotón
Hecelchakán
Hopelchén
Escárcega

- *Coahuila*

Acuña
Frontera
Jiménez
Matamoros
Monclova
Múzquiz
Piedras Negras
Sabinas

- *México*

Almoloya de Juárez
Apaxco
Atenco
Atizapán de Zaragoza
Atlacomulco
Calimaya
Coacalco de Berriozábal
Cuautitlán
Chalco
Chimalhuacán
Ecatepec de Morelos
Huixquilucan
Ixtapaluca
Ixtapan de la Sal
Ixtlahuaca
Jilotepec
Lerma
Metepec
Morelos
Naucalpan de Juárez
Nezahualcóyotl
Nicolás Romero
Ocoyoacac
Oro, El
Otzolotepec
Paz, La
San Mateo Atenco
Tecámac
Tenancingo
Teotihuacán

- *San Luis Potosí*

Cedral
Ciudad Fernández
Ciudad Valles
Ebano
Matehuala
Ríoverde
San Luis Potosí
Santa María del Río
San Vicente Tancuayalab
Soledad de Graciano Sánchez
Tamazunchale
Venado
Matlapa

- *Sinaloa*

Ahome
Concordia
Culiacán
Elota
Escuinapa
Fuerte, El
Guasave
Mazatlán
Mocorito
Navolato

- *Sonora*

Agua Prieta
Cajeme
Cananea
Empalme
Guaymas
Hermosillo
Navojoa
Saltillo
San Juan de Sabinas
San Pedro
Torreón

- *Colima*

Colima
Comala
Coquimatlán
Cuauhtémoc
Manzanillo
Minatitlán
Tecomán
Villa de Alvarez

- *Chiapas*

Comitán de Domínguez
Huixtla
Margaritas, Las
Motozintla
Ocosingo
Palenque
Pichucalco
San Cristóbal de las Casas
Tapachula
Tonalá
Tuxtla Gutiérrez
Venustiano Carranza

- *Chihuahua*

Camargo
Cuauhtémoc
Chihuahua
Juárez
Nuevo Casas Grandes
Uruachi

- *Distrito Federal*

Alvaro Obregon
Azcapotzalco
Benito Juárez
Coyoacán
Cuajimalpa de Morelos
Cuauhtémoc

Gustavo A Madero
Iztacalco
Iztapalapa
La Magdalena Contreras
Miguel Hidalgo
Milpa Alta
Texcoco
Tlalmanalco
Tlalnepantla de Baz
Toluca
Tultitlán
Zinacantepec
Cuautitlán Izcalli
Valle de Chalco
Solidaridad

• *Michoacán*
Apatzingán
Buenavista
Huandacareo
Irimbo
Jacona
Maravatío
Lázaro Cárdenas
Morelia
Ocampo
Tacámbaro
Tuxpan
Uruapan
Villamar
Zamora
Zitácuaro

• *Morelos*
Atlatlahucan
Axochiapan
Ayala
Cuautla
Cuernavaca
Emiliano Zapata
Huitzilac
Jiutepec
Puente de Ixtla
Temixco
Tepalcingo
Tepoztlán
Tlaltizapán
Tlaquiltenango
Xochitepec
Yautepec
Yecapixtla
Zacatepec de Hidalgo
Zacualpan de Amilpas
Nogales
Puerto Peñasco
San Luis Río Colorado
San Ignacio Río Muerto

• *Tabasco*
Balancán
Cárdenas
Centro
Comalcalco
Cunduacán
Huimanguillo
Jalpa de Méndez
Jonuta
Macuspana
Nacajuca
Paraíso

• *Tamaulipas*
Altamira
Ciudad Madero
Mante, El
Matamoros
Nuevo Laredo
Reynosa
Río Bravo
Tampico
Valle Hermoso
Victoria
Xicoténcatl

• *Tlaxcala*
Apizaco
Calpulalpan
Carmen Tequexquitla, El
Chiautempan
Huamantla
Hueyotlipan
Ixtacuixtla
Mazatecochco
Contla de Juan Cuamatzi
Tepetitla de Lardizábal
Natívitas
Panotla
San Pablo del Monte
Santa Cruz Tlaxcala
Teolocholco
Tetla de la Solidaridad
Tláhuac
Tlalpan
Venustiano Carranza
Xochimilco

• *Durango*
Durango
Gómez Palacio
Oro, El
Peñón Blanco
Santiago Papasquiaro
Nuevo Ideal

• *Guanajuato*
Abasolo
Acámbaro
Allende
Celaya
Guanajuato
Irapuato
León
Moroleón
Pénjamo
Salamanca
Salvatierra
San Felipe
San Francisco del
Rincón
Santa Cruz
Xichú
Yuriria

• *Guerrero*
Acapulco de Juárez
Alcozauca de Guerrero
Atoyac de Alvarez
Coyuca de Benítez
Coyuca de Catalán
Chilapa de Alvarez
Chilpancingo de los
Bravo
Iguala de la
Independencia
José Azueta
Juan R. Escudero
Pungarabato
San Marcos
Taxco de Alarcón
Teloloapan
Tlapa de Comonfort

• *Nayarit*
Acaponeta
Ahuacatlán
Compostela
Huajicori
Xalisco
Ruíz
Santiago Ixcuintla
Tecuala
Tepic
Tuxpan
Bahía de Banderas

• *Nuevo León*
Anáhuac
Apodaca
Aramberri
Galeana
San Pedro Garza García
General Escobedo

Guadalupe
Juárez
Montemorelos
Monterrey
San Nicolás de los Garza
Santa Catarina

• *Oaxaca*
Acatlán de Pérez Figueroa
Ciudad de Huajuapan de León
Oaxaca de Juárez
San Agustín Yatareni
San Antonio de la Cal
San Juan Bautista Cuicatlán
San Juan Bautista Tuxtepec
San Juan Lalana
San Sebastián Tutla
Santa Catarina Juquila
Santa Cruz Xoxocotlán
Santa Lucía del Camino
Tlalixtac de Cabrera

• *Puebla*
Amozoc
Atlixco
Coronango
Chiautzingo
Chiconcuautla
Tlaxcala
Tlaxco
Tocatlán
Totolac
Xicohtzinco
Yauhquemecan
Zacatelco
San Juan Huactzinco

• *Veracruz*
Amatlán de los Reyes
Boca del Río
Camerino Z. Mendoza
Coatepec
Córdoba
Coscomatepec
Cosoleacaque
Choapas, Las
Xalapa
Medellín
Minatitlán
Nogales
Orizaba
San Andrés Tuxtla
Temapache
Tihuatlán
Túxpam
Veracruz
Tres Valles

• *Hidalgo*
Acatlán
Atotonilco de Tula
Huejutla de Reyes
Ixmiquilpan
San Felipe Orizatlán
Pachuca de Soto
Tepeapulco
Tula de Allende
Tulancingo de Bravo
Zacualtipán de Angeles

• *Jalisco*
Arandas
Atotonilco el Alto
Autlán de Navarro
Ayotlán
Barca, La
Zapotlán El Grande
Cocula
Cuquío
Guadalajara
Lagos de Moreno
Ocotlán
Ojuelos de Jalisco
Poncitlán
Puerto Vallarta
Quitupan
Salto, El
San Juan de los Lagos
Tala
Tlajomulco de Zúñiga
Tlaquepaque
Tonalá
Zapopan
Zapotlán del Rey
Puebla
San Andrés Cholula
San Martín Texmelucan
Tehuacán
Tlatlauquitepec
Xicotepec

• *Querétaro*
Amealco de Bonfil
Pinal de Amoles
Arroyo Seco
Cadereyta de Montes
Colón
Corregidora
Huimilpan
Marqués, El
Pedro Escobedo
Querétaro
San Juan del Río
Tequisquiapan

• *Quintana Roo*
Cozumel
Felipe Carrillo Puerto
Isla Mujeres
Othón P. Blanco
Benito Juárez
Lázaro Cárdenas
Solidaridad
Juan Aldama
Juchipila
Mazapil
Nochistlán de Mejía
Pánuco
Pinos
Río Grande
Sain Alto
Sombrerete
Tepetongo
Tlaltenango
Villa de Cos
Villa García
Zacatecas

• *Yucatán*
Chemax
Hocabá
Hoctún
Hunucmá
Kanasín
Mérida
Motul
Progreso
Ticul
Tizimín
Umán

• *Zacatecas*
Fresnillo
Guadalupe
Jerez

Municipalities included in the three rounds

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