Structural factors and the "War on Drugs" effects on the upsurge in homicides in Mexico

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Abstract

Violence has increased all around Mexico in the last years, reflecting an uprise in the rate of homicides, and especially after some federal intervention took place to fight the drug cartels in some states. In this paper we use data at the municipal level to link social and institutional factors with the rates of homicides. We exploit the entrance for federal army interventions in 2007 and 2008 in some states to fight drug cartels. Using different estimation methods, we find that inequality, access to social security and income, as well as local provision of security and law are relevant in explaining homicides. We also find that the army interventions have increased not only drug related homicides, but also general homicides in municipalities under intervention compared with those with no intervention.

Keywords: homicides, inequality, drugs, army intervention

JEL: C23, D31, H56, K42

1. Introduction

Mexico has experienced during the last years an increase in the rates of violence, especially measured with homicides. According to the Global Peace Index presented by the Institute for Economic and Peace, in 2011 Mexico was ranked 121 among 153 countries, where the 153 is the most violent, while in 2007 for example was ranked in place 79th.

Even though Mexico has become worldwide infamous for the high rates of female homicides in the border city of Ciudad Juarez, it is also true that such city has comparable rates to other Mexican cities and are not statistically significant from those cities after controlling for other local factors (Alburquerque and Vemala, 2008), pointing to a more spread violent phenomena than thought.

Besides the fight between the different drug cartels to control geographical areas, in 2007 (technically at the end of 2006) the federal government, in agreement with some states and upon request from the governor asking for more army presence, started the joint military operations (Operativos Conjuntos Militares), and then those states experienced an increase in homicides, sparkling a debate about to what extend such interventions are the main factor explaining the uprising in homicides experienced since then.

Even though several studies have analyzed how structural factors such as poverty, education, racial composition, and changes in family structure are important explanations for homicides rates (Land et al, 1990; Baller et al, 2001, among many others), few studies have tried to analyze structural changes in geographical homicides (Messner et al, 2005) or specific police intervention in cities (de Mello and Schneider, 2010). For Mexico, De la Torre (2008) analyzed how inequality has been the main factor behind social violence, but only some studies have correlated homicides with other factors for adolescent homicides (Gonzalez-Perez et al, 2009), or compared feminicide rates in several cities along the border with other areas (Alburquerque and Vemala, 2008), or even the expiration of a gun law in the US affecting crime in Mexico (Chicone, 2011; Dube et al, 2011), but none have related social and economic factors, the spatial effects, or the specific joint intervention of the army in some states, with the trend in homicides and the uprise experienced during the last years.

The debate in Mexico, however, can be mostly found in the public opinion field rather than in the academics. As example, see the discussions in the magazine Nexos, where several regular contributors have tried to argue how the intervention could be affecting in a spiral of violence and how the strategy to fight cartels can be improved (Escalante, 2011; Merino, 2011; Guerrero, 2010). One conclusion in all of them is the need for analysis to have a better understanding of violence and what is happening.

In this study, we analyze how structural social and economic factors, such as inequality and other social variables, as well as institutional, have an incidence on the rates of homicides at the municipal level in Mexico. Moreover, we explore the fact that some of the states entered at different years (2007 and 2008) at the army intervention offered by the federal government, while other states still remain without entering into such interventions, to explore the possibility that part of that uprising is due to those interventions. In order to do so, we put together different data sets, and contrast different estimation models including the spatial, and negative binomial models, exploring as well a difference-in-difference model with the panel structure of the data.

This paper is structured as follows: in section 2 we present the literature relating social and institutional factors to homicides, as well as some literature on specific programs and the incidence on the rate of homicides. Section 3 presents the models to be used and the data, analyzing the patterns of homicides and covariates. Section 4 analyses the results of the models as in OLS, spatial, and panel with difference in difference. Finally, section 5 outlines some conclusions and implications.

2. Previous literature on factors related to crime

Socioeconomic factors have been widely studied as main determinants of crime levels, especially for developed countries, where the data allows for such analysis. As Tcherni (2011) points, there are three structural factors, which she call The Big Three, that have usually accounted for most explanations on determinants of homicidal violence: poverty and low education, the racial composition of the population, and the disintegration of the structure of families.

Analyzing the links between poverty and inequality with violent crime has been a matter of debate since a theoretical framework is lacking, and the empirical analysis provides with different conclusions. Even though for some the condition of poverty is a detonator of violence given that those poor may want to achieve more material rewards and therefore will be willing to commit criminal offenses (see for example Merton, 1938). According to Patterson (1991), there is no such relation between poverty and crime, as when controlling adequately for other relevant variables, the relation becomes spurious for homicide or other felonies. Inequality however has become relevant in explaining some measures of crime (Fajnzylber et al, 1998; Kelly, 2000, among others).

For some, inequality and poverty creates social disorganization, where the society cannot control the informal activities of the individuals (Shaw and McKay, 1942), or making those in the low scale of income to receive lower returns from legal activities, therefore being attracted to illegal and more rewarding (Becker, 1968). De la Torre (2008) found for Mexico that inequality, in a context of growth, has been a main factor in the uprise of social violence, such as the Zapatista movement, or for other small movements. This author arguments that inequality is more related to the “social web” and since the perceived distance between those having less and those having more become a sense of dissatisfaction with, and unjustice of, the outcomes in a society and then becomes a factors of violence.

Education has usually pointed as one of the main factors increasing the awareness of consequences of illegal activities and thus higher education reduces criminal activities, while increasing social cohesion. However, education not necessarily has been found with a negative effect on crime. Ehrlich (1975) found, after controlling for income inequality, that education is positively and significantly related to some particular crimes in the US, which may be possible to the extent that education raises the marginal product of labor within the crime industry relative to other legal activities.[1] In Fajzinberg et al (1998) education levels are mostly not significant in explaining crime rates in Latin American countries.

Unemployment has also been studied as one factor increasing homicides and general crime. Even though there is no a theoretical framework linking unemployment with crime, most of the empirical research has found a positive link on property crimes (Lin,

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1 In analyzing the propensity to commit corruption in Mexico, Guerrero and Rodriguez-Oreggia (2008) find that the higher the educational level of the individual, the higher the probability of committing such acts, in a context of diluted provision of the state of law.

2008; Raphael and Winter-Ebmer (2001) and others also on violent crime (Hooghe et al, 2010). The labor market condition of the youth has also been hypothesized to exert an effect on crimes. In this regard, Ihlanfeldt (2007) focused on job accessibility of young within poor areas in cities and the relation with drug crimes, and using a short panel of data with fixed effect finds even modest improvements in jobs can reduce drug crimes in those areas. In general, it seems that local labor market opportunities are relevant for the development of crime, as Gould et al (2002) shows using data for the US and finding that low skilled unemployment and wages are determinants of crime, but especially that with increasing in the wages of low skilled the reduction in crime is substantial.

Other factors affecting homicides rates are how crowded are the areas (Kelly, 2000), local economic characteristics, racial composition and society disruption (Techerni, 2011). A highly fragmented society is more probable to avoid legal instances for resolving conflicts, which then are solved through violence (Heimer, 1997).

In addition the institutional capacity at the local level may be relevant for the pattern that homicides takes. The usual factor is the number of police, in the logic that enforcement is better provided with a larger number of them, which increases the costs for individual to commits law offenses. Levitt (1997) for example, discern the endogeneity between crime and allocation of police using electoral cycles in the US, finding for large cities that there is a negative effect on crime from the presence of more policemen. However, those results were replicated finding the effect to be no significant (see McCrary, 2002). In DiTella and Schragrodsky (2004) the event of a terrorist attack in Buenos Aires is used to isolate the effect of allocation of police on crime. They only find a significant effect reducing car theft in close blocks to those with more police.

In other study, de Mello and Schneider (2010) assessed the introduction of improvements in the provision of security in Sao Paulo on homicides. They use panel data linking the demographic structure, adoption of unified data, a database of criminals and regulations on fire arms possessions with a sharp drop in homicides comparatively with other Brazilian cities. Their findings suggest that the only factor explaining such drop in homicides is the change in demography in the long run. However, still needs this analysis to control for other addition variables that may have affected such decline in homicides.

Even the policies implemented in other areas may affect the rates of homicides in different places. For example, Chicoine (2011) used the expiration of the US federal assault weapons ban to estimate the effect on homicides in Mexico, using a difference-in-difference strategy with state level data and using as treatment states with drug cartels the author finds an increase of about 16.4% in homicides due to the expiration of the weapons ban in the US. In a similar vein, Dube et al (2011) also focus on homicides in Mexico as result of the same ban, and using municipalities close to the border with the Texas and Arizona ports of entry, compared to those next to California, they find an increase of about 40% due to the expiration and flows of guns to Mexico.

Other set of studies has focused on the geographical transmission of crimes. Baller et al (2001), for example, suggest that there are mechanism of transmission of crime for grouped geographical units, thus there is a need to use spatial tools to determine the effects of factors associated that can differ in geography. Using data for the US counties, they find persistent spatial autocorrelation, which means structural factors are not the only factors affecting crime.

Besides these strands of literature, another line of research has argued that the activity in the illicit drug market has an incidence on the levels of violent crime. In this regards there are two main streams of literature as identified by Ousey and Lee (2007). The first, the law enforcement and systemic violence models suggest that whenever drug markets become more active it is reflected in the increase in homicides, and those illegal activities are a form of self-help in a context where law is not well provided and enforced (see for example Black, 1983 and Goldstein, 1985). The second suggest that rises in homicides are due to the aging in drug participants and also that changes in structural factors are associated to movements in homicides related to the drug markets (Golub and Johnson, 1997; Zimring and Hawkins, 1997).

Grogger and Willis (2000) identified the rise in the use of cocaine in US metropolitan areas with data from the 1970 to 1991, using difference in difference in strategy with the entrance of illicit drug in the area and controlling for other unobserved differences, they find a 10% increase in crime rates including violent crime and homicides, due to the crack cocaine entrance. Messner et al (2005) analyzed for US cities the rise in what is called “homicide epidemic”, a period in the last two decades of the last century with a sharp increase in homicides, with rates even higher for young population. These authors find that such epidemic was the result of a diffusion process with significant earlier rises in cities with extreme socioeconomic deprivation.

In this paper we add to the literature the analysis of a country with a government that has declared a “war on narco”, and setting the entrance of federal forces in some states requiring such program at difference time. In doing so, there is a field for the analysis of the pattern of homicides in a country that already have been with comparative high levels of violence, and where social and institutional issues are a matter of concern: high levels of poverty and inequality, low wages and productivity, high regional differences in living conditions, and high corruption. In doing this we formally address the structure of the data by using different estimation techniques aiming to provide a robust analysis regarding contemporary factors associated with homicides in Mexico. In the next section we present the models for this analysis and the data to be used.

3. Models and Data

3.1 Data

a. Data on homicides

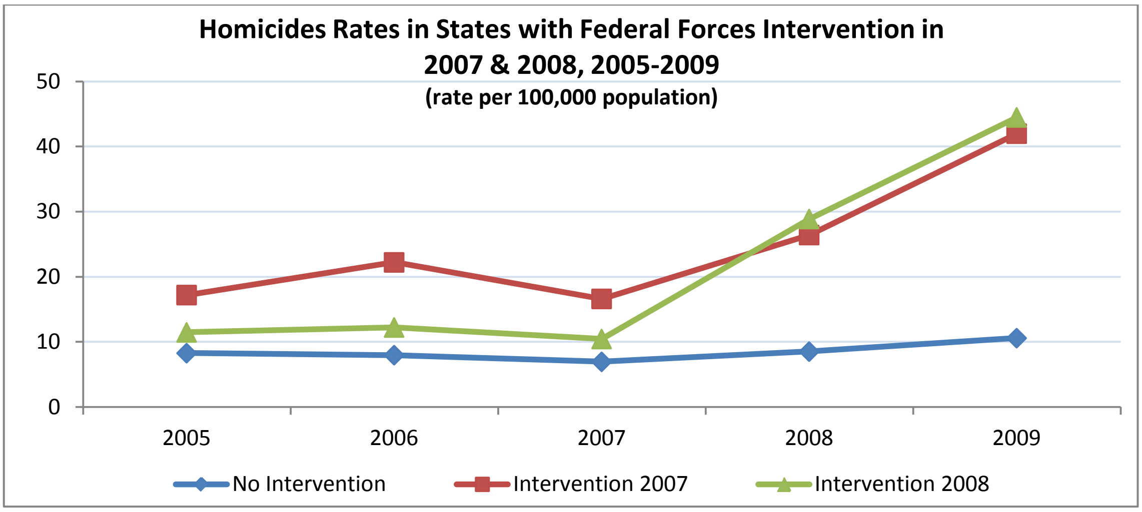
The federal government offered the states to start join army interventions with the purpose of containing and weakening the structure of drugs organization. These interventions are upon request from the governor of a state, who considers federal army can help to provide with security and fight the drug cartels. According to the federal government, such interventions are organized jointly with the states and with intelligent units. These interventions supposedly provide with intelligence, administration, and justice according to Presidencia de la República. States joined only in 2007 and 2008. In 2007 joined: Michoacán, Guerrero, and Baja California; and in 2008: Nuevo León, Tamaulipas, Chihuahua, Sinaloa and Durango.

We are interested in determining social and institutional factors affecting the increase of homicides in Mexico, in addition to determining the effect derived from the jointly army intervention between the central government and some states in 2007 and 2008. The data for homicides is published by INEGI. This database considers all types of homicides as in the international classification ICD-10 code(X85-Y09) covering the year 2005 through 2009.

Using this source, we standardize homicides in a rate per 100,000 inhabitants in each municipality. We first have to check whether there is a different pattern in the rates of homicides before and after the intervention according to the state of municipalities, which is presented the next Figure. We separated the ratio in states with intervention starting in 2007, in 2008, and without intervention.

Figure 1 displays the rates for homicides, where we can observe that there is a high increase in those states with interventions, compared with those without interventions. This may suggests that besides the interventions and fight on drug cartels, it seems that there is a spreading violent activity, measured as general homicides, that has coincided with the federal interventions

Figure 1



Source: Own calculations using data from INEGI

Besides to measure to what extent the increase in homicides has increased due to the interventions as it seems to be suggested from the previous graph, we will also consider the effects derived from other pre existing factors such as those social and institutional, which condition the evolution of the differences in those rates. In addition those covariates can shed some light on what factors are more related to the upsurge in homicides to which public policy can be designed and implemented. Since we have data in homicides at the municipal level, the regression models will use covariates mostly at that level, but some information is only available at the state level. One main issue is availability of the data for those covariates, since data at the municipal level depend mostly on census and other specific databases and surveys, our covariates are lagged to the period under analysis of homicide data which is 2005-2009. In this sense we have data previous to the implementation of the army interventions, and reduces the problem of endogeneity with homicides that could arise in the period.

b. Covariates

For selecting covariates, we are based on factors in the literature in the previous section. The rate of unemployment of the youth is one variable that may be determinant in the increase in homicides if we consider that the lack of opportunities may make crime attractive. Even though, as we previously mentioned, there is no consensus on such effect, we include this variable as a proxy for opportunities available for the young. We take data from the 2000 Population Census.

Other covariate included is the average years of schooling in the municipality. Education is considered a predictor of violent crime since it also may represent possibilities to develop, while also more educated individuals may be more conscious of the negative effect of violence. Data here is the average years of schooling in each municipality from the 2000 Population Census.

Inequality, as mentioned previously, may have an incidence on social dissolution and lowering rewards for low income individuals to be in legal activities. Here we have the Gini Index at the municipal level as calculated by CONEVAL for 2005. A complementary variable is poverty. However, in most of the studies this variable is correlated with inequality and other social factors making difficult to separate the effect. Here we include the average monthly income of a household in the municipality, from the 2000 Population Census.

Heterogeneity of the population and social fragmentation also may affect the rates of homicides and violence. Here we have measures of the percentage of population which is indigenous, the percentage of births without social security, and the percentage of interstate migrants. Data for these variables are from the 2000 Population Census and the 2005 Counting of Population.

We also include the percentage of population working in agriculture. This variable proxies on the one hand for economic opportunities in the area, since earnings associated with agriculture are usually lower, and on the other for how attractive is the local market for drug related activities. The higher the agriculture activity, the lower the acquisition power of individuals for the market of drugs. This variable is measured with the 2000 Population Census. In addition we control for urban areas with a dummy variable. We introduce a dummy if the municipality has bee identified as port for entry of drugs to the country as reported in Stratford (2011).

We introduce some controls for institutional characteristics of the localities. Using data from the 2004 Surveys to Municipal Presidents, we identified with a dummy those municipalities that provided with public security with local municipal forces, or with another dummy if the provision was with the state forces. In addition, we took data from administrative records reported by INEGI in 2005, at the state level, with the ratio of sentences issued relative to preliminary investigations. This is a proxy for the administration of justice in that state.

One variable that has been addressed in several studies in developed countries, the number of police, is not available at the municipal level, and when is possible to get some figures on police at the state level, reports are for different years according to when the state reports. Also the criteria for reporting is unclear, for example some report police labeled as “local corporation” or “preventive forces” that for some is municipal, and for others state level, or both. When contrasting the few sources, the figures differ, and some report about 400 municipalities without any own police force. However, to some extent we account for this variable when using the dummies for provision of public security at the municipal and state level mentioned above.[2]

In addition, since the implementation of the interventions is a response to the homicides, we will instrument both interventions using variables such as the rate of growth of corruption for getting back a stolen car, and the rate of growth of corruption for getting free from ministerial justice, both indicators published by transparency Mexico, the branch of Transparency International. Also we use distance to the next border with the US, distance to state’s capital, and differencing for interventions 2007 a dummy for governor election in that year, while for intervention 2008 a dummy for governor election in 2009 (in 2008 there were no elections).

The covariates are presented in descriptive statistics in Table 1.

[2] Citizen participation would also be relevant, however the measure from the Encuesta de Presidentes Municipales leaves the president to declare subjectively how this participation is in the area.

Table 1 Descriptive Statistics

Variable	Year	Description	Source	Mean	SD
Total Homicide Rates	2005-2009	Total Homicides Rates per 100,000 population	Estadisticas Vitales, Datos de Mortalidad, INEGI.	12.5	18.6
Drug Homicide Rates	2007-2010	Drug related homicides Rates per 100,000 population	Base de Datos de Fallecimientos Ocurridos por Presunta Rivalidad Delincuencial, Presidencia de la Respublica. (last access January 2011)	7.5	24.6
Youth Unemployment	2000	Percentage of economically active population aged 15 to 24 years old unemployed	Censo General de Poblacion y Vivienda 2000, INEGI.	0.2	0.7
Schooling Years	2000	Average years of schooling	Censo General de Poblacion y Vivienda 2000, INEGI.	1.6	0.3
Gini Index	2005	Gini Index	Consejo Nacional de Evaluacion de la Politica Nacional, CONEVAL.	-0.9	0.1
Housheold Income	2000	Average (Monthly) Household Income	Censo General de Poblacion y Vivienda 2000, INEGI.	7.6	0.8
% Indigenous Population	2000	Percentage of Indigenous population	Censo General de Poblacion y Vivienda 2000, INEGI.	1.1	2.3
% Births without SS	2005	Percentage of Births without Social Security	Secretaría de Salud/Dirección General de Información en Salud, Estimaciones con base en las Proyecciones de la Población de México 2005 - 2030.	4.2	0.4
% Agricultural Employment	2000	Percentage of population employed in the agriculture sector	Censo General de Poblacion y Vivienda 2000, INEGI.	3.5	1.0
% Interstate Migrants	2005	Percentage of inter-state migrants	Conteo de Poblacion y Vivienda 2005, INEGI.	2.2	1.2
Local Public Security	2004	Public Security provided by local municipal police forces (dummy variable)	Encuesta Presidentes Municipales 2004, Secretaria de Desarrollo Social.	0.8	0.4
State Public Security	2004	Public Security provided State police forces (dummy variable)	Encuesta Presidentes Municipales 2004, Secretaria de Desarrollo Social.	0.1	0.3
% Sentence/Preliminary Investigation	2005	Percentage of Sentences relative to Preliminary Investigation	Registros administrativos, Estadisticas judiciales en materia penal, INEGI.	3.0	0.5
Urban	2005	Municipality with population size >= 15,000 inhabitants (dummy variable)	Own calculation with data from INEGI.	0.4	0.5
Port	2010	Municipality with port of enty or exit of drug trafficking (dummy variable)	Stratford Global Intelligence Report 2010.	0.0	0.1
Cars	2001, 2005	Paid a bribe to recover a stolen car. Growth 2001-05	National Index of Corruption and Government, Transparencia Mexicana.	-0.2	0.6
Arrested	2001, 2005	Paid a bribe to avoid being arrested. Growth 2001-05	National Index of Corruption and Government, Transparencia Mexicana.	-0.5	0.7
Elections 2007	2007	Election for governor in 2007		0.1	0.3
Elections 2009	2009	Election for governor in 2009		0.1	0.3
Distance to the border		Distance from each municipality to the U.S. border	Own elaboration.	739.9	269.4
Distance to capital		Distance from municipalities to each State capital	Own elaboration.	105.4	75.7

Note: Continuous variables in logs

One concern is how covariates may be correlated affecting the estimates (Kelly, 2000). For this reason we display the correlations between covariates in Table 2.

Table 2 Correlation in covariates

TABLE. CORRELATION AMONG THE VARIABLES

	Total Homicide Rates	Drug Rivarly Homicide Rates	Youth Unemployment	Schooling Years	Gini Index	Houshehold Income	% Indigenous Population	% Births without SS	% Agricultural Employment	% Interstate Migrants	Local Public Security	State Public Security	% Sentence/Preliminary Investigation
Total Homicide Rates	1												
Drug Rivarly Homicide Rates	0.59	1											
Youth Unemployment	0.03	0.06	1										
Schooling Years	-0.02	0.09	0.19	1									
Gini Index	0.10	0.11	0.13	0.15	1								
Houshehold Income	0.01	0.16	0.19	0.33	0.40	1							
% Indigenous Population	-0.04	-0.17	-0.17	-0.33	-0.20	-0.40	1						
% Births without SS	0.05	-0.06	-0.23	-0.27	-0.13	-0.50	0.24	1					
% Agricultural Employment	0.07	-0.03	-0.35	-0.32	-0.20	-0.62	0.27	0.61	1				
% Interstate Migrants	-0.05	0.03	0.22	0.24	0.15	0.30	-0.25	-0.29	-0.41	1			
Local Public Security	0.01	0.08	0.01	0.07	0.14	0.16	-0.09	-0.06	-0.01	0.03	1		
State Public Security	0.00	-0.03	-0.02	-0.01	0.05	0.03	-0.06	-0.01	-0.03	0.00	-0.49	1	
Investigation	0.10	0.22	0.03	0.16	0.30	0.30	-0.34	-0.18	-0.12	0.05	0.12	0.03	1
Urban	-0.05	-0.01	0.17	0.17	0.31	0.44	-0.20	-0.24	-0.39	0.21	0.08	0.04	0.24
Port	0.04	0.05	0.04	0.05	0.02	0.13	-0.02	-0.15	-0.18	0.11	0.00	0.00	0.06
Cars	0.03	0.04	0.11	0.15	0.27	0.22	-0.29	-0.01	-0.13	0.15	0.05	0.08	0.05
Arrested	0.12	0.18	0.13	0.20	0.09	0.21	-0.10	-0.17	-0.16	0.10	0.15	0.00	0.25
Elections 2007	-0.01	-0.01	-0.06	-0.04	-0.11	0.03	0.08	-0.02	0.00	-0.08	0.14	-0.06	0.24
Elections 2009	0.02	0.10	0.04	0.18	0.08	0.17	-0.17	-0.18	-0.10	0.04	0.02	0.04	0.29
Distance to the U.S. border	-0.11	-0.34	-0.15	-0.36	-0.18	-0.38	0.46	0.32	0.27	-0.19	-0.12	-0.01	-0.42
Distance to capital	0.24	0.25	0.00	0.03	0.09	0.05	-0.02	-0.08	0.12	0.02	0.10	0.01	0.24

Correlations seem to be stronger for the Gini index, and urban municipalities, and the ratio of sentences to preliminar investigations. Additionally we will perform variance inflation factor to test for multicollinearity of the covariates after running a regression.

c) The spatial variation of homicides

The first step of the spatial analysis consists in determining whether our dependent variable is a stochastic phenomenon or on the contrary, follows particular spatial patterns resulting in spatial association in the data. The statistic Moran's I is widely employed for testing the presence of spatial dependence in observations[3]. It provides a global statistic for assessing the degree of spatial autocorrelation between observations as a function of the distance separating them. As showed in Table 3, the test for spatial autocorrelation indicates significance levels across years for both types of homicides, but more important is the change in the magnitude of the Moran's I. The magnitude of

[3] Another measure commonly used to identify spatial dependence/independence is the Geary's *c* statistic. For a more detailed description of various ways, globally and locally, of identifying spatial nature of the data we refer to Getis et al. (1996).

significant clusters for general homicides rates in 2009 is almost twice as compared to 2005.

Table 3 Global Moran's I for Testing Spatial Autocorrelation in Total Homicides

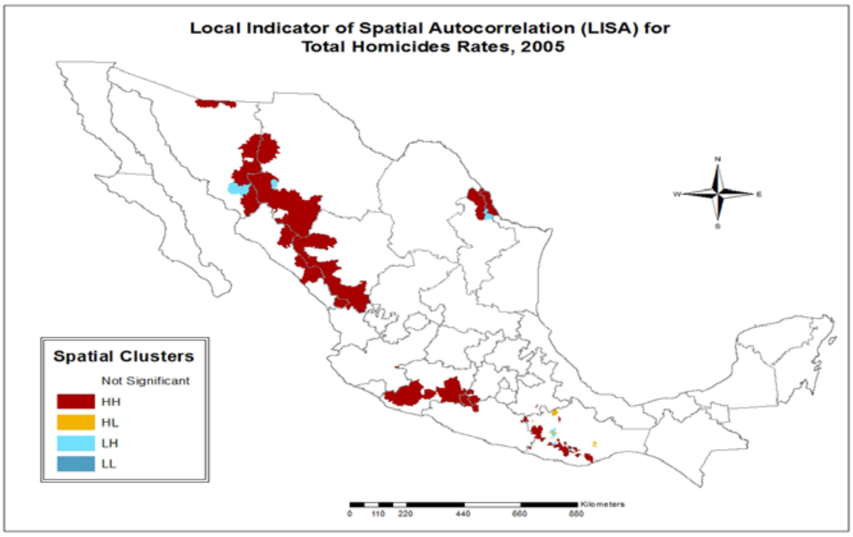
	Year	
	2005	2009
Total Homicides	0.158***	0.383***

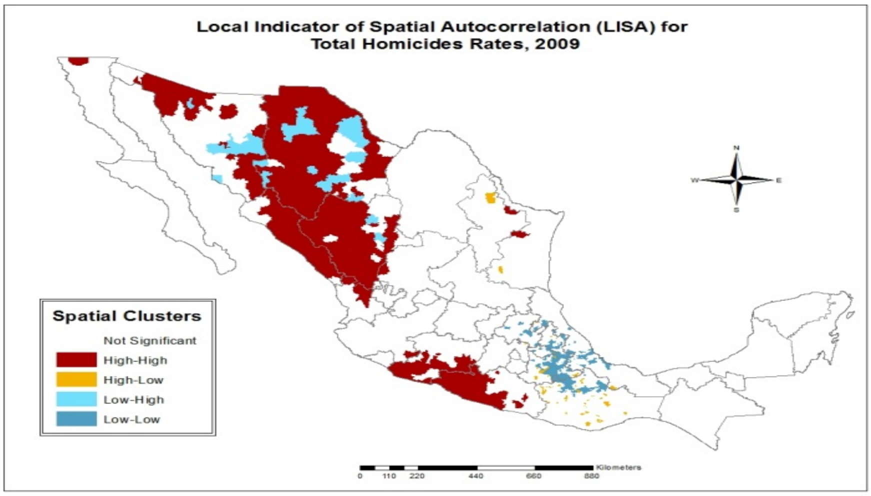
*** Significant at 1% level.

Nonetheless, global statistics provide only a limited set of spatial association measurements by not considering the case of local variations in spatial autocorrelation. Recently, various forms of local measures, such as local Moran's I and Geary's *c*, have been developed for use in cases where local variation is suspected. In the case of local Moran's I or as known, local indicator of spatial association (LISA), it allows the decomposition of the global indicator which in turn helps to explore the extent of significant clustering with values similar in magnitude around a particular observation (Lloyd, 2007).

In search of local variations of spatial autocorrelation in the homicides rates, we perform the respective LISA statistic. Figure 2 show the distribution of significant spatial clusters of total homicides for the years 2005 and 2009. The maps show the distribution of four different types of spatial clustering: a) High-High (HH): a municipality with high value and its neighbors too; b) High-Low (HL): a municipality with a high outlier and its neighbors low values; c) Low-High (LH): a municipality with an low outlier and its neighbors high values; d) Low-Low (LL): a municipality with a low value and its neighbors too. Note that HH local clusters of homicides exhibits, first an increase in the clustering, and a well-defined corridor of municipalities within the states of Chihuahua, Durango, Sinaloa and Sonora, and to a lower extent within Guerrero and Michoacán.

Figure 2





3.2 Model

We are interested in measuring the effects of social factors, and also of the joint interventions between stats and the federal government against crime, on the homicides rates. Several studies present cross section or average rates in a regression controlling for other covariates. Here, we present two models, first in a cross section setting averaging the annual rates of homicides to use as dependent variable, and in a second model we implement a difference-in-difference strategy to differentiate the implementation of the joint interventions. Additionally, since we are dealing with municipal data, we measure the extent of the spatial effects in a spatial regression.

In the cross section data, the dependent variable h is the average of the annual rate of homicides per 100 thousand inhabitants, with a model as follows:

$$h_j=\alpha+\beta 0X_j+ \beta\ 1I_j+\varepsilon_j \qquad (1)$$

Where X is a set of social and institutional variables in municipality j, I denotes if the municipality is in a state entering the force intervention (2007 or 2008) and ε is the error term. However, under this specification the dependent variable only takes into account positive values, while in homicides this variable is a non negative integer (0, 1, 2, etc); that is, it does not consider zeros or is left truncated. Truncation leads to inconsistent parameters until the model is modified to include them (Cameron and Trivedi, 2005). Therefore, count data model can model the specification to include zeros following a Poisson distribution with parameter λ related to x:

$$\ln \lambda i = x'_i\beta \qquad (1a)$$

This specification can be corrected for overdispersion if that is the case, as will be explained in the results section, we will be using instead of a Poisson a Negative Binomial specification which relaxes the assumption that the variance of the dependent equals the mean (Cameron and Trivedi, 2005).

One drawback is that our dependent variable may not be randomly distributed among municipalities, raising the possibility to use spatial analysis techniques. As discussed above, certain municipalities exhibit high values of homicides rates leading thus the existence of clustering within regions and states. Therefore, we can formally address such spatial autocorrelation in order to ameliorate potential bias issues when modeling factors associated with our dependent variable.

In order to empirically address the spatial autocorrelation resulting from the uneven spatial distribution of homicides across municipalities, we estimate spatial econometric models. In doing this we account spatial dependence on the relationship between homicides rates and social factors previously discussed. A general regression equation modeling spatial dependence can be represented as follows:

$$Y = \rho WY + X\beta + \varepsilon$$
$$\varepsilon = \lambda W\varepsilon + \mu \qquad (2)$$
$$and\ \mu \sim N(0, \sigma^2 I)$$

where Y represents the vector of dependent variables, X is a matrix of independent variables, ε is a vectors for random terms, and W is the spatial weight matrix[4]. These spatial weight matrices represent the "degree of potential interaction" between neighboring locations (Anselin et al., 1988). The parameters ρ and λ are scalar spatial parameters measuring the degree and type of spatial dependence. For example, suppose the case in which $\rho \neq 0$ and $\lambda=0$, the resulting is what is called a spatial lag model or spatial autoregressive model:

[4] Typically, the elements of the weight matrix are derived usually from information about contiguity in the observations. Contiguity means that an observation shares a common boundary with one or more observations. In general, there are three kinds of weight matrices: contiguity (either rook or queen contiguity), distance and k-nearest neighbor. For more information about the properties of each one of spatial matrices see Anselin (1988).

$$Y = \rho WY + X\beta + \varepsilon \qquad \text{(2a)}$$

where ρ reflects the spatial dependence inherent in the data or the average influence that the neighboring observations have on one specific observation. In this case, estimating (1) by OLS will lead to biased and inconsistent estimators as a consequence of the endogenous dependence variable. The other type of spatial dependence arises when $\rho = 0$ and $\lambda \neq 0$. In this case the regression equation takes the form of a spatial error autocorrelation model:

$$\begin{aligned} Y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \mu \end{aligned} \qquad \text{(2b)}$$

where λ is the scalar parameter measuring the degree of spatial dependency in the residuals. One theoretical difference between (2) and (3) is that in the autoregressive model it is typical that all error terms are correlated in the spatial error model and the residuals are only correlated to their immediate neighbors, as specified in weigh matrix *W* (Fotheringham et al. 2000; pp. 170).

Both models are estimated and as described in the result section, the spatial lag model resulted significant in explaining the type spatial dependence in the data. Nevertheless, this model exhibits endogeneity of the spatially lagged dependent variable, which is included as regressor, with the error term violating thus the assumptions under which OLS produces unbiased estimates of the regression coefficients (Kubrin, 2003). As a corrective method, several authors (Anselin, 1990; Land and Deane, 1992; and Kelejian and Prucha, 1998) have proposed a two-stage least squares (2SLS) technique to derive consistent estimators in spatial effects models with potential variables. The endogeneity of the spatially lagged dependent variable can also be addressed by means of an instrumental variables or two stage least squares approach [Anselin 1988, 1990; Land

and Deane (1992), Kelejian and Prucha (1998)]. Furthermore, we develop an estimation of spatial instrumental variables (spatial-IV) models for endogenous explanatory variables to address the simultaneous bias of army federal intervention for the years 2007 and 2008 and the increase in homicides. The spatial models considers an instrument variable for each year consistent with the explanation in the prior section.

Up to now we have only modeled homicides as average of the period and controlling for covariates and a dummy for federal intervention in 2007 and 2008. However, with data before and after the federal interventions it is possible to determine a more precise effect from such interventions in the rate of homicides, comparing municipalities with and without intervention before and after they started. This is under the difference-in-difference estimation with panel data, and assuming that unobserved heterogeneity is time invariant. One way to deal with time invariant unobserved heterogeneity is controlling for initial factors in the municipalities, thus, reducing the potential problem that nonrandom assignation of interventions can bias the estimation from the interventions.

We implement a difference-in difference strategy, using an I for municipalities in states that joined the intervention in year t, with a model:

$$h_{jt}=\alpha+\beta 0X_{jt}+ \beta\ 1I_{jt}+\beta 2\tau+ \beta 3I^{*}\tau+ \varepsilon_{jt} \qquad (3)$$

where $\beta 3$ denotes the average effect from the federal intervention on the homicide rates and X is composed of a set of pre program characteristics. This model is also adapted to count data with a negative binomial model. The instruments previously mentioned will be interacted with both treatment variables to exploit heterogeneity in such areas to consider a full model for difference-in-differences.

4. Results

Here we present the results for the models on cross section, panel with difference-in difference, and the spatial model. Variance inflation factors performed after regression indicates that multicollinearity is not a problem since all values are much lower than 10.

Since the statistics confirm that there is overdispersion in the data of homicides (variance higher than mean), strongly skew to the right, we implement a Negative Binomial regression, since the Poisson regression still gives biased coefficients, and given that the Poisson goodness of fit test is significant, rejecting the null hypothesis that the distribution fits the data. The Negative Binomial presented instead have significant Likelihood ratio test of alpha, suggesting this regression is better than Poisson.

a) Results for cross section

Table 4 presents result for the homicide rates as count data in Negative Binomial regressions using the total sample, as well dividing in urban and rural municipalities, also there are two sets of regressions, one with covariates, and the other with covariates but instrumenting both interventions.

Variables used for instrumenting are: the rate of growth of corruption regarding two aspects, getting a stolen car, and getting free from justice, also we use distance to the main border with the US and to capital of the state, and for differencing between both treatment a dummy for governor elections in 2007 and 2009 respectively. These variables were selected they reflect to some extent the dilution of law and of institutions, the political interest in reducing violence, and the distance to the likely main markets for drug.

For these to be good instruments have to be correlated with the endogenous variables but not with the error term, and should not be directly significant for the dependent variable, homicides. The instrument for intervention 2007 is correlated in 0.89 with that variable, while the instrument for 2008 has a correlation of 0.85 with that variable. The variables are not significant if used directly in a regression for homicides. Also, they are not significant when used for the residuals. Therefore, they seem to be good instruments for interventions 2007 and 2008.

In table 4, youth unemployment is mostly positive but no significant in increasing the rate of homicides drug rivalry related, except for rural areas when not using the IV. Years of schooling is not significant.

The Gini index increases its magnitude to an elasticity of 1.1 for total homicides, while 1.2 for urban and 1.6 for rural municipalities, in the second set of results, with IV for interventions, the coefficient increases. These results support the previous findings of De la Torre (2008) regarding inequality as the center of social violence. Household income is significant for urban homicides with an elasticity of 0.17, but not significant for areas, hinting the potential market for drugs that cartels could be fighting.

Table 4. Negative Binomial Regression Results for Total Homicides Rates

	Models			Model with IV for Federal Intervention in 2007 and 2008		
	Total	Urban	Rural	Total	Urban	Rural
Youth Unemployment	0.055	0.001	0.076*	0.069	0.028	0.080
	(0.0365)	(0.0513)	(0.0447)	(0.0427)	(0.0481)	(0.0517)
Schooling Years	0.070	0.140	0.081	-0.035	0.061	-0.037
	(0.1206)	(0.1085)	(0.1572)	(0.0999)	(0.0869)	(0.1680)
Gini Index	1.142***	1.205***	1.615***	1.597***	1.895***	2.063***
	(0.3482)	(0.4618)	(0.4413)	(0.2890)	(0.3053)	(0.4060)
Household Income	0.004	0.174*	-0.005	-0.055	0.173**	-0.081
	(0.1219)	(0.1045)	(0.1207)	(0.0762)	(0.0770)	(0.0925)
% Indigenous Population	-0.015	0.002	-0.039	-0.005	0.008	-0.026
	(0.0334)	(0.0337)	(0.0445)	(0.0135)	(0.0195)	(0.0219)
% Births without SS	0.248**	0.355**	0.193**	0.299***	0.358***	0.256**
	(0.1173)	(0.1486)	(0.0927)	(0.0908)	(0.0804)	(0.1185)
% Agricultural Employment	0.053	0.011	0.355***	0.056*	0.024	0.391***
	(0.0524)	(0.0555)	(0.0826)	(0.0333)	(0.0325)	(0.0888)
% Interstate Migrants	-0.009	0.019	-0.007	-0.017	-0.002	-0.008
	(0.0385)	(0.0564)	(0.0323)	(0.0334)	(0.0333)	(0.0368)
Local Public Security	-0.199*	0.067	-0.239	-0.225***	0.057	-0.244**
	(0.1058)	(0.0878)	(0.1486)	(0.0759)	(0.0789)	(0.1061)
State Public Security	-0.020	0.113	0.037	-0.077	0.053	0.035
	(0.1817)	(0.1308)	(0.2662)	(0.1095)	(0.1368)	(0.1943)
% Sentence/Preliminary Investigation	-0.310	-0.265*	-0.392	-0.284***	-0.230***	-0.398***
	(0.2017)	(0.1551)	(0.3596)	(0.0588)	(0.0576)	(0.1278)
Urban	-0.210			-0.103*		
	(0.1286)			(0.0599)		
Port	0.676	0.447		0.627***	0.493**	
	(0.3414)	(0.2788)		(0.1828)	(0.2200)	
Federal Intervention 2007	1.107***	1.199***	0.903***	1.008***	1.175***	0.805***
	(0.1536)	(0.1242)	(0.2932)	(0.1020)	(0.1005)	(0.1334)
Federal Intervention 2008	1.316***	1.164***	1.499***	1.666***	1.285***	2.048***
	(0.3346)	(0.2793)	(0.4866)	(0.1219)	(0.1239)	(0.1777)
Constant	3.037*	0.675	2.878*	3.732***	1.327*	3.569***
	(1.6867)	(1.5367)	(1.7166)	(0.8612)	(0.7336)	(1.0117)
Log-pseudolikelihood	-8299.86	-3395.83	-4604.32	-8321.53	-3457.18	-4598.04
N	2412	1043	1369	2412	1043	1369

***, **, * Significant at 1%, 5%, and 10% respectively. Boostrap standard errors in parentesis for the models with instrumental variables. Otherwise, cluster at the state level standard errors.
Instruments are: rates of growth of corruption for getting a stolen car back, and for getting free from law, the distance to the border and to Mexcio City, and elections in 2007 and 2009.

The share of indigenous population is no significant. Births without access to social security are positive and significant in all cases, ranging from 0.2 to 0.35 for rural or urban homicides. Agricultural employment has a positive significant elasticity only for rural municipalities. Migration is no significant for any of the models.

The institutional variables are significant at some extent. Local public security is negative and significant for total general homicides, and for rural homicides, with around 0.24 of elasticity. State public security is no significant. The ratio of sentences to preliminary investigation is negative and significant for urban homicides, but when using IV for interventions become significant for all models. Urban and port of entrance are significant when using IV in the models.

The variables for federal intervention are both significant and positive. Those municipalities in states with intervention starting in 2007, have coefficients for general homicides of about 1.1, 1.19 and 0.9 for total, urban and rural areas, which means about 20.1, 18.5, and 21.4% increase on the mean annual rate of homicides. It has similar coefficients using the IV.

The entrance to interventions in 2008 is also positive and significant with 1.316, 1.16 and 1.49 for total, urban and rural areas, meaning an increase of about 21.8, 16.5 and 30.21% in the mean annual rate of general homicides compared to municipalities with no intervention. Using IV for this intervention results in a significant increase to 27.5, 17.85, and 41.3% in homicides, strongly positive and significant in any case.

Up to now, there are significant effects on the rate of both types of homicides from social factors, institutional characteristics, and especially from the fact that some states entered into the intervention in 2007 and 2008. One must acknowledge, however, that since we are dealing with areas, there is the issue that spatial dependence can bias the estimation. Thus, in next section we present result using spatial econometric models.

b) Results for spatial analysis

As discussed above, spatial dependence could lead to the presence of autocorrelation in the error term which in turn makes OLS inefficient estimators. An appropriate estimation technique considering spatial effects is Maximum Likelihood Estimation (MLE), giving thus consistent and efficient parameters (Anselin 1988).

A crucial aspect of the spatial regression results is to discuss the differences from the two types of spatial models described in equations (2a) and (2b). On the one hand, the spatial lag model assesses the possibility of “diffusion” effects among municipalities that directly influence a particular outcome of their neighbors. In terms of the variable of interest, this model tells us whether homicide rates in a particular municipality indeed influence the level of its neighbors. On the other hand, the spatial error model suggests the possible existence of omitted variables in the right hand side of the regressions (Voss et. al, 2006). This means that homicides rates may be related to additional factors other than those included in the model and which effects are captured through the residuals.

Following Anselin (2005, p. 198) decision rule, from the spatial diagnostics we look for the larger and significant Robust Langrage Multiplier (LM) test, finding significance levels exclusively in all estimated spatial lag models. In these regressions we address the issue of the skewed distribution toward zero in homicides rates by means of standardizing or dependent variables. In doing this, the regressions consider the 2,454 total number of municipalities. Hence, the interpretations of the results are based on standard deviations changes of homicides rates. Table 5 shows the results from OLS (column 1) and MLE (column 2) for the spatial lag model[5]. This table also includes a spatial 2SLS model (column 3) and the spatial model with instrumental variables for federal army interventions in 2007 and 2008, column 4 and 5 respectively[6].

In general, the results from controlling for spatial autocorrelation and endogeneity issues seem to confirm previous findings. We found that higher levels of inequality are positively associated with total homicides. Specifically, a 1 point increase in the Gini index it is associated with an increase in the range of 0.40 to 0.60 standard deviations in total homicides depending of the estimated model.

Our measure of social fragmentation, percentage of births without social security, shows statistical significance and positively impact homicides rates with slightly higher effects when the model instrumented army intervention in 2008. Furthermore, agricultural employment appears significant and positively associated with homicides in the spatial 2SLS and spatial IV for the year 2007.

Local provision of public security shows the expected sign and significance levels particularly in model of column 4, when instrumenting for army intervention in 2007. This effect lower significance levels once the army intervention occurs in 2008. Note that our proxy for the administration of justice in the state level (the ratio of sentences issued relative to preliminary investigations) shows significant deterrent effects associated with homicides rates. The negative impact upon homicide rates associated

[5] In order to limit space we only show the results from the spatial lag model, although those obtained from the spatial error model are available upon request.

[6] Due to software capabilities we limit one instrument per estimated model. For example, model in column 4 consider the municipalities with no intervention prior to but those with federal army intervention in 2007. Consequently, model in column 5 includes municipalities with no intervention prior to but those with army intervention in 2008.

with 10 point increase on this ratio rates ranges between 0.51 to 1.13 standard deviations depending of the model considered.

The instrument variables assessing the effects of army interventions in 2007 and 2008 (see columns 4 and 5) show high significance levels at 99% and are found to be positively correlated with total homicides. Nonetheless, the impact of 2008 federal interventions on drug related homicides seems to be greater as in 2007. This is, while municipalities that had 2007 intervention show an increase on drug-related homicides of approximately 0.46 standard deviations as compared to those with no such intervention, in 2008 the associated effect is approximately 0.72 standard deviations.

Finally, the results from the spatial lag models also provide a measure of the degree of a “diffusion” process in homicides rates. The estimation of the spatial 2SLS (see column 3) model shows a significant spatial lag coefficient (ρ) suggesting that, homicides rate increases in a particular municipality are also associated with increases in neighboring municipalities. Specifically, the results indicate that a given 10 point increase in the homicide rate for municipality *i*, the associated effects in its neighboring is approximately 0.80 standard deviations.

Table 5. OLS and Spatial Regression Results

	Dep. variable: Stand. Total Homicides Rates				
	1	2	3	4	5
	OLS	ML Spatial-Lag	Spatial 2SLS	Spatial IV (sample: mun. with no intervention but intervention 2007)	Spatial IV (sample: mun. with no intervention but intervention 2008)
Youth Unemployment	0.018	0.006	0.008	0.013	0.030
	(0.0183)	(0.0162)	(0.0184)	(0.0165)	(0.0191)
Schooling Years	-0.007	-0.005	-0.012	0.003	-0.009
	(0.0085)	(0.0075)	(0.0085)	(0.0084)	(0.0087)
Gini Index	0.559***	0.401***	0.484***	0.395***	0.603***
	(0.1138)	(0.1006)	(0.1145)	(0.1425)	(0.1490)
Houshehold Income	0.002	0.001	0.006	-0.013	-0.019
	(0.0162)	(0.0143)	(0.0161)	(0.0200)	(0.0231)
% Indigenous Population	0.002	0.001	0.005	-0.008*	0.005
	(0.0061)	(0.0054)	(0.0061)	(0.0049)	(0.0053)
% Births without SS	0.074**	0.069**	0.055	0.049	0.089**
	(0.0380)	(0.0335)	(0.0381)	(0.0359)	(0.0366)
% Agricultural Employment	0.033**	0.017	0.040**	0.030***	0.017
	(0.0161)	(0.0142)	(0.0161)	(0.0115)	(0.0124)
% Interstate Migrants	-0.007	0.001	-0.001	-0.011	-0.005
	(0.0114)	(0.0101)	(0.0115)	(0.0133)	(0.0136)
Local Public Security	-0.065*	-0.036	-0.049	-0.067**	-0.058*
	(0.0333)	(0.0294)	(0.0333)	(0.0316)	(0.0314)
State Public Security	-0.020	0.003	0.010	-0.014	0.003
	(0.0542)	(0.0478)	(0.0544)	(0.0485)	(0.0495)
% Sentence/Preliminary Investigation	-0.101***	-0.051*	-0.069***	-0.113***	-0.097***
	(0.0301)	(0.0266)	(0.0308)	(0.0240)	(0.0214)
Urban	-0.072**	-0.042*	-0.064**	-0.044*	-0.084***
	(0.0281)	(0.0248)	(0.028)	(0.0243)	(0.0252)
Port	0.211	-0.054	0.290*	0.273***	0.227
	(0.1580)	(0.1393)	(0.1581)	(0.1374)	(0.1888)
Federal Intervention 2007	0.539***	0.255***	0.412***	0.457***	
	(0.0482)	(0.0438)	(0.0565)	(0.0813)	
Federal Intervention 2008	0.656***	0.322**	0.504***		0.715***
	(0.0471)	(0.0435)	(0.0589)		(0.3304)
Constant	0.378	0.161	0.258	0.464	0.562*
	(0.2737)	(0.2414)	(0.2734)	(0.3007)	(0.0992)
Spatial Lag coefficient		0.517***	0.079***		
		(0.0235)	(0.0188)		
R-square	0.63	0.31	0.13	0.10	0.10
Robust LM(lag)	60.25***				
Likelihood Ratio Test		417.98***			
N	2454	2454	2454	2236	2255

***, **, * Significant at 1%, 5%, and 10% respectively. Robust standard errors are reported in parentheses for the spatial 2SLS and spatial IV models.

c) Result for panel difference-in-difference

In this section we present the results using the data as panel for equation (3) in Table 6, where it displays results using the Negative Binomial regression. In this Table, DD07 and DD08 denote the effect of being a municipality in intervention state 2007 or 2008 respectively after such intervention takes place, compared with municipalities with no intervention. In this case we do not separate in urban and rural samples since separating the panel causes the model not to converge.

The difference-in-difference estimation for both interventions, starting in 2007 and 2008, are positive and significant. For municipalities starting interventions in 2007, there is an increase of 11-14% in the rate of homicides due to the army intervention, while those municipalities in states starting interventions in 2008, there is an increase of about 47-52% in homicide rates due to the interventions, compared to municipalities in states with no interventions.

Youth unemployment is no significant. The average years of schooling is no significant, consistently with the previous results in this paper, except when using interactions between variables and treatment dummies. The Gini index, household income, are positive and significant, the Gini with a higher magnitude pointing also to the effect from inequality in rising conflicts through homicides. Births without social security are positive and significant in explaining general homicides.

Indigenous population and agricultural employment are both negative and significant, while migration is here positive and significant. Urban municipalities and port of entry are also significant and positive in increasing the rates of homicides.

The institutional variables are mostly not significant, when measured through provision of public security at the local or state level. Measured through the ratio of sentences to previous investigations are negative and significant pointing thus to a positive effect in increasing this ration in reducing homicides.

Table 6. Negative Binomial Regression Results for Total Homicides Rates		
	No interactions	with Interactions
DD07	0.113**	0.145***
	(0.0499)	(0.0515)
DD08	0.476***	0.519***
	(0.0571)	(0.0574)
Youth Unemployment	0.006	-0.003
	(0.0262)	(0.0261)
Schooling Years	0.074	0.173***
	(0.0629)	(0.0639)
Gini Index	2.183***	1.870***
	(0.1608)	(0.1697)
Household Income	0.294***	0.304***
	(0.0340)	(0.0340)
% Indigenous Population	0.011	-0.019**
	(0.0089)	(0.0095)
% Births without SS	0.197***	0.256***
	(0.0594)	(0.0607)
% Agricultural Employment	-0.119*	-0.200***
	(0.0262)	(0.0267)
% Interstate Migrants	0.030*	0.028*
	(0.0171)	(0.0171)
Local Public Security	0.010	-0.001
	(0.0493)	(0.0493)
State Public Security	0.104	0.082
	(0.0761)	(0.0759)
% Sentence/Preliminary Investigation	-0.117***	-0.095**
	(0.0415)	(0.0458)
Urban	1.750***	1.665***
	(0.0422)	(0.0431)
Port	0.385***	0.181
	(0.1917)	(0.1983)
Federal Intervention 2007	1.020***	0.090
	(0.0671)	(0.3378)
Federal Intervention 2008	0.399***	0.239
	(0.0660)	(0.1617)
Constant	-2.530***	-3.885***
	(0.4867)	(0.5087)
Log-pseudolikelihood		
N	12060	12060

***, **, * Significant at 1%, 5%, and 10% respectively.
Control group 5 states are: Nayarit, Sonora, Coahuila, Morelos and Quintana Roo. 9 states are the 5 plus Jalisco, Guanajuato, Zacatecas and Veracruz. Regressions with year
States with intervention 2007: Baja California, Guerrero and Michoacan.
States with intervention 2008: Chihuahua, Durango, Sinaloa, Nuevo Leon, and Tamaulipas
Interactions with both treatments and variables used as IV in Table 4

In addition, we have performed some robustness checks that we present in Table 7, which displays results for the difference-in-difference estimator for both interventions. There are 7 panels with different estimations using the model with interactions as in Table 6.

The first, panel A, presents the difference in difference estimation without additional covariates, and the lower panel B the full model of interactions with state level fixed effects. [7] In both cases results are similar to the main panel. In any case, the effects from the difference in difference estimations are slightly higher in magnitude without controlling for other covariates, while with state fixed effects results are also slightly higher, especially for interventions starting in 2007.

One of the critics to the difference-in-difference models is the control group used. Here we have been using all municipalities in states with no interventions. Therefore, we are checking robustness of results considering different control groups in next panels. First, in panel C we restrict the control to municipalities first in 5 states with high increase in violence (Nayarit, Sonora, Coahuila, Morelos, and Quintana Roo), while in panel D we add to the control group other 4 states with high evolution in the rate of homicides (Jalisco, Guanajuato, Zacatecas, and Veracruz) in Panel D. Of these 9 states, there are 4 which have sporadic intervention that are not permanent as those entering in 2007 and 2008 (Coahuila, Jalisco, Nayarit, Sonora, and Veracruz). In both cases only interventions starting in 2008 are significant and positive, with a lower magnitude than previous models.

Also, we identified municipalities in states with no intervention bordering states with intervention, taking them as control group, first using all municipalities in intervention states in Panel E, and then we restrict even more to only municipalities bordering the others in no intervention states in Panel F. The magnitude for interventions starting in 2008 increases in both cases, but those in 2007 are still no significant.

[7] In the case of count data we have municipalities with zeros in all years, therefore using municipal fixed effect in this case results in those municipalities out of the sample, thus we use state level fixed effects.

For Panel G we performed a propensity score matching with difference-in-difference. Following Lechner (2002) we applied two treatments for each intervention in 2007 and in 2008, using as covariates for the propensity the pre program variables included in the models, and limiting to the region of common support with the interactions models applied with variables used for IV in Table 4. Matching is used with kernel estimations. Here, results for both interventions are positive and significant, with magnitudes similar to the full model with interactions and state level fixed effects in panel B.

In general, results in Table 7 are robust to estimation, showing that the intervention in 2007 and 2008 in some states have an incidence in the rise of homicides, possible creating a spiral of homicides due to some mechanism that in not know from this data. But what it is relevant, is that social variables, such as inequality, income, and social security coverage, are significant in explaining the rise in violence in Mexico as shown from these results.

Table 7. Negative Binomial Regression Results for Homicides Rates

	Negative Binomial
A. WITHOUT OTHER CONTROLS (N=12270)	
DD07	0.154**
	(0.0620)
DD08	0.496***
	(0.0697)
B. WITH STATE LEVEL FIXED EFFECTS (N=12060)	
DD07	0.150***
	(0.0518)
DD08	0.565***
	(0.0576)
C. CONTROL GROUP 5 STATES WITH VIOLENCE BUT NO OPERATIVO (N=2840)	
DD07	-0.057
	(0.0769)
DD08	0.330***
	(0.0786)
D. CONTROL GROUP 9 STATES WITH HIGH VIOLENCE BUT NO OPERATIVO (N=4990)	
DD07	-0.005
	(0.0600)
DD08	0.398***
	(0.0645)
E. CONTROL GROUP BORDERING MUNICIPALITIES VS ALL MUNICIPALITIES WITH INTERVENTION (N=2620)	
DD07	0.001
	(0.0806)
DD08	0.405***
	(0.0828)
F. ONLY BORDERING MUNICIPALITIES IN STATES WITH & WITHOUT INTERVENTION (N=1135)	
DD07	-0.020
	(0.1112)
DD08	0.409***
	(0.1397)
G. PROPENSITY SCORE DID FOR INTERVENTION VS NO INTERVENTIONS (N= 7805, 5390)	
DD07	0.173***
	(0.0537)
DD08	0.501***
	(0.0619)

***, **, * Significant at 1%, 5%, and 10% respectively.

Control group 5 states are: Nayarit, Sonora, Coahuila, Morelos and Quintana Roo. 9 states are the 5 plus Jalisco, Guanajuato, Zacatecas and Veracruz.

States with intervention 2007: Baja California, Guerrero and Michoacan.

States with intervention 2008: Chihuahua, Durango, Sinaloa, Nuevo Leon, and Tamaulipas.

DD07 & DD08 denotes difference-difference estimator for intervention 2007 & 2008 respectively

Finally, we are also interested in the differential effects from the pre program variables in municipalities with intervention compared to those with no intervention. For that reason, we performed in the difference-in-difference estimation a set of interactions between the pre program variables with the municipalities with intervention. These interactions are the marginal effect from the specific variable, i.e. assuming that there is different effect from the structural variables in municipalities under intervention. The estimated coefficients for those interactions are presented in Table 8.

Table 8. Interactions: Covariates with Intervention

	Total Homicides
Youth Unemployment	-0.055
	(0.0651)
Schooling Years	0.184
	(0.1827)
Gini Index	1.502***
	(0.4902)
Household Income	0.101
	(0.0836)
% Indigenous Population	0.057**
	(0.0248)
% Births without SS	-0.273*
	(0.1640)
% Agricultural Employment	0.256***
	(0.0638)
% Interstate Migrants	0.023
	(0.0466)
Local Public Security	-0.190
	(0.1618)
State Public Security	-0.575**
	(0.2412)
% Sentence/Preliminary Investigation	-0.082
	(0.1499)
Urban	-0.535***
	(0.0923)
Port	-0.068
	(0.4041)
Constant	-2.601***
	(0.5477)
Log-pseudolikelihood	-33344.382
N	12060

***, **, * Significant at 1%, 5%, and 10% respectively.

Control group 5 states are: Nayarit, Sonora, Coahuila, Morelos and Quintana Roo. 9 states are the 5 plus Jalisco, Guanajuato, Zacatecas and Veracruz

States with intervention 2007: Baja California, Guerrero and Michoacan.

States with intervention 2008: Chihuahua, Durango, Sinaloa, Nuevo Leon, and Tamaulipas.

Inequality measured with the Gini index is positive and with a larger magnitude. Other significant variables with the interaction are indigenous population, births without social security, agricultural employment, state public security and urban municipality.

Additionally, we have run a set of the analysis using homicides related to narco rivalry instead of total homicides. This data has been published in Presidencia de la Republica for years 2007-2010, and has not been updated since then. However, this database has been questioned on the methodology for accounting such homicides (see Merino, 2011, or Escalante, 2011).[8] Results are similar to those presented here, but also income becomes significant pointing perhaps to a size of the market for drug effects.

Thus, results in general suggest that, besides the obvious effect from the interventions, inequality, as well as coverage of social security, may be also at the core of the rise in homicides not only for those drug related but also in general. These results are consistent with research in other countries (for example in Kelly, 2000, or Fajnzylber et al, 1998). Findings also support De la Torre (2008) results for Mexico putting inequality at the center of social violence, even though in this case is violence in homicides.

5. Conclusions

This paper has analyzed the effects from structural social and institutional factors on homicides trends in Mexico. Using rates of homicides at the municipal level, we link the data with variables such as inequality, income, youth unemployment, and

[8] A priori one should think that narco related homicides are included in the total, however data does not check, if we rest narco homicides to the total there is about 8% of municipalities with a negative difference in a single year. Thus, we focused on the paper only in the total official data released by INEGI. The data I available online at http://www.presidencia.gob.mx/base-de-datos-de-fallecimientos/

institutional as the provision of security and law. We exploit the fact that after the federal government declared “was on drug cartels” offered states for intervention with federal forces to combat cartels. In this regards, some states initiated interventions in 2007 and other in 2008, remaining several states with no intervention.

We applied different methodologies to check for the robustness of the results, using average in the period under analysis, spatial analysis, and difference-in-difference with panel of data using different control groups, and propensity score matching with difference-in-difference.

The results obtained through all the methods here analyzed indicate that social and institutional factors are relevant in explaining the upsurge of homicides. Inequality, income, and the lack of social security are relevant for increasing crime. Results support previous findings with inequality at the center of violence in Mexico (see De la Torre, 2008), suggesting that social spending can improve to close disparities between socioeconomic strata in order to dilute the spiral of violence. The provision of law also seems relevant for decreasing general homicides, although with a weak effect that turns no significant in some cases.

The federal interventions in different states starting in 2007 and 2008 are strongly and positive related to increasing homicides in municipalities within states with interventions, compared with municipalities in states with no intervention. Even though interventions are focused on reducing the drug cartels and their violence, it seems that they have uprised general homicides as well. The mechanics behind the growth in violence due to interventions is not clear at all. Escalante (2011), for example, suggests that since the interventions represent a violent enforcement of law, the usual agreements between several interest groups for illegal activities but keeping violence in relative lower levels has been broken, therefore affecting all aspects of violence.

It has to be noted also that even though we performed different methods, there is the possibility that, since criminal activity is not a complete observed activity (i.e. burial graves with executed not yet found, etc), we suffer still from some unobservables biasing the results since the panel is still short. However, robustness of the findings is consistent with the different specifications presented in this analysis. In this regard much more research need to be done to understand how to decrease the spiral of violence and homicides in the Mexican municipalities, but from this research it is suggested the need for a coordinated social policy to improve local social indicators, and especially decreasing inequality, as well as to increase local institutional capacities.

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