"Essays on the Economics of Crime in Mexico"

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Leticia y José Guadalupe

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INTRODUCTION

This thesis consists of three essays on the Economics of Crime in Mexico covering the period 1997-2010. The aim of this introductory section is to briefly provide a non-technical overview of the essays. The discussion of the contribution of this work to the existing literature will be carried out separately in each essay.

Even though crime has for a long time been a present threat for the Mexican economy and society, this research project was motivated by the public security problem being faced by the Mexican Federal Government and the Mexican population during the last six years. It has been widely reported that in December 2006 the Mexican federal government deployed the military to the Mexican north border to the United States in an effort to directly combat the drug trafficking organizations (DTOs) operating especially in that part of the country. From that year onwards Mexico has experienced a dramatic and unprecedented increase in the levels of violence. This violence erupted in three forms: DTOs fighting each other for the control of the drug routes to the United States, the military and police forces fighting against the DTOs and the violence experienced by the population in forms of extortion, kidnapping & homicide by the DTOs and civilian population´s deaths due to the crossed fire among DTOs, the military and /or police forces (Ríos 2012, Dean 2012).

The thesis looks at the influence of this phenomenon on three important aspects of Mexico: The tourism industry, the threat of organized crime towards the Mexican youth and the spread of drug crime throughout the country.

The increasing violence in Mexico starting in 2006 went quickly reported around the world. Several countries started issuing travel warnings to visit the country. For instance the Australian government made its alert public through its Department of Foreign Affairs and Trade: *"Travellers may become victims of violence directed against others"*.[1] Accordingly, the Mexican Senate urged the Mexican Federal Executive to provide fiscal incentives to the tourism industry as a way to palliate the negative impact on tourism due to the fight against DTOs. At the same time the Mexican Senate called on the Ministry of Tourism to intensify the promotion of Mexico abroad as a secure tourism destination.[2]

After petroleum sales, and remittances, tourism is an important source of income for the Mexican economy. As of now there is no empirical investigation of the impact that crime has on tourism across Mexico. Thus, the first chapter deals with the question whether violent crime exerts any effect on tourism in Mexico during the period 1997-2010 by implementing unique disaggregated data of tourist arrivals at the sub-national level. According to Neumayer (2004) one of the limitations in the economics of tourism literature is the availability of tourist arrivals data at the sub-national level. The paper uses homicides as a proxy for violent crime and uses a panel data set for the 31 Mexican federal states and Mexico City. After dealing and discussing the potential endogeneity in the relationship violent crime–tourism the results suggest a negative and significant effect of homicides on the number of tourists arriving. This finding is robust to alternative estimation techniques and samples. Furthermore, when disaggregating the tourist arrival data into local and international, international tourists seem to be more intimidated from homicides than locals.

Certainly the violence exerted by the DTOs and the authorities have not only had a negative economic impact on Mexico but it has also represented a burden for the Mexican society. Given

[1] See Australian Department of Foreign Affairs and Trade, May 12th 2012, http://www.smartraveller.gov.au.

[2] See El Universal, January 06th 2011, http://www.eluniversal.com.mx.

that Mexico is a relatively young country with the majority of its population falling into the age range of 12 to 29 years, the second chapter highlights the vulnerability of the youth who are faced with lack of education opportunities, unemployment and live in a highly criminal environment. Specifically, this essay asks whether the availability of large young male cohorts, or male 'youth bulges', low education, and high youth unemployment eases recruitment to DTOs and may contribute to explain variance in violent crime across Mexican states over time. The article tests these propositions empirically in one of the first sub-national studies of violent crime in a developing country. It is further the first study to look at youth bulges and violence, either political or criminal, in the context of both education and employment, a unique opportunity granted by the rare availability of such data for Mexican states. The results suggest that while youth crime and high homicide rates in Mexico are not associated with the ebb and flow of the male youth population, both high youth unemployment and low youth education are associated with higher levels of crime and homicide. And in this context, the relative size of the male youth population does matter. The paper posits that by not investing in the education of the youth, policymakers would make a big failure in not taking advantage of the demographic bonus Mexico counts with. This is important not only in terms of public security policy but also in terms of long run development.

Beyond any doubt, drug trafficking and the violence it generates is a complex phenomenon for which there is no easy way out. Over the last thirty years Mexican authorities have relied heavily on the armed forces in the fight against drug trafficking by deploying troops for crop eradication, drug seizures and other counter-narcotics operations (Astorga and Shirk 2010, Kenny and Serrano 2012). This deterrence strategy accelerated greatly during the Fox and

Calderón administrations[3] and has been largely criticized by scholars, the media, prominent personalities such as former U.N. General Secretary, Koffi Annan, as well as NGOs in Mexico and abroad who question whether it was the best strategy available to authorities (HRW 2012, 2013).

These critics argue that by solely implementing deterrent policies violent crime would not stop. Rather, they claim that as a result of these policies drug-related conflicts spread to regions which were previously unaffected. Following on this and according to the literature on the economics of crime, geographical space has gained importance since crime in general is affected not only by local factors but also by the characteristics of neighboring areas (Ratcliffe, 2010). Thus, it might be the case that one deterrence policy could represent a gain to one region but a cost to another by displacing criminal offenders to other regions. However, as argued by Morris (2012) and Skaperdas (2001), drug trafficking in Mexico and organized crime in general emanates out of the lack of power created by the absence of state enforcement. In this way, a noticeable pattern of corruption involves a type of revolving door, whereby state security officials leave government service to work for the DTO´s and DTO´s members infiltrate and work within the government (Morris 2012).

In this sense, the last essay empirically investigates whether and how drug-related crime in a given Mexican state spreads to its neighboring states. It implements spatial econometric techniques to a panel data set for the 31 Mexican federal states and Mexico City over the period 1997-2010. The results suggest a positive and significant diffusion effect of crimes related to drugs after controlling for political and socio-economic characteristics of regions. Furthermore,

[3] This corresponds to the 2000-2006 period for the Fox administration and to the 2006 to 2012 period for the Calderón administration.

after controlling for drug enforcement in neighboring states to state *i*, the findings suggest weak evidence for a deterrent effect. This implies that authorities' deterrence measures in neighboring states to state *i* weakly reduce drug crimes in state *i*.

Chapter I

Does Violent Crime Scare Tourists Away? Panel Data Evidence from 32 Mexican States

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I.1 INTRODUCTION

Does violent crime deter tourists from visiting Mexico? According to the United Nations World Tourism Organization (UNWTO 2011), Mexico was ranked in 2011 as the 10th place to visit in the preferences of international tourists. Conversely, the country was ranked 121 out of 153 countries by the Global Peace Index in the same year, with 153 being the most violent country. In the year 2006 the Mexican government decided to give a frontal fight to the different drug trafficking organizations (henceforth DTOs) operating all across the Mexican territory. As a result of this strategy violent crime in the form of homicides started to dramatically increase (Ríos 2012). Thus, it was not uncommon to read since the end of 2006 the headlines of international and national newspapers reporting the increasing wave of violence in Mexico. This has had a negative impact on the Mexican society. For instance, Braakman (2012) provides evidence on some of the non-monetary costs of crime in Mexico. His results show that men and women in Mexico change their behavior in response to victimization risks or actual victimization. These changes include the carry of a weapon for men and the change of transportation methods for women. Moreover, as a reaction to the violent fighting among the DTOs, which occurred in the year 2010 in the municipality of Mier, in the northern Mexican State of Tamaulipas, about 95% of the population was forced to abandon the town. This municipality together with many smaller municipalities along the Mexican-U.S. border became virtual ghost towns.[4] A further example is the Mexican industrial capital, Monterrey. Despite its reputation as the most competitive and developed in the country (Mexican Institute for Competitiveness 2012), this city has been in several occasions scenario of increasing violence due to the different DTOs fighting against each other. This had a negative impact on the

[4] See CNN Mexico,12th May 2012, http://mexico.cnn.com and The Economist, 12th May 2012, http://www.economist.com.

emerging medical tourist industry in that city. In other words, fewer tourists required to stay in Monterrey for medical purposes.[5]

Moreover, after the intensification of violence from early 2007 onwards, analysts in the U.S. and Mexico have argued that there is a strong similarity between terrorism and attacks by the DTOs in Mexico.[6] Other scholars directly argue that the Mexican DTOs are terrorists and explain that the tactics, organization and their goals are homogenous to those used by terrorist organizations, (Longmire and Longmire 2008). For instance after the detonation of hand grenades in a crowded public square in Morelia, capital of the state of Michoacán on Mexico´s Independence Day in September 2008, local and international media have gone as far as qualifying these attacks as terrorism. Local newspapers reported the getaway of tourists on the following day.[7] Further examples of terrorism-like events occurred in 2008, 2010 and 2011 in the states of Sinaloa, Chihuahua, Tamaulipas and Nuevo León where vehicles deliberately went off either in parking lots or near to police stations.[8] Following on this, more than one country[9] has recommended their citizens not to choose this country for holidays. Travel warnings for international tourists describe this kind of events in their alerts and express their worries about the integrity of people, as pointed out by the Australian Department of Foreign Affairs and Trade in their Travel Advice for Mexico: *"Travellers may become victims of violence directed against others."*[10] It has been documented in Neumayer (2004) that tourists are sensible to violent events happening in their holiday destination and which can harm their physical integrity. He points out that if violent events repeatedly occur and increase their intensity, the authorities of the origin of

[5]See: The Economist, May 27th 2010, http://www.economist.com
[6] See: The Economist, November 15th 2010, http://www.economist.com
[7] See: The Economist, May 27th 2012, http://www.economist.com
[8]See: El Sol de Hidalgo, September 17th 2008, http://www.oem.com.mx/elsoldehidalgo
[9]Travel Warning as of February 8th 2012 U.S. Department of State. Bureau of Consular Affairs.
Travel Warning as of April 4th 2012 Foreign Affairs and International Trade Canada.
[10]See: Australian Department of Foreign Affairs and Trade, May 12th 2012, http://www.smartraveller.gov.au

tourists start warning their citizens against visiting that particular destination. Despite the importance of the tourism industry for the Mexican economy, there is no empirical evidence analyzing the extent to which violent crime affects tourism in Mexico. This paper aims at filling this gap in the literature. For this purpose, I use a unique dataset on tourist arrivals in each of the 31 Mexican states and Mexico City. The advantage of these data is the distinction between arrivals of international tourists from those of local tourists for the 1990-2010 period. I expect international tourists to be more intimidated by crime than local tourists. The latter benefit from their location in the country and thus directly know what is going on on the ground, while the former are mainly informed by what they read, hear or see in the news. In this respect, different scholars in economics, criminology and psychology have studied the implications of these information asymmetries for tourism as a result of political conflicts among countries and terrorism. For instance, Fielding and Shortland (2009) analyze how the US tourist flows to Israel are affected as a result of the actual intensity of the Israeli-Palestinian conflict and the intensity reported in US television news coverage. Their results suggest that if alternative sources of information are costly, then tourists may infer the current level of risk in travelling to Israel from the television news. A similar conclusion is provided by Romer et al. (2003) who argue that viewing local television news is related to increased fear of and concern about crime. Furthermore, Sunstein (2003) argues that one or two terrorist incidents will have a significant impact on thought and behavior of people, with exaggerated risk perceptions a likely result of the substantial publicity given to such incidents. Following on this, due to social interactions, knowledge about terrorist incidents spreads rapidly through the population and this in turn greatly aggravates fear. Earlier on, Morley (1998) highlighted that individuals are assumed to overcome missing information about destinations thanks to the contact with people which previously visited those countries. Moreover, Clerides et al. (2008) argue that information gaps are solved thanks to the activity of tour operators and travel agencies. They find that tour operators provide a better matching for quality with price and result in a more efficient market outcome. Given these previous studies it is plausible to argue that violent crime in Mexico is likely to facilitate a generic impression of unrest being spread all over the country.

In general, the articles studying tourism demand concentrate on the analysis of international tourism flows, neglecting the demand for national tourism. Due to the availability of tourism flow data, the period of study is restricted to 1990-2010. However this period takes into account the scaling up of crime during the years 2007-2010 when the Mexican government started to directly fight organized crime. The findings show that international tourist flows are more affected than local tourist flows after controlling for violent crime, income, price level, urbanization, weather, and infrastructure. As a starting point I propose a dynamic panel data model with fixed effects. According to Nickell (1981) the inclusion of the lagged dependent variable in a model with fixed effects results in biased estimates when the time dimension of the panel is small. Thus, in order to correct for this bias I implement the Least Square Dummy Variable estimator (LSDV) developed by Bruno (2005). Next I propose the use of two instruments to account for the potential reverse causality in the tourist arrivals and violent crime variables. This procedure allows me to account for the potential reverse causality only but not for the bias arising from the lagged dependent variable. Following on this, I obtain the fitted values of the first stage regression from the 2SLS procedure and use them in the LSDV estimation instead of the violent crime variable. This allows me to control not only for the lagged dependent variable bias but also for the potential reverse causality in the variables tourism arrivals and violent crime.

The rest of the paper is organized as follows: Section I.2 provides a review of the emerging literature on tourism demand and crime. Section I.3 explains the data selection based on the literature on tourism demand and presents the empirical methodology. Section I.4 discusses the results, while the last section concludes. The conclusion is followed by an appendix including graphs and robustness checks.

I.2 LITERATURE REVIEW

I.2.1 Tourism Demand and Crime

The literature on crime and tourism is small. Most work on the impact of crime on tourism concentrates on qualitative evidence as for instance, De Albuquerque and McElroy (1999) for the Caribbean, and Ferreira and Harmse (2000) for South Africa. Both studies rely on comparing available tourist crime victimization data in order to illustrate how crime affects tourism. De Albuquerque and McElroy (1999) first revise the recent history of violent and property crime in several Caribbean destinations and then highlight three hypotheses regarding the link between tourism and crime. The first of these hypotheses states that tourists in mass destinations are more likely to be victims of serious crimes than residents. The second hypothesis looks at the crime and victim type, and claims that tourists are more likely to be victimized by property crime and residents by violent crime. Lastly, the third hypothesis argues that the victimization rates are influenced by tourist density levels. The argument behind is that once tourism densities go beyond certain threshold levels and there are more visitors in certain locations, they are much more likely to be careless with their valuables, to visit dangerous areas and thus are much more likely to be easy preys for criminals. Albuquerque and McElroy (1999) use data on victimization of tourists provided by the Royal Barbados Police Force for the period 1989 till 1993 and data of

Barbados` resident victimization rates. By residents they refer to the inhabitants of Barbados and not to local tourists. Basically they compare the datasets of tourist victimization with the resident´s dataset and arrive at their conclusions without implementing any econometric methodology. For this aim they show three tables. The first one shows figures on nine different crimes committed against tourists and residents for the 1989-1993 period. Based on these figures they state that tourists are relatively secure in Barbados except from being victims of robbery. The second table presents the same offenses for the 1989-1993 period in the form of rates (per 100,000 persons). By doing so, they attempt to compare levels of victimization among members of the host and guest group. They conclude from these figures that the local population is more likely to be victimized by violent crime and tourists are more victimized by property crime and robbery.

The third table presents monthly data from 1990 to 1993 on the resident equivalent visitor population and tourist victimization rates for violent and property crime. Their figures show that the property crime rate against tourists is several multiples greater than the violent crime rate.

As a further research agenda they acknowledge the need to explore whether overall crime rates and victimization come along with mass tourism development, or whether observed crime rates are influenced by island-specific determinants.

In the same vein Ferreira and Harmse (2000) offer a qualitative study for South Africa. They gather statistics on the 37 most committed crimes in the main urban areas of this country for the year 1997. Their work does not offer an econometric analysis and concentrates in the comparison of crime across the main South African urban areas. Contrary to De Albuquerque and McElroy (1999) they do not present any hypothesis but highlight the importance of the international media and its influence on tourist perception of South Africa. Moreover they also describe that tourists can change their preferences for a specific holiday destination if crime is present and in this way a so called spillover effect is expected.

Different to the previous studies, the work by Levantis and Gani (2000) is one of the few quantitative studies on the issue. They study how crime affects the arrivals of tourists in four small Caribbean and four South Pacific islands states. As dependent variable they use the country`s share of total tourism flows to the region. They prefer this tourism measure over tourist expenditure, because the former better captures the deterrent effect of crime on travel to the desired destination. This is similar to Neumayer (2004), who also prefers tourism flows as a dependent variable since this is a more precise variable than tourists` expenditures. Levantis and Gani (2000) construct time series data from 1970 to 1993. Regarding the crime variable they argue that is not possible to compare crime rates across nations since the data availability and crime classifications are different across their sample. This is the reason as to why they construct an index of the incidence of crime for each country in order to compare the trends in crime. Only the index of the incidence of crime and its lagged value are used in their model due to the lack of data for other determinants of tourism at the country level. They find that crime negatively affects the demand for tourism.

I.2.2 Tourism and Crime in Mexico

Several developing countries have seen tourism as a strategy for economic development and as the United Nations World Tourism Organization documents, tourism provides about 6 to 7% of the world´s jobs and millions more indirectly via the multiplier effect in other sectors. Furthermore, it accounts for 30% of the world´s exports of services (US$ 1 trillion a year) and 45% of the total export of services in developing countries (UNWTO 2010). More specifically, for Mexico the tourism industry contributed 8.9% of the country´s GDP in the year 2009 and is after oil exports and remittances the third source of foreign currency for the country (Tourism Ministry of Mexico 2011-2012). Since it is one of the most important industries of the country, it is of paramount importance to identify the role played by violent crime.

As of now there is no empirical evidence arguing that organized crime is targeting the tourism industry in Mexico as a way to exert political pressure on the Mexican government. According to Dell (2011), the motivation for violence among the DTOs is the fight to take over the control of the routes of drugs from Mexico to the United States. Following on this, the increasing violence in Mexico consists primarily of drug traffickers killing each other.

More recently, Ríos (2012) has investigated why violence has dramatically increased in the last 4 1/2 years in Mexico. According to her research, the wave of violence hitting Mexico can be explained, on the one hand, by homicides as a result of traffickers fighting each other when competing for territories and on the other, by the enforcement operations taken by the Mexican Federal Government to arrest drug traffickers. These enforcement operations have had a negative externality on the country. Ríos (2012) calls this a self-reinforcing equilibrium; more precisely, the situation in which the government weakens the structure of the DTOs and this in turn fuels the incentives of DTOs to fight among them and eliminate the weakest DTOs. In the short run the costs of this strategy are reflected in an increase in violence. In the long run, the DTOs will weaken enough so that violence will stop.

Undoubtedly, this situation has put lot of burden on the Mexican society and damaged the reputation of the country. Given that tourism represents one of the most important industries in Mexico, I analyze whether there is an effect of violence on the tourism industry.

I.3 DATA AND METHOD

The data used in the paper is a panel dataset across 32 Mexican states (including the Federal District, also known as Mexico City) during the 1990–2010 period. The following specification estimates the tourists arrivals (TA_{it}) (logged), in state i in year t as a function of past tourist arrivals, $\ln TA_{it-1}$, homicides $\ln H_{it}$ and a vector of control variables Z_{it}:

$$\ln TA_{it} = \alpha \ln TA_{it-1} + \gamma \ln H_{it} + \beta Z_{it} + \nu_i + \lambda_t + \omega_{it} \quad , \qquad (1)$$

where ν_i denotes state fixed effects to control for unobserved state specific heterogeneity in the panel dataset, λ_t represents time specific dummies and ω_{it} is the error term. I cluster the standard errors by state to deal with concerns with serial correlation.

On the one hand, Mexico is a very diverse country in terms of traditions, culture and geography. All these factors are captured by state fixed effects. On the other hand, the time specific dummies capture common year's shocks such as tourism advertising abroad on behalf of the central government through the Mexican Tourism Ministry. The inclusion of a lagged dependent variable is theoretically plausible since it allows me to control for the loyalty of tourists to the different Mexican states and the Federal District. For the dependent variable I follow Neumayer (2004) and use the log number of tourists arriving in each of the 31 Mexican states and the Federal District. The data report the amount of tourists arriving in hotels in state *i* in Mexico in year *t*, reported by the National Institute for Statistics and Geography (INEGI hereafter) for the 31 Mexican states and the Federal District.

In 2005 INEGI was delinked from the Ministry of Finance and became an autonomous institution. The main task of INEGI is to conduct the population and economic censuses across Mexican states and Municipalities. Through their local offices INEGI collects the arrival of tourists' data from each of the local Tourism Ministries in each state and the Federal District. By law, hotels in Mexico have to report the amount of tourists who required overnight accommodation to the local Tourism Ministry. These figures form part of the statistical yearbooks of each state and Mexico City. Through its website, INEGI provides all the statistical yearbooks for all states and the Federal District which contains, among several other variables, the arrival of tourists as explained above.[11] An advantage of these data is the fact that the number of tourist arrivals can be separated into international and national tourist arrivals. Unfortunately, the dataset does neither provide information on the different nationalities of international tourists nor on the states of origin of the local tourists.

I use three variables of tourist arrivals. First, I look at overall arrivals of tourists. Second, I separate the international tourist arrivals from the national tourist arrivals and compare the effect that violent crime has on both tourist categories. In order to capture violent crime, I use the number of deaths resulting from homicides reported in state i in year t. The rationale for this is that violent events leading to several killings attract more the attention of local and international media. For instance, at the time of writing of this paper there has been again a mass killing in different locations of Mexico. Soon after this event the coverage of this notice was to be found in several newspapers across the world.[12]

[11] See**:** http://www.inegi.org.mx

[12] See: Le Monde, http://www.lemonde.fr ; BBC, http://www.bbc.co.uk, and Frankfurter Allgemeine Zeitung http://www.faz.net (accessed on May 13th 2012).

The dataset on homicides comes from the yearly mortality statistics gathered by INEGI[13] and corresponds to the period 1990-2010. The homicides are registered in the agency of the Public Ministry of the municipality where the crime took place. This information is then delivered to the local INEGI offices across the different states and forms part of the Mortality Statistics of INEGI.

It is important to mention that for all crime data in Mexico provided by INEGI there is the distinction to be made between the so called "register year" and "occurrence year." The former represents the year in which a criminal offence was registered and the latter shows the exact year in which a criminal offence took place. It is usually the case that criminal offences are not always, for several reasons, reported to the authorities when they happen. Thus the raw data show that there are crimes which for instance occurred in 1990, but are not registered until 1998. Using the occurrence year data I only consider homicides which took place from 1990 onwards since the availability on tourism data starts from 1990 onwards.

Figures I.1, I.2 and I.3 show the number of tourist arrivals across the states during the 1990-2010 period. Figure I.1 shows the highest number of total tourist arrivals in the Federal District, Veracruz, Jalisco and Quintana Roo in this order. From Figure I.2 we can see that most international tourists visit the following states: Quintana Roo, Distrito Federal, Baja California and Jalisco. These states are internationally known for their beaches in the Caribbean Sea and the Pacific Ocean and are home of several archeological parks and Mexican folklore. From Figure I.3, we see that national tourists visit more frequently the Federal District, Veracruz, Jalisco and Guerrero. Figure I.4 shows the number of homicides which took place across states during the 1990-2010 period. It can be seen that most homicides took place in the following states: Estado

[13] For details on mortality statistics see: www.inegi.org.mx.

de Mexico, Federal District, Chihuahua, Baja California, Guerrero, Michoacan, Oaxaca, and Sinaloa. Most of these states are also victims of intense drug violence between the drug cartels and the state police and military forces (Ríos 2012). Furthermore, Figure I.5 shows how violence is distributed across states if we consider homicides as a rate per 100,000 inhabitants. We see that in this case Chihuahua is the most violent state followed by Sinaloa and Guerrero. This is in line with the recent work by Ríos (2012) mentioned above. Next, Figures I.6, I.7, I.8 and I.9 show the raw data for homicides, international, national and overall tourists at the country level respectively. There are interesting issues to be observed in these four figures. First, while the number of homicides decreases from approximately 1995 onwards, the number of international and national tourists increases. Second, as the number of homicides skyrocketed from approximately 2006 onwards, the number of international tourist arrivals decreased to levels of 2002. Third, in relative terms, this drop was less for the national tourist arrivals and fourth we see that national tourism recovers but this is not the case for international tourists.

Having described the two main variables of interest I turn now to the vector of control variables (Z_{it}) which includes other potential determinants of tourist arrivals reported in state *i* during year *t*. I select these control variables from the existing literature on the subject.

The literature on tourism demand has focused on the study of international tourism while neglecting the study of national/local tourism. This literature can broadly be divided in two groups: The first group corresponds to contributions whose aim is to forecast tourism statistics as number of nights of stay, expenditures by tourists and /or the number of tourists arriving. For instance, the work by Witt and Witt (1995), Lim (1997a, 1997b and 1999) and Li et al. (2005) provide a good overview of articles on tourism demand forecasting. The second group of contributions concentrates on explaining its determinants. Within this group, the papers by Crouch (1994), Poirirer (1997), Cothran and Cothran (1998), Sonmez (1998), Sonmez and Graefe (1998), Neumayer (2004), and Clerides et al. (2008) provide an overview of the determinants of international tourism flows.

Crouch (1994) reviews the literature on the determinants of international tourist flows. He argues that research in the 1980´s has found income elasticities of demand above unity confirming in this way the view that foreign travel is a luxury good. I use the natural logarithm of the gross domestic product per capita in state *i* during year *t* as a proxy. I expect a positive and significant effect. A better economic environment enhances appropriate conditions for the stay of tourists. These data were collected from the National Accounts System of INEGI.

Furthermore researchers have used a wide variety of variables to represent prices in their models. In the context of international tourism demand, the variables used to represent prices have been foreign currency prices of tourist goods and services in destinations, the cost of transportation between origin and destination country and the effect of exchange rate variations on purchasing power. Put differently, as consumers, tourists also decide where to go based on the price of the goods they want to purchase; for instance holiday packages, which in some cases include flights and hotel reservations. In order to account for the differences in prices I use the price levels[14] of the main cities in each Mexican state and the Federal District. These data were computed by the Mexican Central Bank and are used in the construction of the main national inflation index. Since the summer 2011, INEGI is responsible for conducting the inflation measurement and for reporting it to the Federal Government and to the public. However, since I

[14] These data are measured as regional consumer price indexes with base year 2010.

only consider the period 1990-2010, these data are taken from the Mexican Central Bank. I expect a negative and significant impact of this variable. Higher prices can induce tourists to visit some other cheaper destination.

Another important determinant of tourism demand is nature. Within this literature, one of the earliest studies addressing how climate in the tourist destination affects the arrival of tourists is the work by Abegg and Koenig (1997) in which they evaluated how predicted changes in weather conditions affected the winter tourism industry in Switzerland. They found that under "winter-normal" climate conditions, 85% of all Swiss ski areas are reliable for the practice of winter sports. Nevertheless if temperatures would rise by 2 grades Celsius, this number would drop to 63%. Along these lines the papers by Faulkner (2001) and Murphy and Bayley (1989) have offered qualitative assessments as to how to deal with natural disasters in tourist locations. Following on this and given the geographic location of Mexico with a coast length of 7,828 kilometers on the Pacific Ocean side and with a coast length of 3,249 kilometers on the side of the Gulf of Mexico and the Caribbean Sea, the country experiences throughout a year several tropical storms which derive in hurricanes of high intensity. Thus, I use the number of hurricanes which caused the worst floods in state *i* during year *t* and construct a dummy variable which takes the value of one if a state was hit by a hurricane in year *t.* In general, a hurricane can hit more than one state in the same year. The data are from the Meteorological National Service[15] and from the Engineering Institute of the National Autonomous University of Mexico (UNAM).[16]

[15]See: http://www.smn.cna.gob.mx (Accessed on October 1st 2012).
[16] See: http://www.iingen.unam.mx (Retrieved on October 1st 2012).

I also include a control variable which accounts for urbanization. This is the amount of people living in urban areas as a share of total population in state *i* during year *t*. I expect a positive and significant effect of this variable since urban areas are known for providing a wide range of amenities for tourists, for instance health services and public transport. This variable is drawn from the population census data compiled by INEGI. Additionally, I control for the transport infrastructure within the country by using the log of the number of kilometers of roads available in state *i* during year *t*. The data are from the Transportation and Communications Ministry of each state. These statistics are as well provided to INEGI and form part of the statistical yearbooks of each state too. I would expect a positive and significant effect of this variable on the arrivals of tourists. Once in the country, tourists might be willing to visit other cities or towns near to their first destination. It is true that some tourists would prefer to use air transportation. However, there is not much variation trough time in the number of airports in each state.

I.3.1 Endogeneity

It can potentially be the case that the number of tourists visiting a country originates more crime. Tourists are new to the destination they visit; this lack of information puts them in a riskier situation more easily than local people. Thus, criminals may see in them an easier prey. This applies to both national and international tourists. While I am not aware of any variable which at the same time exerts any form of variation in the number of tourist arrivals and the number of homicides and is omitted from my specification, in general, the endogeneity problem in an econometric model can not only be due to the reverse causality as outlined above but also due to third omitted variables which affect both of the variables involved.

In order to account for potential endogeneity I employ a Two Stage Least Squares (2SLS) model. The validity of an estimation based on this method relies on the choice of a proper instrument. The instrumental variable must fulfil two criteria. The first one refers to the relevance of the instrument, i.e., it must induce sufficient exogenous variation in the explanatory variable in question, in particular, $Cov[Z, Homicides] \neq 0$. According to Bound, Jaeger and Baker (1995) the F-statistic of the excluded instruments in the first-stage regression should be examined in order to assess the relevance of the instruments. In a further contribution, Staiger and Stock (1997) argue that the selected instruments would be relevant when the first stage regression model´s F statistic reaches the thumb rule threshold of 10. This F-statistic has been criticized in the literature as an insufficient measure of relevance (Stock et al. 2002; Hahn and Hausman 2002 and 2003). Thus, the present paper also shows more powerful tests like the Kleibergen-Paap rk LM statistic (Kleibergen-Paap 2006), which is a statistic for testing the null hypothesis that the equation is underidentified. This test is a heteroscedasticity-robust variant of the Anderson canonical correlation test.[17] As long as the Kleibergen-Paap LM statistic is above the critical value of 10 the used instruments are not considered to be weak.

The second instrument criteria states that the ideal instrument should show $Cov[Z, w] = 0$, i.e., it must not be correlated with the error term of the second-stage regression. This means that the instrument should not affect the arrivals of tourists through other channels than the endogenous variable, controlled for the other variables in the model.

I propose the use of two instruments in an attempt to control for endogeneity in the model: The first instrument is the adult illiteracy rate within the population older than 15 years across the 31 Mexican states and the Federal District. The data come from the Ministry of Education of Mexico. This variable is intended to be a proxy for social exclusion. The rationale here is that social exclusion directly affects the increase in violent outcomes. For instance, the work by

[17] See: Kleibergen and Paap (2006) for further details.

Caldeira (2000); Heinemann and Verner (2006), Borjas (1995); Katzman (1999), Buvinic, Morrison and Orlando (2002) and Beato (2002) show that socially excluded communities have higher illiteracy rates, higher numbers of homicides, higher percentages of employment in the informal sector, higher child mortality and an underdeveloped urban infrastructure. Following on this, illiteracy impedes the opportunities for participation in the labour market and thus reduces the income of individuals and their chances to be included in society. For instance, using data from two groups of British adults born in 1958 and 1970, Parsons (2002) found a significant association between repeated offending and poor literacy or numeracy scores, particularly among young men.

In addition to these arguments, the work by Lochner and Moretti (2004) states that education may affect crime in several ways. First, it increases the wage rate of individuals, thereby increasing the opportunity cost of committing a crime. Second, if arrested, the punishment would be more costly for the more educated than for the less educated, i.e., the time out of the labor market due to incarceration represents a higher opportunity cost for those educated. They find that education significantly reduces crime. Based on this, it is reasonable to expect that illiteracy exerts variation in the homicide variable. On the other hand, there is no reason to suspect that illiteracy is directly correlated with the dependent variable, i.e., tourists arrivals, in particular when controlling for economic welfare in the estimation. As outlined in the second section of the paper, tourism demand is influenced by different factors than illiteracy.

The second instrument is a proxy for the severity of punishment of committing a homicide. According to Becker´s model of crime and punishment (Becker 1968) an individual would compare the expected utility of participation in legal and illegal activities. If punishment is more severe, it follows that the cost of deviating from “good behavior” is higher and the crime rate is reduced. Thus, such a variable would induce a direct variation in the homicide rate but does not directly influence the arrival of tourists. Following this literature, I construct a variable which proxies for the severity of punishment by calculating the rate of incarceration of people who have committed a homicide across the Mexican States and the Federal District within the period 1990-2010. For this aim I use the data coming from INEGI. This dataset registers the criminals who have been arrested on charges of homicide and who have been dictated an imprisonment sentence. Thus I divide the number of imprisoned persons with sentence in state *i* at time *t* by the amount of homicides which took place in state *i* at time *t* and multiply this by one hundred. It could be that more homicides lead to a higher incarceration rate, however the number of imprisonment sentences depends on the quality of the judiciary system and thus an increase in homicides does not necessarily mean that the incarceration rate will increase as well (Zepeda 2004). The judiciary system is responsible for effectively punishing those individuals who have committed a homicide. However, as documented in the media[18] and in the literature, impunity is a rampant problem of the judiciary Mexican system and the incarceration of innocent people is not an exception, (Zepeda 2004).

I.4 EMPIRICAL RESULTS

Table I.1 presents the baseline results capturing the effect of homicides on the arrival of overall tourists, international tourists and national tourists implementing the model outlined above.[19] Beginning with column 1 in table I.1, the results show that, when using the homicide data from INEGI and holding other factors constant, a one percent increase in homicides leads to 0.12

[18] See: La Jornada, http://www.jornada.unam.mx (Retrieved on October 7th 2012).
[19] According to the Hausman test, the fixed effects model is preferred over the random effects model. The test result is available upon request.

percent decrease in tourism, at the 5% significance level. It is interesting to ask whether this effect is similar or not for international and national tourists. I expect that international tourist are more deterred by violent crime than national tourists. The latter have more information to what is happening in the country. Thus, they have the advantage of better knowing where violence is worst and where not. The former receive the information about crime in Mexico through the international news. When a criminal event of high impact takes place, this is promptly communicated in the international media. Following on this, the countries of origin of the international tourists warn their people not to visit certain places in the country or better to choose completely other destinations for holiday. In order to consider this, column 2 shows the effect of violent crime/ homicides on the arrival of international tourists. When holding other factors constant, a one percent increase in homicide leads to a 0.31 percent decrease on the international tourist arrivals. This effect is significant at the one percent level. It is interesting to see that the effect of violent crime on international tourism is bigger than tourism in general. Next, I look at whether this effect is the same or not for national tourists. This is done in column 3 which shows that, holding other factors constant, the effect of homicides on national tourist arrivals is a significant decrease of 0.9 percent at the 10% significance level. In general this first table of results shows that violent crime actually deters both types of tourists however this effect seems to be stronger for the international visitors.[20]

Relying on these results, it is not possible yet to give a definitive answer to the research question of the paper. According to Nickell (1981) and Hsiao (1986), in a short fixed effects panel model, the correlation between the error term and the lagged dependent variable may render the estimates of the parameters biased and inconsistent. This issue is quite serious in panel

[20] The difference of the coefficients is statistically significant at the 5% level. I tested for the significance of the difference in a nested model, interacting an international tourist dummy with all explanatory variables and the state and year dummies. The results are not shown in order to save space.

data sets with a small number of time series observations. Increasing the number of units would not lead to better estimates if the number of time series observations remains small (Anderson and Hsiao, 1982). In order to obtain consistent estimators, one possibility could be to implement instrumental estimators. Nevertheless it is important to note that, although GMM and IV estimators possess good asymptotic properties, these estimators are still biased in a finite sample application, when n is small, (Bruno 2005a, 2005b). I follow Potrafke (2009) and use the Dynamic Bias corrected Least Squares estimator proposed by Bruno (2005a, 2005b). Using asymptotic expansion techniques, Kiviet (1995, 1999) calculates approximation formulas for correcting the finite-sample bias of the least square estimator. In a further paper, Bun and Kiviet (2003) redevelop Kiviet´s (1999) bias approximation using a simpler expression. Bruno (2005a) generalizes the bias approximation formula of Bun and Kiviet (2003) and extends the analysis for unbalanced panels. The bias-correction procedure involves consistent estimates as a first step. These consistent estimates are based on one out of the three following estimators, namely the Anderson-Hsiao, Arellano-Bond and Blundell-Bond estimators. I choose the Blundell-Bond (1998) system GMM estimator since it is superior with respect to the other two in terms of efficiency (Baltagi 2008).[21] Table I.2 presents the results of the model when implementing the Dynamic Bias Corrected Estimator (henceforth LSDV) proposed by Bruno (2005).

The estimates of homicides coefficients in table I.2 are similar in magnitude to the previous Fixed Effects specification. Looking at the first column and keeping all other variables constant, a one percent increase in homicides leads to a reduction of 0.12 percent in the arrivals of tourists in general; this is statistically significant at the 10% level. Further, column 2 shows the results

[21] As in Potrafke (2009), the results obtained from this method refer to the Blundell and Bond (1998) estimator as the initial one. The instruments are collapsed as suggested by Roodman (2006). I also undertake 50 repetitions of the procedure to bootstrap the estimated standard errors. The results are similar when changing the number of repetitions to 100, 200 or 500.

for the foreign tourist arrivals specification. In this model a one percent increase in homicides results in fewer arrivals of foreign tourists by 0.30 percent, all else equal. This result is similar to its corresponding Fixed Effects version in Table I.1. However, the result under the LSDV estimator is significant only at the 5% level. Until this point the results in table I.2 are similar to those in table I.1. Looking next at column 3, and contrary to the Fixed Effects specification, the arrivals of national tourists seem not to be affected by violent crime since the significance of the violent crime variable disappears in this model. Thus, violent crime has a bigger negative effect on the arrival of international tourists than on the arrival of national tourists.[22] As previously mentioned, this can be due to information asymmetries in the sense that national tourists might be better informed than the international tourists and thus, they may be less concerned about high criminality in states in general as long as they know how to avoid risky situations.

With respect to the control variables, table I.1 shows that prices matter for the local tourists only. We see that, holding other factors constant, a one percent increase in the price level reduces the arrivals of national tourists by 0.3 percent. In contrast, price levels are not a significant determinant of international tourism flows. Most of the international tourists visiting Mexico are coming from the United States, Canada and European countries belonging to the European Monetary Union. It could be argued that since the international tourists possess a higher purchasing power, prices are more a concern for local tourists. However, this effect is only significant at the 10% level. Furthermore this variable is no longer significant in table 2.

Arguably, the higher the concentration of people in cities, the higher are the victimization rates of crimes as pointed out by Gaviria and Páges (2002) in their study on Patterns of crime victimization in Latin American cities. However, cities not only have problems but also

[22] In the LSDV Bruno estimation, the difference of the coefficients is statistically significant at the 10% level (not shown).

advantages as agglomeration of services and amenities which are attractive for tourists. Thus, holding other factors constant, a one percent increase in the share of people living in urban areas leads to a 0.3 percent increase in the arrival of tourists. This effect is significant at the 5% level in table I.1 under the fixed effects specification. Table I.2 shows for this variable a coefficient of 0.033 percent, at a significance level of 10%. Additionally, international tourists are more attracted to urban areas than national tourists. This is consistent in both tables.[23] However the LSDV estimations show significance at the 10% level for both types of tourists and tourists in general. Finally, I expect path dependence in tourist arrivals, i.e., past arrivals of tourists explaining a part of today´s arrivals. For instance, if visitors of a certain location have an enjoyable experience during their stay, they might visit the same location or country again in the future. They may also influence other fellow citizens when they return back to their place of residence by recommending places to visit. We see in tables I.1 and I.2 that past tourist arrivals do matter for today´s arrivals. These results remain significant at the 1% level for international and national tourists and both together. Interestingly, I do not find any effects of per capita GDP, storms and highways.

So far the LSDV estimator has taken into account the bias inherent in the model due to the inclusion of the lagged dependent variable. However there is still a further issue to be dealt with, namely the potential reverse causality of the variables tourism and homicides. Since the dynamic bias-corrected estimator does not account for this problem,[24] as a next step I present in table I.3 the results of the 2SLS estimation with state and time fixed effects using the external instruments introduced in the previous section.

[23] In the nested model of both the fixed effects model and the LSDV Bruno estimation, the difference of the coefficients is statistically significant at the 10% level (not shown).

[24] Despite the use of system GMM as an initial estimator, the LSDV Bruno (2005) estimator sets only the lagged dependent variable as endogenous but does not control for the endogeneity of further explanatory variables in the model. For details see Bruno (2005a) and Bruno (2005b).

Table I.3 reports the results for the second stage regressions followed by the first stage regressions for each of the three subsamples; namely total of tourists, international tourists and national tourists. In order to obtain the instrumental variable estimation, I regress the variable homicides on tourist arrivals and all other regressors at the first stage. In this way the predicted values of homicides are obtained which then enter into the second stage regression to obtain an unbiased estimator for the homicide variable. If it happens to be the case, the weakness of the instruments will render the coefficient of the homicide variable biased. By the same token, this bias will be negatively correlated with the first stage F-statistic of the null hypothesis that the coefficients of the instruments (illiteracy rate and incarceration rate) equal zero. Staiger and Stock (1997) argue that in order to avoid this problem the first stage F-statistic should show a value larger than 10. As can be seen at the bottom of table I.3, the models show an F-statistic of 22.51, 21.51 and 21.82 for the three tourists specification categories, rejecting in this way the null hypothesis that both of the selected instruments are not relevant. The Kleibergen-Paap underindentification LM test rejects as well this null hypothesis with test scores of 11.71, 11.14 and 11.27 suggesting that the implemented instruments are adequate to identify the equation. Furthermore, the Hansen J-statistic with p-values of 0.88, 0.19 and 0.81 shows that the null-hypothesis of exogeneity cannot be rejected at the conventional level of significance.

Column 1 of table I:3 shows that, keeping all other variables constant, a one percent increase in homicides leads to a 0.22 percent decrease of tourism as a whole. This effect is significant at the 5% level. Furthermore, the first stage regression of the first model, displayed in Column 1a, shows that an increase in the illiteracy rate by one percentage point increases homicides by 0.16 percent, all things else hold constant. This result is significant at the 1% level. In this way, illiteracy as a proxy for social exclusion causes violent crime to increase. Next, if the incarceration rate due to homicides increases by one percent, violent crime is reduced by 0.004 percent. This effect is statistically significant at the 1% level.

Interestingly, as column 2 shows, there is no significant effect of homicides on the arrival of international tourists. However, the endogeneity test for all three models at the bottom of table I.3 shows that the null hypothesis of exogeneity of the homicides variable cannot be rejected (with p-values of 0.35, 0.99 and 0.24). According to this test there is no reverse causality going from tourism to homicides. In this sense, the results of the LSDV Bruno estimator provide the preferred estimation since this method is superior to the (2SLS) fixed effects estimation which does not control for the Nickell (1981) bias inherent in the lagged dependent variable.

I.5 CONCLUSION

This paper has investigated whether there is an effect of violent crime on tourism in Mexico for the 1990-2010 period. The contribution of the paper is twofold. First, addressing endogeneity the paper finds that the impact of violent crime on tourism in Mexico is negative and significant. Second, this paper investigates whether international tourists or local tourists are more affected by violent crime. Due to the lack of data, previous research has concentrated only on the analysis of international tourism flows. First, my findings show that tourist arrivals in Mexican states are reduced by increased violent crime. Second, international tourists appear to be more intimidated by violent crime than local tourists. As argued in previous research by Morley (1998) and Clerides et al. (2008), information asymmetries play a role in tourism demand. Thus by living in the country, local tourists know better where crime is higher than international tourist do. For instance, an average Mexican would certainly know that violent crime is less in the state of Guanajuato than in the state of Tamaulipas or any other state in the north border to the United States. On the other hand, international tourists are mostly informed by what they hear or read in the news.

In terms of tourism policy the findings suggest that by better informing and promoting tourism in Mexico abroad this negative effect could be alleviated. Efforts on behalf of the Mexican Federal government have recently been made. Future studies might look at whether these investments in tourism promotion have been effective. Using spatial econometric techniques, further research on this topic could look at whether tourists move to different locations in order to avoid dangerous regions.

Table I.1: Tourist Arrivals, Total, International and National (1990-2010): State fixed Effects estimations

	(1)	(2)	(3)
Variables	**Tourists Arrivals: Total**	**Tourists Arrivals: Foreign**	**Tourists Arrivals: National**
LDV (log) t-1	0.580***	0.474***	0.635***
	(0.0629)	(0.0860)	(0.0521)
Homicide (log)	-0.123**	-0.307***	-0.0944*
	(0.0570)	(0.105)	(0.0537)
Price level	-0.0265	-0.0424	-0.0336*
	(0.0225)	(0.0410)	(0.0194)
State per Capita GDP (log)	0.0187	0.490	-0.0161
	(0.318)	(0.550)	(0.300)
Urbanization	0.0282**	0.0603**	0.0296**
	(0.0126)	(0.0268)	(0.0113)
Storms	-0.0293	-0.0357	-0.0338
	(0.0415)	(0.0809)	(0.0391)
Roads (log)	-0.00795	-0.133	0.0183
	(0.0826)	(0.220)	(0.0777)
Constant	5.038***	3.631	3.960**
	(1.825)	(3.389)	(1.776)
Hausman test p > chi2	0.00	0.00	0.00
Year and State dummies	YES	YES	YES
Number of States	31	31	31
Number of Observations	497	492	494
R-squared	0.535	0.326	0.603
Method	Fixed Effects	Fixed Effects	Fixed Effects

Robust standard errors clustered by state in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table I.2: Tourist Arrivals, Total, International and National (1990-2010): Dynamic bias corrected estimator

Variables	(1) Arrivals: Total	(2) Arrivals: Foreign	(3) Arrivals: National
LDV (log) t-1	0.697***	0.567***	0.730***
	(0.0483)	(0.0515)	(0.0461)
Homicide (log)	-0.118*	-0.295**	-0.0896
	(0.0678)	(0.134)	(0.0673)
Price level	-0.0317	-0.0485	-0.0383
	(0.0276)	(0.0512)	(0.0329)
State per Capita GDP (log)	0.101	0.481	0.0977
	(0.405)	(0.645)	(0.333)
Urbanization	0.0332*	0.0662*	0.0355*
	(0.0201)	(0.0338)	(0.0193)
Storms	-0.0124	-0.0278	-0.0302
	(0.151)	(0.0957)	(0.0506)
Roads (log)	0.0124	-0.108	0.0457
	(0.151)	(0.296)	(0.130)
Year and State dummies	YES	YES	YES
Number of States	31	31	31
Number of Observations	497	492	494
Method	LSDV	LSDV	LSDV

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table I.3: Tourist Arrivals, Total, International and National (1990-2010):
Fixed Effects 2SLS estimations (Instruments: Illiteracy rate and Imprisonment rate due to homicide)

Variables	(1) Total Arrivals	(1a) First stage regression	(2) Foreign Arrivals	(2a) First stage regression	(3) National Arrivals	(3a) First stage regression
		Homicide (log)		Homicide (log)		Homicide (log)
Dependent Variable- (log) t-1	0.569***	-0.071	0.478***	-0.063**	0.623***	-0.071
	(0.0549)	(0.0488)	(0.0808)	(0.0299)	(0.0475)	(0.0499)
Homicide (log)	-0.218**		-0.241		-0.207**	
	(0.0901)		(0.2021)		(0.0886)	
Illiteracy		0.149***		0.147***		0.144***
		(0.0305)		(0.0312)		(0.0302)
Imprisonment rate		-0.004***		-0.004***		-0.004***
		(0.0011)		(0.0011)		(0.0011)
Price level	-0.031	-0.017	-0.046	-0.015	-0.0381**	-0.018
	(0.0216)	(0.0237)	(0.0382)	(0.0244)	(0.0193)	(0.0248)
State per Capita GDP (log)	0.132	-0.049	0.612	0.021	0.0832	-0.025
	(0.3098)	(0.5019)	(0.5023)	(0.4885)	(0.288)	(0.4964)
Urbanization	0.029**	0.039*	0.057**	0.042	0.0310***	0.039*
	(0.0122)	(0.0205)	(0.0269)	(0.0200)**	(0.0108)	(0.0206)
Storms	-0.029	-0.011	-0.038	-0.008	-0.033	-0.011
	(0.0394)	(0.0320)	(0.0759)	(0.0329)	(0.0369)	(0.0326)
Roads (log)	-0.016	0.062	-0.100	0.060	-0.00029	0.056
	(0.0741)	(0.0925)	(0.1911)	(0.0938)	(0.0722)	(0.0948)
F-statistic		22.51		21.51		21.82
Hansen J (p-value)		0.8827		0.1904		0.8187
Kleibergen Paap LM test		11.71		11.14		11.27
Endogeneity test (p-value)		0.3462		0.9893		0.2376
Year and State dummies	YES	YES	YES	YES	YES	YES
Number of States	31	31	31	31	31	31
Number of Observations	494	494	489	489	491	491
R-squared	0.5309	0.5802	0.3273	0.5837	0.598	0.5793
Method	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS

Robust standard errors clustered at the state level in parentheses *** p<0.01, ** p<0.05,*p<0.1.

I.1 Appendix

Outliers

In order to identify outliers in the previous estimations I implement graphs showing the linear relationship between homicides and (total, international, national) tourist arrivals, controlling for all other explanatory variables. Using these graphs I identified those observations which lie far away from the regression line and removed them from the dataset.

For the Total Tourists Arrivals model the removed observations were the five lying at the bottom (see Figure I.A), for the International Tourists Arrivals models the removed observations were the three lying at the bottom and four lying above the regression line with the largest distance (see Figure I.B). Finally, for the National Tourists Arrivals models the removed observations were the four lying at the bottom which show the largest distance to the regression line (see Figure I.C). Tables I.1a, I.2a and I.3a show the regression results after having removed these observations.

Table I.1a still shows that homicides reduce total tourist arrivals; this effect has a magnitude of minus 0.11 percent and is significant at the 10% level. Interestingly, the effect of violent crime on national tourist arrivals is now significant at the 5% level and with a value of minus 0.11 per cent. Furthermore, the effect of homicides on international tourist arrivals is now of minus 0.23 percent and significant at the 5%. In general table I.1a shows that after excluding the outliers the results are similar to those in table I.1 in the sense that the effect of violent crime on the arrival of international tourists is bigger than the effect observed on the national tourist arrivals.[25]

[25] The difference in the nested model is statistically significant at the 5% level (not shown).

Looking now at table I.2a, the results are also similar to those in table I.2. Column one of table I.2a shows that, all things else equal, a one percentage point increase in homicides reduces tourist arrivals by 0.11 percent. This effect is significant at the 10% level. Further, column 2 indicates that a one percentage point increase in homicides, all else equal, leads to a reduction in international tourist arrivals by 0.22 percent. This figure is significant at the 1 % level. On the other hand, column 3 shows that, all else equal, a one percentage point increase in homicides reduces the arrival of national tourists by 0.11 percent. This effect is significant at the 10% level.

Table I.3a shows the results for the 2SLS estimation after removing the above mentioned outliers. Column 1 shows that, all things else equal, a one percentage point increase in homicides reduces tourist arrivals by 0.25 percent. This effect is significant at the 1% level. Column 2 shows that, all things else equal, a one percentage point increase in homicides leads to a reduction in the arrival of international tourists by 0.30 per cent. Different than table I.3, this effect is now significant at the 10% level. Continuing with column 3 and keeping all other controls constant, a one percentage point increase in homicides reduces the arrivals of national tourists by 0.24 percent. This effect is significant at the 1% level.

Furthermore, after the removal of the outliers, the F statistic, the Kleibergen-Paap underindentification LM test and Hansen test still lend support to the relevance and the validity of the implemented instruments.

In detail, the F statistic shows the values of 22.43, 21.61 and 22.09 for the total, international and national tourist arrivals respectively. Additionally, the Kleibergen Paap LM test shows the values of 11.7, 11.11 and 11.21 for the three models. These tests strongly show that the used instruments are relevant. Furthermore and as in table I:3, the Hansen J-statistic with p-values of

0.84, 0.45 and 0.88 shows that the null-hypothesis of exogeneity cannot be rejected at the conventional level of significance for all three models.

As explained before, the LSDV Bruno estimator accounts only for the bias inherent in the lagged dependent variable, while overlooking the potential endogeneity in the homicide variable. In order to correct for this shortcoming, I re-estimate the model with the LSDV Bruno estimator using the fitted values of the first stage regression from the 2SLS estimation and replace the homicide variable with them. Table I.4 shows the corresponding results. From column 1 can be seen that, all things else equal, a one percentage point increase in the fitted values which explain homicides, reduces tourist arrivals by 0.18 percent. This effect is significant at the 10% level. Column 2 shows that, all things else equal, a one percentage point increase in the fitted values which explain homicides, reduces international tourist arrivals by 0.29 percent. This effect is significant at the 10% level. The last column shows the effect of a one percentage point increase in the fitted values explaining homicides on the national tourist arrivals. This amounts to a reduction of 0.17 percent. This effect is significant at the 10% level. These last results show that the negative effect of violent crime on tourist arrivals is not driven by the neglect of the potential endogeneity of the homicide variable in the LSDV Bruno estimator.

Table I.1a: Tourist Arrivals, Total, International and National (1990-2010): Fixed Effects estimations

Variables	(1) Tourists Arrivals: Total	(2) Tourists Arrivals: Foreign	(3) Tourists Arrivals: National
Dependent Variable- (log) t-1	0.589***	0.554***	0.630***
	(0.0518)	(0.0534)	(0.0531)
Homicide (log)	-0.112*	-0.229**	-0.106**
	(0.0563)	(0.0959)	(0.0487)
Price level	-0.016	-0.0515	-0.0305*
	(0.0202)	(0.0441)	(0.0168)
State per Capita GDP (log)	-0.349	0.390	-0.322
	(0.288)	(0.522)	(0.278)
Urbanization	0.0377***	0.0604**	0.0359***
	(0.0122)	(0.0231)	(0.0113)
Storms	-0.0329	-0.0353	-0.025
	(0.0343)	(0.0649)	(0.0369)
Roads (log)	0.038	0.001	0.0517
	(0.0660)	(0.204)	(0.0592)
Constant	4.321**	-0.0154	3.866**
	(1.678)	(2.928)	(1.753)
Hausman test p > chi2	0.00	0.00	0.00
Year and State dummies	YES	YES	YES
Number of States	31	31	31
Number of Observations	492	485	490
R-squared	0.914	0.914	0.915
Method	Fixed Effects	Fixed Effects	Fixed Effects

Robust standard errors clustered by state in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table I.2a: Tourist Arrivals, Total, International and National (1990-2010): Dynamic bias corrected estimator

Variables	(1) Arrivals: Total	(2) Arrivals: Foreign	(3) Arrivals: National
LDV (log) t-1	0.669***	0.643***	0.714***
	(0.0406)	(0.0611)	(0.0373)
Homicide (log)	-0.107*	-0.219***	-0.102*
	(0.0583)	(0.0821)	(0.0575)
Price level	-0.020	-0.057	-0.033
	(0.0293)	(0.0598)	(0.0254)
State per Capita GDP (log)	-0.285	0.409	-0.229
	(0.336)	(0.667)	(0.345)
Urbanization	0.042***	0.067**	0.041***
	(0.0165)	(0.0262)	(0.0128)
Storms	-0.029	-0.026	-0.0239
	(0.0405)	(0.0659)	(0.0439)
Roads (log)	0.057	0.053	0.071
	(0.130)	(0.287)	(0.129)
Time dummies	YES	YES	YES
Number of States	31	31	31
Number of Observations	492	485	490
Method	LSDV	LSDV	LSDV

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table I.3a: Tourist Arrivals, Total, International and National (1990-2010):
Fixed Effects 2SLS estimations (Instruments: Illiteracy rate and Imprisonment rate due to homicide)

	(1)	(1a)	(2)	(2a)	(3)	(3a)
Variables	**Total Arrivals**	**First stage regression**	**Foreign Arrivals**	**First stage regression**	**National Arrivals**	**First stage regression**
		Homicide (log)		Homicide (log)		Homicide (log)
Dependent Variable- (log) t-1	0.572***	-0.071	0.548***	-0.07**	0.616***	-0.068
	(0.0443)	(0.0488)	(0.0478)	(0.0307)	(0.0492)	(0.0500)
Homicide (log)	-0.251***		-0.305*		-0.242***	
	(0.0802)		(0.1821)		(0.0787)	
Illiteracy		0.15***		0.15***		0.145***
		(0.0303)		(0.0308)		(0.0301)
Imprisonment rate		-0.005***		-0.005***		-0.004***
		(0.0011)		(0.0011)		(0.0011)
Price level	-0.022	-0.020	-0.06	-0.017	-0.035**	-0.020
	(0.0198)	(0.0237)	(0.0397)	(0.0244)	(0.0174)	(0.0248)
State per Capita GDP (log)	-0.239	-0.068	0.583	0.026	-0.238	-0.056
	(0.2622)	(0.4996)	(0.4862)	(0.4845)	(0.2490)	(0.4937)
Urbanization	0.040***	0.04*	0.060***	0.041**	0.038***	0.040*
	(0.0112)	(0.0204)	(0.0219)	(0.0199)	(0.0101)	(0.0205)
Storms	-0.032	-0.009	-0.035	-0.007	-0.024	-0.009
	(0.0320)	(0.0317)	(0.0606)	(0.0326)	(0.0340)	(0.0326)
Roads (log)	0.020	0.060	0.008	0.0589	0.027	0.057
	(0.0600)	(0.0926)	(0.1758)	(0.0927)	(0.0551)	(0.0950)
F-statistic		22.43		21.61		22.09
Hansen J (p-value)		0.8486		0.4525		0.8801
Kleibergen Paap LM test		11.7		11.11		11.21
Endogeneity test (p-value)		0.1075		0.6083		0.1098
Year and State dummies	YES	YES	YES	YES	YES	YES
Number of States	31	31	31	31	31	31
Number of Observations	489	489	482	482	487	487
R-squared	0.6312	0.5825	0.4529	0.5879	0.6736	0.5797
Method	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS

Robust standard errors clustered by state in parentheses *** p<0.01, ** p<0.05,*p<0.1.

Table I.4: Tourist Arrivals, Total, International and National (1990-2010): Dynamic bias corrected estimator

	(1)	(2)	(3)
Variables	**Arrivals: Total**	**Arrivals: Foreign**	**Arrivals: National**
LDV (log) t-1	0.665***	0.570***	0.723***
	(0.0510)	(0.0455)	(0.0520)
Homicide (log) (fitted values) [26]	-0.179*	-0.288*	-0.173*
	(0.0995)	(0.172)	(0.0952)
Price level	-0.0336	-0.0510	-0.0406
	(0.0306)	(0.0543)	(0.0285)
State per Capita GDP (log)	0.188	0.626	0.179
	(0.439)	(0.732)	(0.369)
Urbanization	0.0329	0.0635**	0.0359**
	(0.0212)	(0.0282)	(0.0176)
Storms	-0.0275	-0.0309	-0.0308
	(0.0601)	(0.0929)	(0.0519)
Roads (log)	0.0142	-0.0743	0.0346
	(0.159)	(0.265)	(0.146)
Time dummies	YES	YES	YES
Number of States	31	31	31
Number of Observations	494	489	491
Method	LSDV	LSDV	LSDV

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[26] The fitted values of the potentially endogenous variable Homicide (log) are taken from the first stage regression from the 2SLS estimation.

Appendix I.2: Mexican States

Aguascalientes	Distrito Federal	Morelos	Sinaloa
Baja California	Durango	Nayarit	Sonora
Baja California Sur	Estado de México	Nuevo León	Tabasco
Campeche	Guanajuato	Oaxaca	Tamaulipas
Chiapas	Guerrero	Puebla	Tlaxcala
Chihuahua	Hidalgo	Querétaro	Veracruz
Coahuila	Jalisco	Quintana Roo	Yucatán
Colima	Michoacán	San Luis Potosí	Zacatecas

Appendix I.3: Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Observations
Tourist Arrivals (Total) log	14.15577	1.098107	7.233455	16.31798	589
Tourist Arrivals (Total) log t-1	14.13433	1.107204	7.233455	16.31798	562
Tourist Arrivals (International) log	12.00465	1.668351	5.826	15.62604	586
Tourist Arrivals (International) log t-1	12.00123	1.675661	5.826	15.62604	559
Tourist Arrivals (National) log	13.92622	1.072491	6.952729	16.0395	588
Tourist Arrivals (National) log t-1	13.90193	1.080445	6.952729	16.02846	561
Homicides (log)	5.382426	1.150092	2.484907	8.737774	672
Price Level	57.02784	27.58268	10.48747	98.55759	637
State per Capita GDP (log)	4.146175	.513901	3.386864	6.176142	672
Urbanization	72.61502	14.94279	39.45287	99.76386	672
Storms	.1622024	.368911	0.00	1.00	672
Roads (log)	8.883446	.6622945	7.247081	10.16591	651
Illiteracy Rate	9.54375	5.673183	2.1	29.20	640
Imprisonment Rate	46.57406	39.92938	0.00	247.8261	665

Appendix I.4: Data Definitions and Sources

Variables	Definitions and data sources
Total Tourist Arrivals	The logarithm of *total* number of tourist arrivals in state *i* in year *t*. The data were obtained from Statistical Yearbooks of each Mexican state and Mexico City provided by INEGI.
International Tourist Arrivals	The logarithm of *international* number of tourist arrivals in state *i* in year *t*. The data were obtained from Statistical Yearbooks of each Mexican state and Mexico City provided by INEGI.
National Tourist Arrivals	The logarithm of *national* number of tourist arrivals in state *i* in year *t*. The data were obtained from Statistical Yearbooks of each Mexican state and Mexico City provided by INEGI.
Homicides	The logarithm of total number of homicides committed in state in year *t*. The data were obtained from the Mortality Statistics provided by INEGI. This data is available from 1990 till 2010.
Urbanization	Share of the total population living in urban areas in state *i* in year *t*. The data were own construction based on the information data from the population censuses 1990, 2000, 2010 and population counting 1995, 2005 provided by INEGI.
Price Level	Price level of the main cities in each state and Mexico City. The data were obtained from the Mexican Central Bank. The period is 1990 till 2010.
State per Capita GDP (log)	Own calculation using data on each State GDP and Population in each State. Values are in Mexican pesos, constant prices 2003. The data on State GDP are form the National Accounting System and the Population data are from the population censuses 1990, 2000, 2010 and population counting 1995, 2005. All data are provided by INEGI.
Storms	A dummy variable which takes the value of one if a hurricane hit in state *i* in year *t* and zero otherwise. The data are from the Meteorological National Service and the Institute of Engineering at the National Autonomous University (UNAM) in Mexico City.
Roads	The logarithm of the number of kilometres of highways and paved roads in state *i* in year *t*. The data are from the Ministry of Transport and Communication (SCT Mexico).
Illiteracy Rate	Illiteracy rate of population older than 15 years. Data are provided by the Mexican Education Ministry.
Imprisonment Rate	Rate of imprisonment of people who have committed homicide. Data provided by INEGI.

Figure I.1

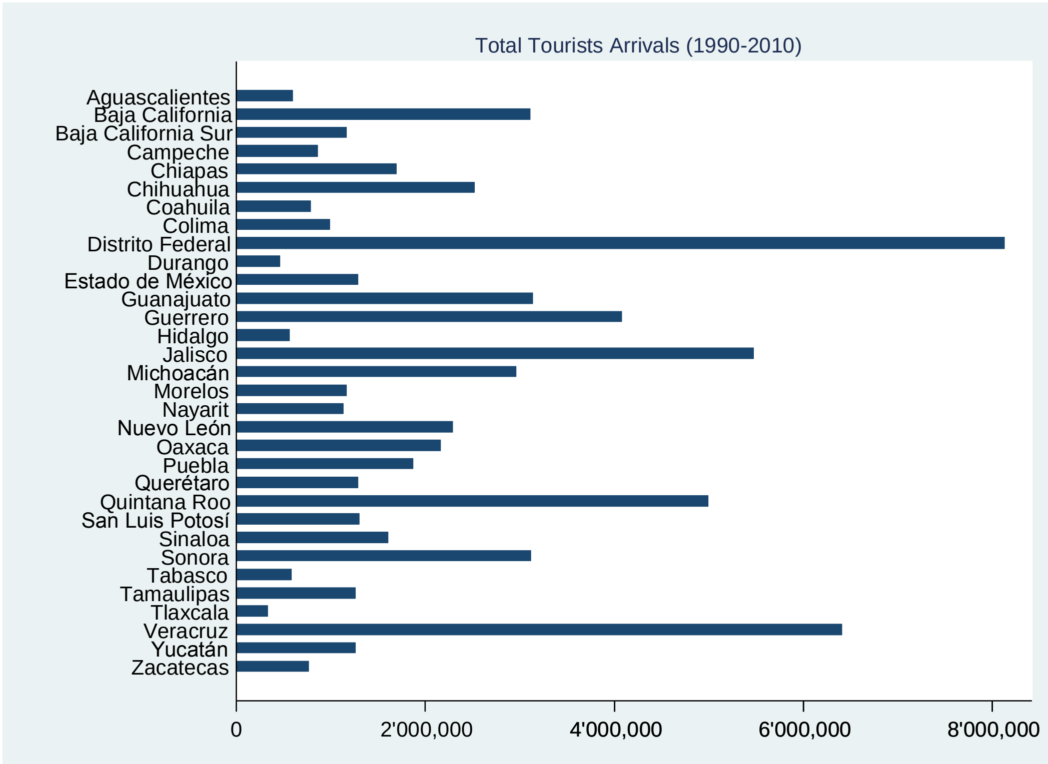
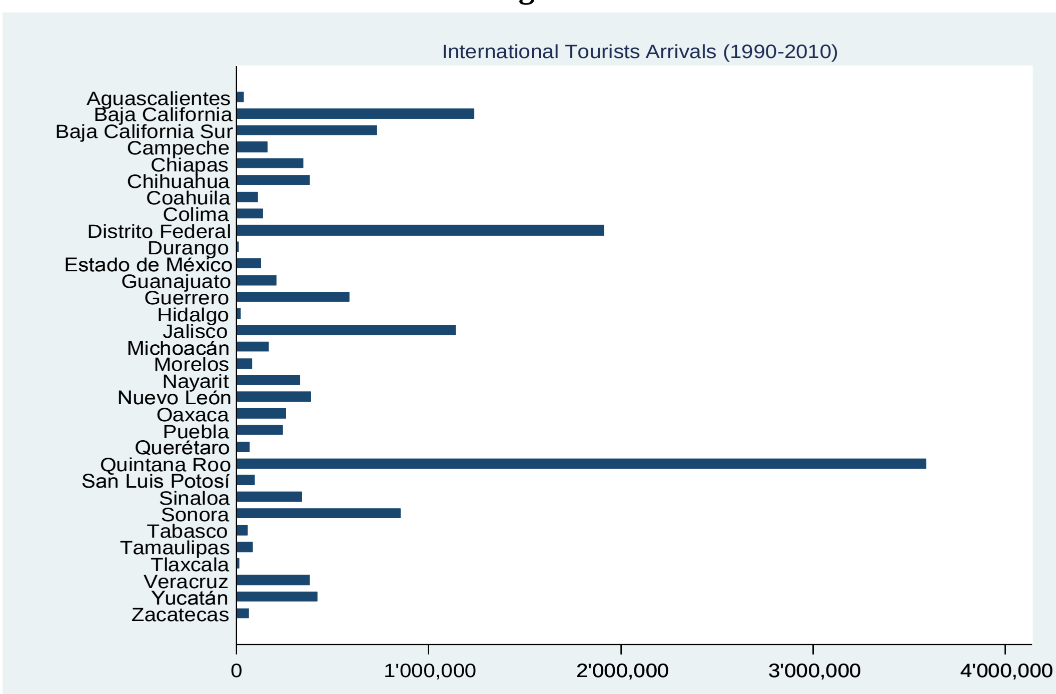


Figure I.2



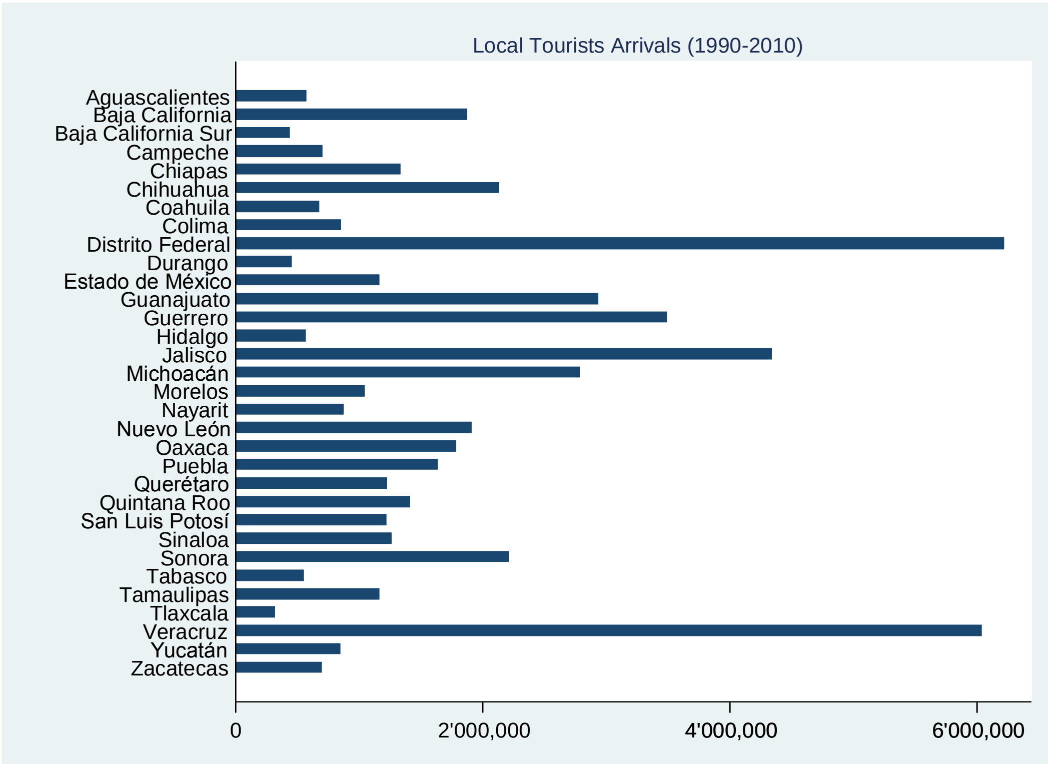


Figure I.3

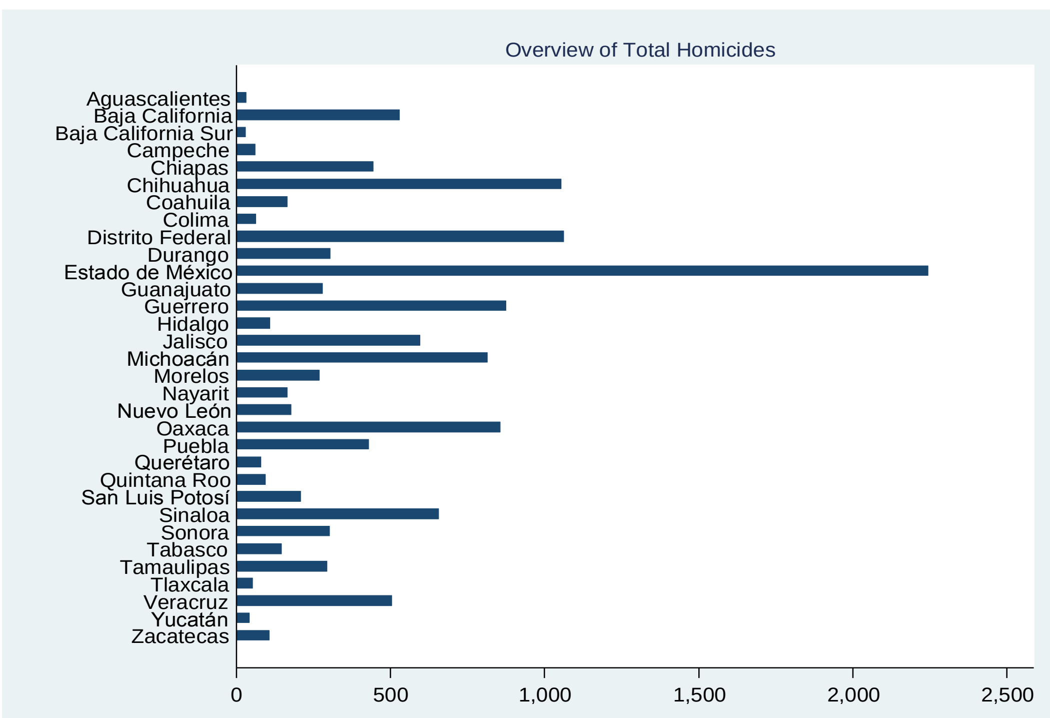


Figure I.4

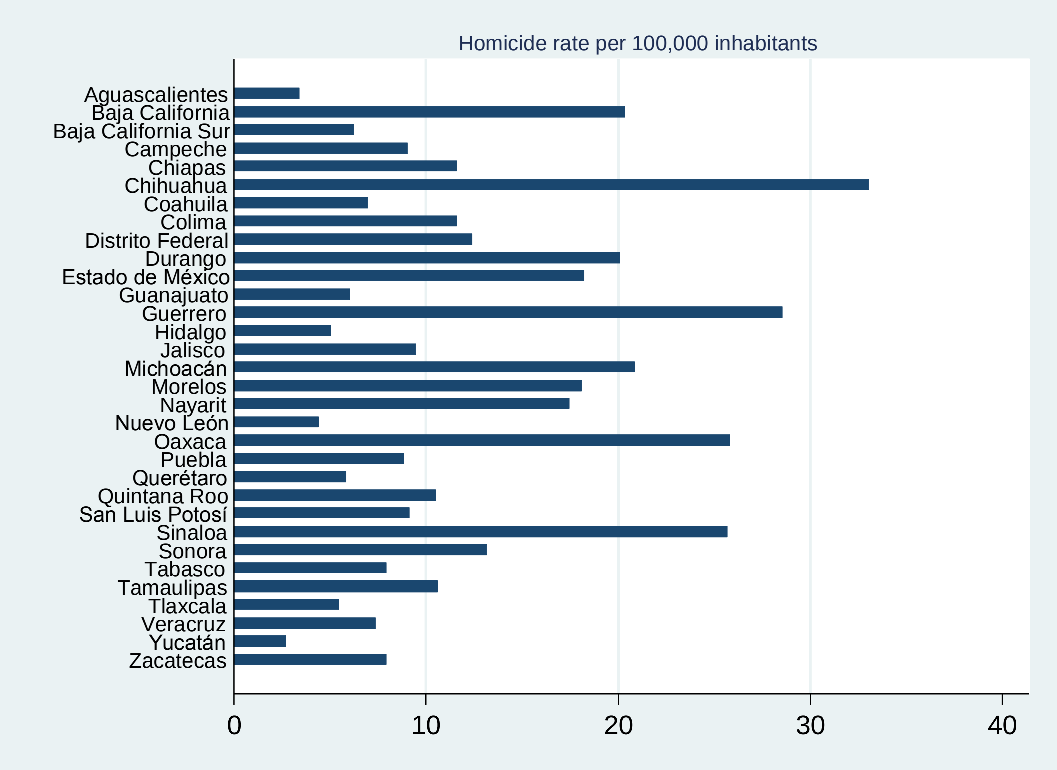

Homicide rate per 100,000 inhabitants
Aguascalientes
Baja California
Baja California Sur
Campeche
Chiapas
Chihuahua
Coahuila
Colima
Distrito Federal
Durango
Estado de México
Guanajuato
Guerrero
Hidalgo
Jalisco
Michoacán
Morelos
Nayarit
Nuevo León
Oaxaca
Puebla
Querétaro
Quintana Roo
San Luis Potosí
Sinaloa
Sonora
Tabasco
Tamaulipas
Tlaxcala
Veracruz
Yucatán
Zacatecas
0
10
20
30
40

Figure I.5

Figure I.6

Figure I.7

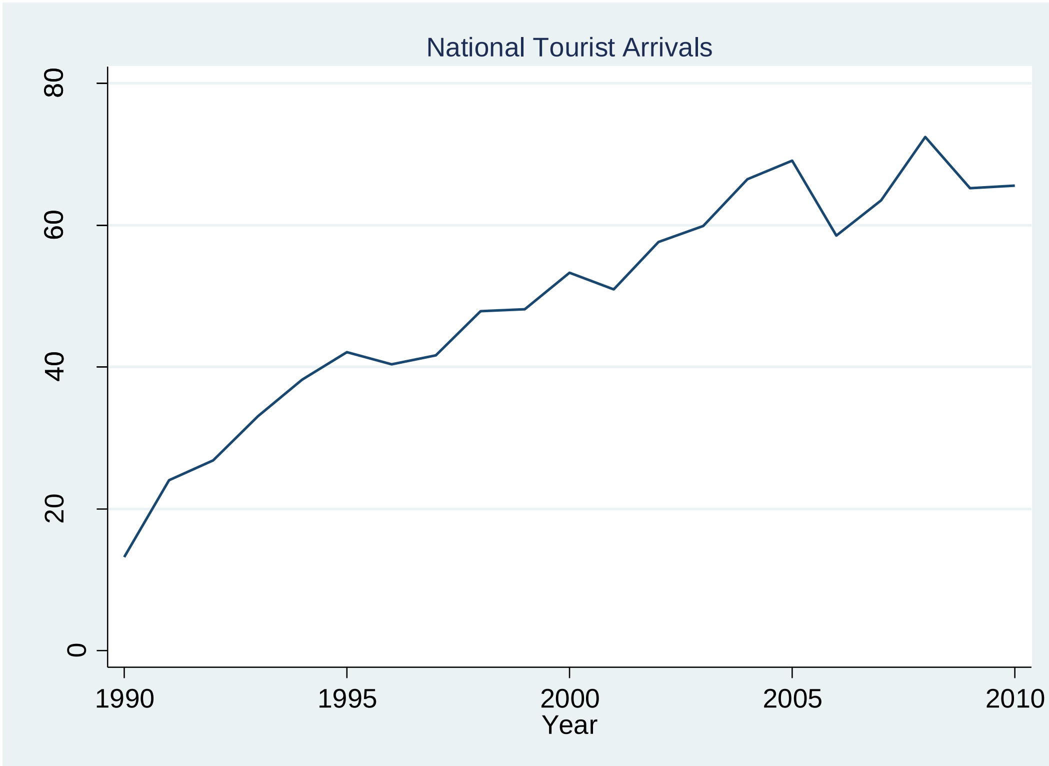


Figure I.8

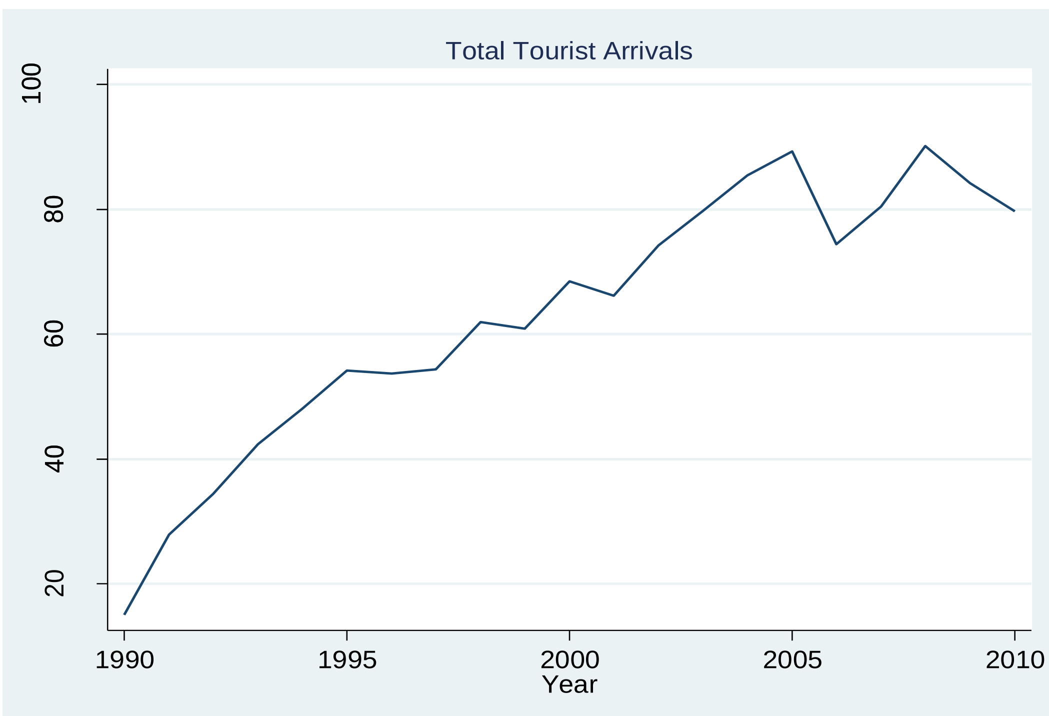


Figure I.9

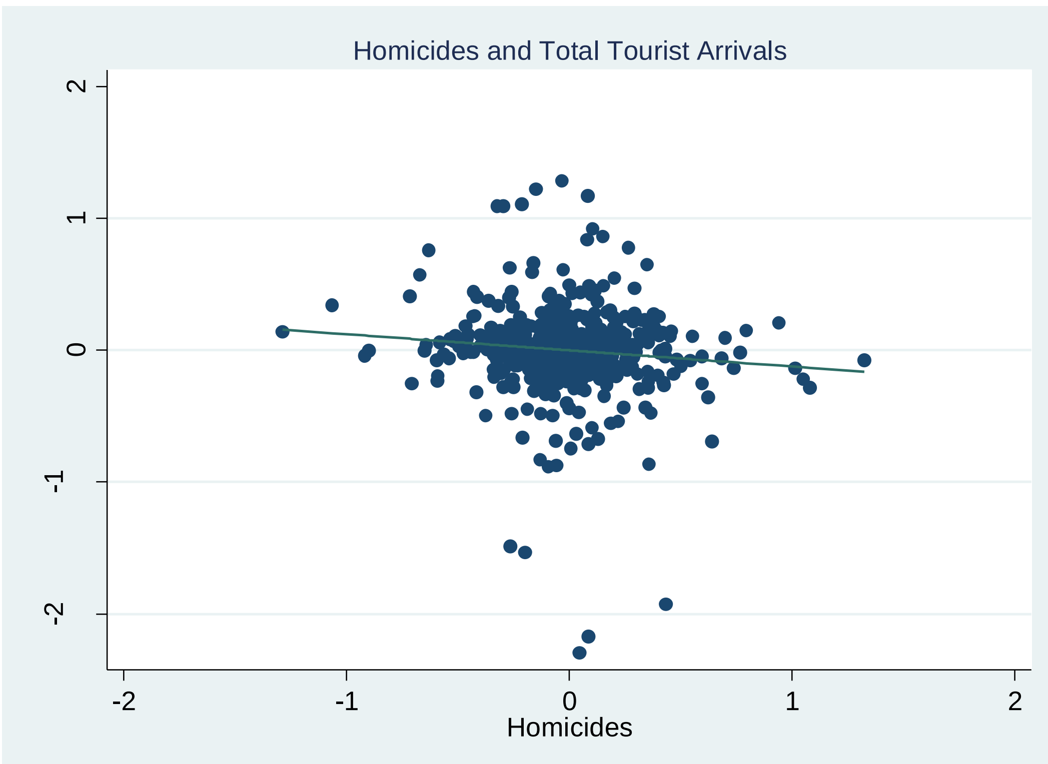


Figure I.A Note: Lineal regression of Total Tourist Arrivals on Homicides.

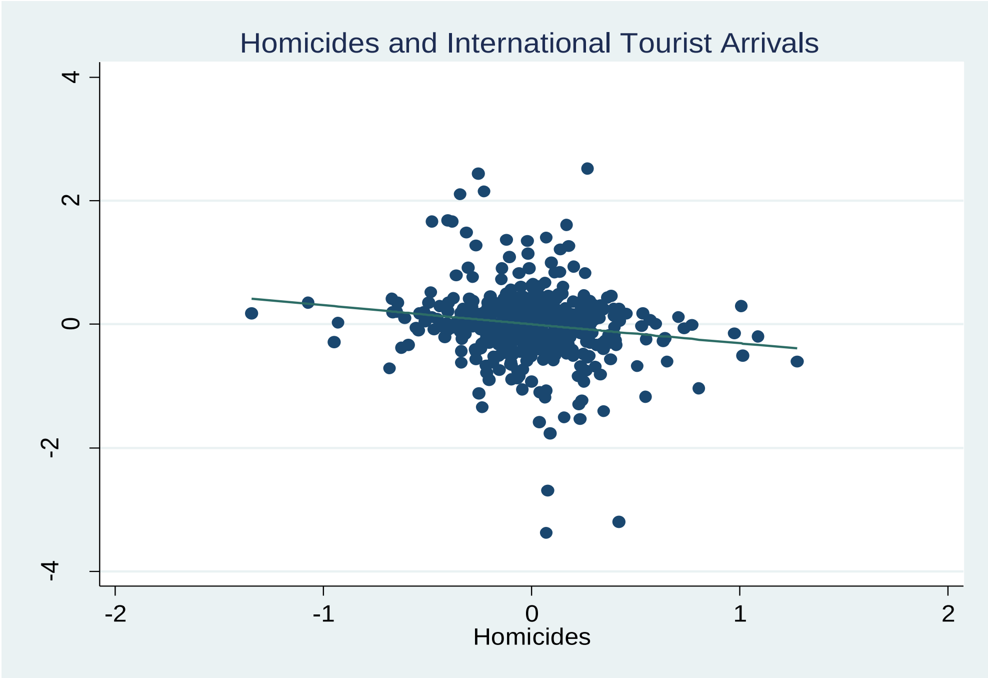


Figure I.B Note: Lineal regression of International Tourist Arrivals on Homicides.

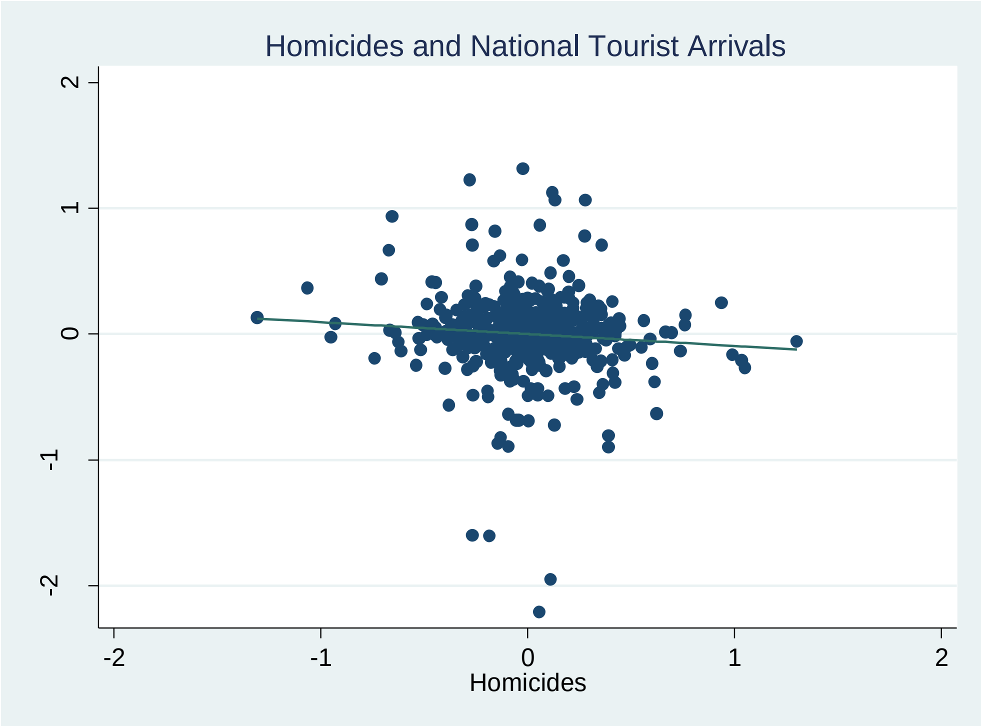


Figure I.C Note: Lineal regression of National Tourist Arrivals on Homicides.

Chapter II

Fear and Loitering in Mexico: The Significance of Age Structure, Education, and Youth Unemployment for Explaining Sub-National Variation in Violent Youth Crime

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II.1 INTRODUCTION

The resemblance between many contemporary civil wars over access to natural resources and the 'drug wars' in Mexico is striking. However, while some scholars have noted the similarities between factors explaining armed conflict and violent crime (e.g., Neumayer 2003: 619) the two phenomena are usually studied separately. This paper addresses the issue of violent youth crime in Mexico employing a theoretical framework, the 'opportunity perspective', which has been a dominating narrative in the civil war literature. This framework emphasizes structural factors providing opportunities for rebel organizations to engage in insurgencies against a state, such as large youth cohorts or 'youth bulges', as well as other factors that determine economic opportunities for the youth like education and unemployment. In the political violence literature it has been noted that 'youth bulges' have historically been associated with times of political crisis and upheaval (Goldstone 1991, 2001) and it has generally been observed that young males are the main protagonists of criminal (Neapolitan 1997: 92, Neumayer 2003: 621) as well as political (Mesquida and Wiener 1996, Elbadawi and Sambanis 2000: 253, Urdal 2006) violence. Generally, the increasing acknowledgement of the role of demographic factors in shaping conflict and international political developments is underscored by recent contributions in the field of political demography (e.g., Goldstone et al. 2012).

Studies of violent crime, in particular studies of homicide rates, have long employed cross-national time-series research designs. Most of these cross-national studies have included few developing countries, however. A much-cited homicide study, Fajnzylber et al. (2002), included only 39 countries, of which the minority were developing countries, citing the problems with low data availability for developing countries as well as underreporting. Underreporting, the authors argue, should not be considered random noise, but measurement error that is systematically correlated with factors assumed to affect crime rates (Fajnzylber et al. 2002: 14).

Furthermore, while sub-national panel studies have become prominent in the civil war literature (e.g. Buhaug and Rød 2006, Urdal, 2008, Østby et al. 2011, Vadlamannati 2011), similar studies of sub-national violent crime outside the US and a few other developed countries are rare. An exception is Dreze and Khera's (2000) study of homicide across Indian states. By assessing variation in violent crime within Mexico over time, this study is less prone to reporting errors as such that stem from cross-national differences in data collection and reporting procedures, although we acknowledge several possible sources of bias. Furthermore, the subnational focus enables the use of data sources - in particular youth unemployment - that are not available for a large number of countries, and may thus not be used in cross-national studies.

Mexico provides an ideal case for testing propositions about the significance of youth opportunities for violent crime. Demographically, Mexico is a relatively young country with the majority of its population falling into the age range of 12 to 29 years. The period of study, 1997-2010, covers a time of significant youth population growth in Mexico. According to the Mexican Institute of the Youth the Mexican youth population aged 12-29 increased by 40.6% between 1990 and 2000.[27] While the overall growth in youth population is slowing down, regional differences in growth rates still exist due to migration and geographic fertility differentials. Detailed demographic, social and crime data further allow us to use econometric methods to consider how large youth cohorts in the context of limited education and employment opportunities affect violent crime.

[27] Instituto Mexicano de la Juventud, (Mexican Youth Institute, 2008).

This study adds to the existing literature in several ways. The article identifies and discusses youth opportunities and their potential implications for violent youth crime, and tests these propositions empirically in one of the first sub-national studies of violent crime in a developing country. It is further the first study to look at youth bulges and violence, either political or criminal, in the context of both education and employment, a unique opportunity granted by the rare availability of such data for Mexican states. Our results suggest that while youth crime and high homicide rates in Mexico are not associated with the ebb and flow of the male youth population, both high youth unemployment and low youth education are associated with higher levels of crime and homicide. And in this context, the relative size of the male youth population does matter. We also report additional results of some significance. In particular, there is an increasing concern that rapid urban population growth around the globe could lead to increasing levels of criminal as well as political violence. While this study finds some support for urban environments being generally more conducive to violent crime in Mexico, the pace of growth in the urban population does not appear to be associated with crime levels.

II.2 THEORY

The literature on youth bulges and violence has in particular focused on the role of large youth cohorts in facilitating spontaneous and low-intensity political violence. Two different explanatory frameworks have primarily informed the discussion, one focusing on opportunities and the other on motives for political conflict. The opportunity framework is particularly relevant for explaining criminal violence, and has a parallel expression in the literature on violent crime (Neapolitan 1997). Neumayer (2003) notes that opportunity theory 'tries to understand variation in violent crime rates in terms of different opportunities or favorable conditions for committing crime'. Fajnzylber et al. (2002: 1-2), basing their approach primarily on Gary Becker's opportunity framework, contend that 'crime rates depend on the risks and penalties associated with apprehension and also on the difference between the potential gains from crime and the associated opportunity cost'.[28]

II.2.1 Youth bulges and violent crime

The opportunity literature, often referred to as the 'greed' perspective (e.g. Collier 2000), has its roots in economic theory and focuses on structural conditions that provide opportunities for an organization to engage in violent activity, whether a rebel group that wages war against a government, or a criminal organization. These are conditions that provide the organization with financial means, such as rents from drug trafficking, or factors that reduce the costs of operation, such as low recruitment costs. Relatively large youth cohorts can reduce the recruitment costs for insurgent groups through the abundant supply of 'rebel labor' with low opportunity cost, increasing the risk of armed conflict (Collier 2000: 94). Similarly, large youth bulges may facilitate recruitment to criminal organizations. Opportunities for violence may be further boosted by a weak government with limited capabilities (Fearon and Laitin 2003, Collier and Hoeffler 2004).

Central assumptions in the opportunity perspective are that organizational structures that may be used for illegal purposes, whether political or criminal, exist exogenously, and that recruits join these organizations in order to obtain a private good. Hence, the collective action problem is presumed to be negligible. Criminal organizations or rebel groups are able to recruit successfully only when the potential gain from joining is so high and the expected costs so low that potential

[28] Arguably, violent crime may also be driven by feelings of disadvantage or unfairness (Fajnzylber et al. 2002: 2) as emphasized in motive-oriented or relative deprivation studies. However, it is empirically difficult to distinguish between these two types of explanations since they yield largely identical predictions (Urdal 2006).

recruits will favor joining over alternative income earning opportunities. Collier (2000: 94) argues that the mere existence of an extraordinary large pool of youth is a factor that lowers the cost of recruitment since the opportunity cost for a young person generally is low. Hence, our base expectation is that:

Hypothesis 1: *In regions with large youth populations relative to the adult population, violent crime rates are higher, everything else being equal*.

However, Hirschi and Travis (1983) argue that age in itself is an insufficient explanation for violence, and that shifting attention towards the meaning or interpretation of the relationship is required. Hence, in the following we consider two factors that are key determinants of youth opportunities: educational attainment and youth unemployment.

II.2.2 Educational opportunities and violent crime

Education is a tool that countries can exploit in order to respond to youth bulges and ease transition problems. But do expanding education opportunities reduce the risk of criminal violence? Collier (2000) argues that higher levels of education among men act to reduce the risk of political violence, resulting from the higher opportunity cost of rebellion for educated men. Since educated men have better income-earning opportunities than the uneducated, they have more to loose and we would expect them to be less likely to join a criminal organization.

Hence, a high level of education is expected to be associated with a reduced risk of violence. While for criminal 'entrepreneurs', a high level of education may in fact lead to higher rewards if it enables more efficient management of illicit activities (Barakat and Urdal 2009), the argument that recruitment of youth to criminal activity is economically less attractive the more highly educated a person is refers to mass participation. In areas with large potential pools of recruits, increasing education can act to reduce this pool. Although the argument that education increases the opportunity cost of youth takes a general form, we focus here on secondary education for young males since they are the primary target for recruitment to criminal organizations.

Hypothesis 2: *In regions with low secondary male education levels, violent crime rates are higher, everything else being equal.*

II.2.3 Youth unemployment and violent crime

The expectation that exceptionally large youth cohorts increase the supply of cheap recruits for criminal enterprises is further supported by studies in economic demography suggesting that the alternative cost of individuals belonging to larger youth cohorts are generally lower compared to members of smaller cohorts due to higher unemployment and thus increased pressure on male wages. According to the 'cohort size' hypothesis, 'other things being constant, the economic and social fortunes of a cohort (those born in a given year) tend to vary inversely with its relative size' (Easterlin 1987, quoted in Machunovich 2000: 236). Increases in relative cohort size arguably result in a reduction in male relative income. Such a direct relationship has been found in several studies using wage data for smaller samples of countries (reviewed in Machunovich 2000: 238). In two cross-national time-series analyses, Machunovich (2000) finds that an increase in relative cohort size is associated with a reduction in fertility, arguably resulting from the depression of male wages while Korenman and Neumark (1997) find that large youth cohorts are associated with a significant increase in youth unemployment rates. So not only do youth bulges provide an unusually high supply of individuals with low opportunity cost, as anticipated by Collier (2000), but an individual belonging to a relatively large youth cohort generally also has a lower opportunity cost relative to a young person born into a smaller cohort. While labor markets differ substantially with regard to flexibility, also within countries, empirical evidence suggests that on average, large youth cohorts are substantially more likely to experience higher unemployment rates (Korenman and Neumark 1997).

While previous studies have identified a theoretical link between youth unemployment and violence, the lack of reliable data for many developing countries has made a direct test of this relationship for large samples of countries difficult. Several studies have instead tried to assess the relationship indirectly by looking at economic growth as youth unemployment is typically associated with poor economic performance. Low economic growth has been identified as a robust predictor of both homicide (Neumayer, 2003) and civil war onset (Collier et al. 2003, Sambanis 2002: 229). Here, we address the relationship explicitly, expecting that:

Hypothesis 3: *In regions with large unemployment among young males, crime rates are higher, everything else being equal.*

Finally, we consider the possible effect on violent crime of the interaction of factors leading to low opportunities for youth. Given the expectations that low education and high unemployment among male youth should be associated with increased levels of violent crime, we would further expect that high unemployment in low-education male strata should be particularly strongly associated with violence, and that the economic opportunities for this group of males may be particularly limited in the context of large male youth bulges.

Hypothesis 4: *The association between large youth cohorts and violent crime is particularly strong in regions where education levels are low and unemployment rates among young men are high, everything else being equal.*

II.2.4 Existing research

Previous studies have found mixed evidence for a relationship between age structure, or 'youth bulges', and violent crime. Hansmann and Quigley (1982) and Pampel and Gartner (1995) both find a significant effect of the age structure on homicide rates in cross-national studies, while Gartner and Parker (1990) find a strong age structure effect on homicide in two (US and Italy) out of five countries, acknowledging that differential patterns within countries may still have affected internal variation in homicide in the remaining three countries. On the hand, Avison and Loring (1986), Fajnzylber et al. (2002), Neumayer (2003), Cole and Gramajo (2009), and Pridemore (2011) do not find statistically significant effects of age structure on crime in country-level panel data analyses. In a meta-analysis of cross-national homicide studies, Nivette (2011) reports that static population indicators were among the group of variables that exerted the weakest effect on homicide. Fox and Hoelscher (2012) find some initial and strong support for the youth bulge hypothesis, although the relationship washes away once controlling for socioeconomic factors. A possible reservation here is that introducing socioeconomic variables also reduces the sample considerably. However, both Fox and Hoelscher's (2012) results as well as Neumayer's (2003) finding that economic growth reduces homicides, point to the salience of socioeconomic factors. Hence, what we should be looking for are conditional factors determining youth opportunities.

There appears to be somewhat stronger, albeit by no means unequivocal, evidence for a link between education and violent crime. Cole and Gramajo (2009) find that male education reduces homicide, Fajnzylber et al. (2002) conclude that higher education levels are associated with less homicide, while Dreze and Khera (2000) found that higher literacy levels moderated criminal violence levels in India. However, some results appear more puzzling: Cole and Gramajo (2009) found that higher female education was associated with higher homicide levels, while Fajnzylber et al. (2002) unexpectedly found that higher education was associated with higher levels of robbery. Furthermore, Pridemore (2011) report inconclusive results with regards to education, while Robbins and Pettinicchio (2012) only found weak support for the assumed beneficial effect of social capital on homicide. Only two of the surveyed studies include unemployment. Pampel and Gartner (1995) did not find a significant effect of unemployment, while Neumayer (2005) reports that unemployment increases levels of both robbery and homicide.

In the civil war literature there has been a certain discussion about the measurement of age structure (Urdal 2006, Barakat and Urdal 2009). Like two authoritative civil war studies by Fearon and Laitin (2003) and Collier and Hoeffler (2004), most of the studies above employ suboptimal measures of age structure. The measure typically used is the 15 to 24 (or 29) year old cohorts relative to the total population, including all cohorts under the age of 15 years in the denominator. Such definition is highly problematic both theoretically and empirically. First, most theories about youth revolt and crime assume that violence arises because youth cohorts experience institutional 'bottlenecks' in the education system or in the labor market due to their larger size compared to previous cohorts. Second, when using the total population in the denominator, youth bulges in countries with continued high fertility will be underestimated because the large under-15 populations deflate the youth bulge measure. At the same time, countries with declining fertility and relatively smaller under-15 populations – which are in a position to experience economic growth driven by age structural change which may be expected to contribute to reduce both criminal and political – score relatively higher. The issue of measurement appears not to have been discussed in the homicide literature, with the lone exception of Fox and Hoelscher (2012).

II.3 DATA AND METHOD

In this section, we describe the data covering all 32 Mexican states, including the Federal district, also known as Mexico City (see Appendix II.1 for details) during the 1997–2010 period, and the estimation specifications. The base specification is shown below.

II.3.1 Estimation Specification

The baseline specification estimates the number of crime incidents committed by the youth (YC_{it}), in state *i* in year *t* as a function of a set of youth opportunity variables YE_{it-1}, and control variables Z_{it-1}:

$$YC_{it} = \gamma YE_{it-1} + \beta Z_{it-1} + \nu_i + \lambda_t + \omega_{it} \qquad (1)$$

where ν_i denotes state fixed effects to control for unobserved state specific heterogeneity in the panel dataset, λ_t are time specific dummies and ω_{it} is the error term. Note that the Hausman (1978) test favours fixed effect over random effect models. For the dependent variable we use the number of federal crimes committed by Mexican males in the age cohort 18–24[29] in state *i* in Mexico in year *t-1* in per capita terms logged. These data are reported by the National Institute for Statistics and Geography[30] (INEGI hereafter) for the 32 states (including the Federal district) for the 1997 through 2010 period (INEGI 2012). Federal crimes include all counts of drug-related crime and other violent organized criminal activity, but exclude 'common crime', providing for an appropriate proxy for violent crime to be tested specifically against youth opportunities (see Appendix II.4 for details). Figure II.1 shows the number of youth federal crime incidents reported across Mexican states during the 1997–2010 period. The states with the highest number of youth federal crimes are Baja California, Sonora, Jalisco, Federal District, Chihuahua and Sinaloa, many of which are heavily affected by drug-related violence.

Our main independent variables in the vector of youth opportunity in equation (1) are: male youth bulge, male youth education attainment rate, and male youth unemployment rate. We define the male youth bulge as 18–24 year old males as a share of all males aged 18 years and above, capturing the dynamics in the younger working-age segments.[31] The demographic data is taken from Mexican population censuses carried out by INEGI across all the 32 Mexican states (including the Federal District) once every 10 years. Once every five years INEGI also conducts random surveys known as population count. Thus, the data used to construct the youth bulge come from the censuses of 1990, 2000, and 2010 (INEGI, 1990; 2000; 2010), and from the population surveys of 1995 and 2005 (INEGI, 1995; 2005). The youth education variable also originates from the census data, as well as the 2005 survey. This variable measures the

[29] A crime is included if at least one of the reported suspects is a male between the ages of 18 and 24. For more details about categories and definitions of federal crimes in Mexico, see Appendix 4 and www.inegi.org.mx (Estadísticas Judiciales en Materia Penal).
[30] See: www.inegi.org.mx/ for more details about INEGI
[31] We have also used the conventional (Urdal 2006) definition of youth bulges measuring 15–24 year old males as a share of male population aged 15 years and above. Our results remain unchanged when we use this alternative measure of youth bulge.

proportion of men aged 18-24 years with at least completed secondary education normalized by the total male population aged 18-24 years. Youth unemployment is defined as the number of males aged 18-24 years who are reportedly unemployed divided by the total male labor force aged 18-24 years. The unemployment and labor force data are available from the Mexican census files for 1990, 2000 and 2010 only (INEGI, 1990; 2000; 2010). Missing years between the reported census and survey observations for the aforementioned variables are interpolated. This is defendable given that demographic and education variables normally change relatively slowly. We do acknowledge, however, that unemployment figures are likely to be much more volatile, and that the interpolation between the census observations is likely to miss some variation. While this is unfortunate, unemployment data based on census records are clearly preferable to less reliable survey data, in particular given our aim to study age-, gender-, and education-specific unemployment across all Mexican states over time.[32]

We further disaggregate the youth unemployment data by the category of education, constructing data that as far as we know have not previously been used to test the youth opportunity and violence nexus. We specifically use *unemployment rate in low education and high education strata* respectively in our subsequent specification (2):

$$YC_{it} = \gamma URlowY_{it-1} + \delta URhighY_{it-1} + \beta Z_{it-1} + \nu_i + \lambda_t + \omega_{it} \qquad (2)$$

Where, $URlowY_{it-1}$ denotes the unemployment rate in low education stratum, while $URhighY_{it-1}$ denotes the unemployment rate in high education stratum in state *i* and year *t-1* respectively. We first collapse the categories for 'no', 'primary' and 'incomplete secondary' education into the *low education stratum*, defined as those males aged 18-24 years with lower

[32] As a robustness check, we have also used an alternative definition of youth measured as the male population between the 18-30 years, also constructing education and unemployment rates for this group.

education than completed secondary level. We then divide the number of men who are unemployed in this category by the total male population aged 18-24 with low education. Note that data on employment by education are available only from the 1990, 2000 and 2010 population censuses. Likewise, we categorise male youth in the *high education stratum* as those aged 18-24 who have obtained completed secondary schooling or higher (including tertiary education). We then construct a measure for *the unemployment rate in the high education stratum* by dividing the unemployed male youth with high education by the total male population with high education in the age group of 18-24 years.

We further examine under what conditions the youth bulge can be associated with an increase in youth crimes using specification (3) below:

$$YC_{it} = \zeta (URlowY \times YB)_{it-1} + \xi (URhighY \times YB)_{it-1} + \gamma URlowY_{it-1} + \delta URhighY_{it-1} + \phi YB_{it-1} + \beta Z_{it-1} + \nu_i + \lambda_t + \omega_{it} \qquad (3)$$

Where $(URlowY \times YB)_{it-1}$ denotes the unemployment rate in low the education stratum interacted with the youth bulge and $(URhighY \times YB)_{it-1}$ is the interaction between the unemployment rate in the low education stratum and the youth bulge in state *i* and year *t-1*. These interactions help examine whether the effect of youth bulges on violent crime are conditional upon the unemployment rates in low vis-à-vis high education strata.

Finally, the vector of control variables (Z_{it-1}) includes other potential determinants of (log) youth crime incidents per capita in state *i* during year *t-1* which we include based on the extant literature on the subject. Here we follow earlier studies by Barakat and Urdal (2009), Demombynes and Ozler (2005), Fajnzylber, Lederman and Loayza (2002), Hashimoto (1987) Miron (2001), and Urdal (2006). Accordingly, we include state per capita GDP (logged) in US$

2003 constant prices[33] and the rate of growth of state GDP in *i* during year *t-1* to proxy for the level of development in states. The income data are available from the National Accounts System of INEGI.[34] Likewise, we also use state population which is drawn from the population census data compiled by INEGI. We further compute two urban population measures, *urbanization* measuring urban population as a share of total population in state *i* during year *t-1* and the rate of growth of the urban population. Urdal and Hoelscher (2012) point out that managing urban development sustainability pose significant challenges for the respective governments and therefore large youth bulge in urban centres could be a source of instability and violence. We then include a measure of state governor elections. We follow Schneider (2013) to generate an indicator for the timing of elections that varies between 0 and 1. For all non-election years, the value is 0. For election years we make use of the following measure: $(12 - (Mn - 1))/12$, wherein Mn is the month in which the state Governor election took place. The data on the exact date and month in which the elections are held in each state are obtained from the state elections results and information published by the Institute of Marketing and Opinion (Instituto de Mercadotecnia y Opinión 2012). Accordingly, for election years this indicator takes smaller values the later the election takes place within the year.[35] The details on variable definitions and data sources are reported in Appendix 3. We estimate all our models with Ordinary Least Squares (OLS henceforth) two-way fixed effects estimator with heteroskedasticity consistent robust standard errors (Beck and Katz 1995).[36]

[33] The data of state per capita GDP were available only in Mexican pesos 2003 constant prices. We use the exchange rate to US$ to convert these data into US$.

[34] For more details see: www.inegi.org.mx/est/contenidos/Proyectos/SCN/C_Anuales/pib_ef/default.aspx

[35] The results remain quantitatively the same if we use a dummy for the governor election years.

[36] The fixed-effects estimator captures factors such as geographic location of states, which are also expected to affect the level of criminal violence.

II.3.2 Endogeneity concerns

It is quite possible that our key explanatory variables capturing youth opportunity are endogenous. That is, it might be that criminal activities attract more youth with low alternative cost towards areas with high crime rates, and especially towards drug-related activities which might maximize their returns in the short run. This could affect the education and unemployment measures. It could also be that high levels of crime deter local investments, driving up unemployment levels. Although the cause for reverse causality is indirect and presumably relatively weak, not taking this endogeneity into account might induce bias in our estimates of the effect of youth opportunity and violent crime. We control for this problem by replicating the OLS fixed effects models using the system-GMM estimator suggested by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). The results are based on the two-step estimator implemented by Roodman (2006) in Stata 12. We also apply the Hansen test to check the validity of the instruments used and the Arellano-Bond test of second order autocorrelation, which must be absent from the data in order for the estimator to be consistent. We treat the lagged dependent variable (i.e., youth federal crime per capita logged) and our measures of youth opportunity in all models as endogenous and the rest of the variables as exogenous. In all our system-GMM regression models we include time dummies. In order to minimize the number of instruments in the regressions, we follow Roodman (2006) and collapse the matrix of instruments.

II.4 EMPIRICAL RESULTS

Table II.1 presents the baseline results estimated using specification (1) capturing the effects of the youth bulge, youth education and youth unemployment rate on youth crime incidents. In

Table II.2 estimating specification (2), we disaggregate the youth unemployment rate by category of education, i.e., separating between unemployment in the low and high education strata. In Table 3, we estimate specification (3) by introducing the interaction between the unemployment rate by education and the youth bulge. Finally in Table II.4, we replace the two youth unemployment measures by education with a measure, 'Density of Low-Opportunity Cost Youth', capturing the overall 'density' of unemployed male youth with low education as a percentage of all male youth. In all the four tables we estimate our models with OLS fixed effects followed by system-GMM to address potential endogeneity concerns. Descriptive statistics are presented in Appendix II.2. Beginning with Column 1 in Table II.1, the results show that our crude measure for the male youth bulge actually has a negative association with youth crime, and this relationship is significantly different from zero at the 5% level. These results do not lend support to those who attribute crimes committed by the youth in Mexico to surge in the youth bulge. However, this effect does not remain statistically significant when we introduce a lagged dependent variable in Column 2. We retain the lagged dependent variable hereafter in all our models. In all tables reported here, the lagged dependent variable remains significantly different from zero at the 1% level. In Column 3 we introduce the youth unemployment rate which is positive, but statistically insignificant. In Column 4, we also include the youth education attainment ratio, finding, as expected, that higher levels of education have a strong negative effect on youth crime. The finding is significantly different from zero at the 5% level. Holding other controls at their mean, an increase in youth education by one unit is associated with 0.2% less youth crime incidents. Both the unemployment rate and the youth bulge variables remain statistically insignificant once controlling for youth education. In the last column, Column 5, we re-estimate the results with system-GMM. While the results remain similar to

Column 4, the youth unemployment rate becomes marginally significant at the 10% level. These results however do not provide clear cut evidence on the effect of youth unemployment and education on youth crime. We therefore disaggregate the unemployment levels among youth by low and high education in Table II.2.

As can be seen in Column 1 Table II.2, we find a positive and significant effect of the youth unemployment rate in the low education stratum, statistically significant at the 10% level. Holding all other variables constant, a standard deviation increase in the youth unemployment rate in the low education stratum is associated with a 0.6% increase in youth crime incidents per head, which is about 4% of the standard deviation of youth crime incidents per head. However, we do not find any statistical significance when we replace this measure with one that estimates unemployment in the high education stratum in Column 2 (Table II.2). These results broadly support our hypothesis that the opportunity cost of engaging in violent crimes is higher among young men in the high education stratum. We re-estimate these models using system-GMM, presented in Columns 3–4 in Table II.2. The results are upheld when using system-GMM, with the effect of the youth unemployment rate in the low education stratum on violent crime remaining statistically significant at the 10% level. The youth unemployment rate in the high education stratum remains statistically insignificant. The Hansen and the Arellano-Bond tests do not reject the GMM specifications at conventional levels of significance across Columns 3–4. The Hansen J-Statistic further shows that the null-hypothesis of exogeneity of the instruments cannot be rejected at the conventional level of significance.

In Table II.3 we turn our attention to the interaction effects between youth bulge and the unemployment rate by education category. First, in Column 1 we interact the youth bulge and the unemployment rate in the low education stratum, and in Column 2 we interact them in the high education stratum. As can be seen in Column 1, we find that the interaction between the youth bulge and unemployment in the low education stratum has a positive effect in explaining the youth crime incidents per head, and that the term is significantly different from zero at the 5% level.[37] This effectively means that states with a higher percentage of male youth in their populations are more vulnerable to youth crime incidents if the unemployment rate among the low education stratum increases. In other words, a youth bulge is not a problem in itself, rather the risk of violence is conditional upon higher levels of youth with low education and thus scant employment opportunities. To better understand how the marginal effect of the youth bulge interacted with the unemployment rate in the low education stratum develops, we illustrate this graphically in Figure II.3. This graph shows the development of the marginal plot of the youth bulge variable interacted with unemployment rate in the low education stratum on youth crime incidents per head. Basically, the marginal plot has an upward direction. This implies that youth bulges increase violent crime if the youth unemployment rate in the low education stratum increases. The marginal effect gains statistical significance after the youth unemployment rate in the low education stratum reaches the median score of 3.5%, meaning that the positive effect is found in states with an unemployment rate among low education stratum higher than 3.5%. In other words, youth bulges are associated with higher levels of federal crimes in states where the youth unemployment rate in the low education stratum is increasing. The three terms are jointly highly significant ($p < 0.0004$).

We now turn to the interaction between the youth bulge and the unemployment rate in the high education stratum in Column 2. The interaction effect is not significantly different from zero. This suggests that larger youth bulges do not appear to increase the risk of violent youth

[37] The youth bulge variable alone has a negative effect in explaining youth crime incidents and interestingly, we now find that unemployment in the low education stratum also has a negative sign. This is largely due to a high correlation (0.96) with the interaction term.

crime even when the unemployment rate in the high education stratum is increasing. As discussed above, this suggests the opportunity costs of engaging in crime are exuberantly higher for the unemployed youth in the high education stratum. We also replicate these results using system-GMM reported in Columns 3–4 in Table II.3. As can be seen, the interaction effect results remain robust to using system-GMM. It is noteworthy that after controlling for potential endogeneity, the statistical significance of the interaction of the youth bulge with the unemployment rate in the low education stratum drops to the 10% level. The Hansen J-Statistic in all the three columns shows that the null-hypothesis of exogeneity of the instruments cannot be rejected at conventional levels of significance.

Lastly, in Table II.4, we use a variable, 'Density of Low-Opportunity Cost Youth', capturing the overall 'density' of unemployed male youth aged 18-24 with low education measured as the share of the total male youth population in that age group. We restrict our specification to only include unemployment in the low education stratum since the relative number of unemployed youth with low education is the quantity of greatest theoretical relevance to the opportunity perspective. As can be seen, the density of unemployed youth with low education is positive and significantly different from zero at the 5% and 1% levels in OLS fixed effects and System-GMM estimations respectively (Columns 1 and 2). In Columns 3 and 4 we interact the youth bulge with the density variable. As can be seen, the interaction effect is positive and significantly different from zero at conventional levels of significance in both the OLS and GMM estimations. In fact, the marginal effect gains statistical significance after the youth unemployment density in the low education stratum reaches the median score of around 2.3% (figure not shown). These results show that irrespective of whether we use the measure for the unemployment rate or density, unemployment in the low education stratum is the best predictor of youth crime indents in Mexico.

Before moving further towards robustness checks, we will briefly discuss the results of the control variables. Interestingly, we do not find any robust evidence for an impact on violent youth crime of both per capita state GDP, the rate of growth of state GDP, and state population. Likewise, after controlling for fixed effects we don't find any effect of urban population growth on youth crime, hence increasing urban population pressure does not seem to increase violent crime. However, like others, we do find a strong positive effect on youth crime of the level of urbanization, which is consistent with the idea that urban environments are more conducive to violent crime (e.g., Urdal and Hoelscher 2012). The variable capturing the timing of elections is associated with fewer number of crime incidents during the run-up towards governor elections. This might be due to two reasons. First, there is every possibility of under reporting of crime incidents during the run-up towards elections by the incumbent government.[38] Second, it is also plausible that the incumbent governor would impose measures aimed at reducing violence during the election period, signalling to voters her/his commitment to control crime and restore law and order. We also cannot rule out the possibility that the result is driven by a combination of the two factors.

II.4.1 Robustness checks

We have examined the robustness of our main findings in the following ways. First, we used alternative measures for the youth bulge, youth unemployment, and education variables. Departing from the measure of 18–24 year old men, we used 18–30 year old men as a share of all men aged 18 years and above. We also computed the federal crime incidents registered under the

[38] For details on state elections see: imocorp.com.mx/CAMPO/zSIEM/ELEC_X_ANIO/ResultadosWeb.asp

age group of 18–30 years. Likewise, we also used the 18-30 age group to compute the unemployment rate by category of education. Using our alternative measures does not alter our results significantly. We still find that the unemployment rate in the low education stratum matters most. The results for the interaction between the youth bulge and the unemployment rate in the low education stratum remain robust. Second, we re-estimated our OLS fixed effects models with negative binomial models where we used the dependent variable as an event count of youth federal crime incidents in the male 18-24 year category. We also control for time and state specific dummies. The results estimated using negative binomial method remains qualitatively similar to those reported in Tables II.1–II.4, estimated using the OLS fixed effects approach. The unemployment rate in the low education stratum remains positive and significantly different from zero at the 1% level across all the negative binomial estimations. Third, in some of our OLS fixed effects models the Hausman test rejects fixed effects. Thus, we estimate all the models using random effects. The results remain robust to using random effects instead of fixed effects. Fourth, we also estimate our OLS baseline results using the Newey-West method which allows us to compute an AR1 process for autocorrelation and obtain Huber-White corrected robust standard errors that are robust to heteroskedasticity (Newey and West 1987). Replacing the OLS estimation method with Newey-West does not alter the baseline estimations. Fifth, as an additional test for robustness, we exclude the few observations with extreme values in youth crime incidents reported.[39] Excluding outliers, the baseline results are qualitatively unchanged, suggesting that our results are not driven by extreme values.

Finally, we have also examined the effects of youth opportunities on homicide rates across Mexican states. Unfortunately, reliable age-specific perpetrator data for homicides are not

[39] We use ‘avplot’ in Stata 12 to identify the outliers in youth federal crime incidents.

available.[40] We use homicides per 100,000 population logged as the alternative dependent variable. The data are collected by INEGI on an annual basis and available for all the 32 states in Mexico from 1990 to 2010.[41] Compared to the youth crime incident data, the homicide data may not be as vulnerable to underreporting as they appear to be consistently reported across states. The results for the homicide models generally uphold our baseline results reported in Tables II.1 and II.2, i.e. the unemployment rate in the low education stratum contributes to explain variation in homicide rates after controlling for relevant socio-economic factors. However, it is noteworthy that we could not replicate the results on the interaction between youth bulge and unemployment rate in the low education stratum as reported in Table II.3. The results of these robustness checks are not reported due to brevity, but they are available upon request.

II.5 CONCLUSION

This article investigates potential causes for the variation in violent youth crime across Mexican states, with a particular focus on the role of youth opportunities. Building on an 'opportunity framework' prominent both in the civil war and criminology literatures, we initially hypothesized that violent crime should vary with demographic age structure, so that states with large 'youth bulges' should have higher levels of violent crime, 'everything else being equal'. This expectation is not borne out by the empirical models, however, as our measure for the male youth bulge is consistently negatively associated with violent crime rates. We further hypothesized that the two factors that arguably most strongly determine the actual opportunity

[40] Note that the available age specific data for homicides show several shortcomings. For instance, they do not show variation in some years for some states. Furthermore, there is a sudden drop and jump in several years for most of the states. Therefore, we rather use the data coming directly from the mortality statistics (which doesn't provide homicides by age groups).

[41] For details on mortality statistics see: www.inegi.org.mx/est/contenidos/espanol/proyectos/continuas/vitales/bd/mortalidad/anexos/introduccion.asp?s=est&c=11142.

cost for youth, levels of education and employment, should be associated with crime levels, and particularly so when low education levels and high unemployment levels occur in states with large male youth bulges. These much more specific expectations regarding youth opportunities are not easily tested for global cross-national samples due to data limitations. The availability of reliable and comparable census data for Mexico, providing age and gender-specific educational attainment and unemployment rates at the state level, allow for a detailed sub-national panel study of youth opportunities and violent crime. Our empirical models, also taking into account possible confounding factors and endogeneity, find strong support for the importance of youth opportunities. This pertains in particular to educational attainment as our models consistently find low levels of education to be strong predictors of high levels of violent crime. We further find that high unemployment among men with low education is clearly associated with higher crime rates, and that this effect is amplified by an interaction with large male youth bulges. No similar effect is found for high unemployment among men with higher education levels, suggesting that the higher opportunity cost of youth with at least completed secondary education may serve as a barrier against recruitment to criminal organizations. This study provides some crucial insights into the complex root causes for the high levels of violent crime in Mexico. While being a mid-income country with relatively well developed institutions, Mexico is experiencing a *de facto* lack of territorial control over certain geographical areas to drug cartels, and levels of violence that vastly surpass most contemporary armed conflicts. As such, improving knowledge of structural factors determining violent crime and ultimately building increased capacity to reduce crime will improve not only the situation for the Mexican population, but also the general security situation of the greater region. Furthermore, the findings reported here may have implications for understanding the drivers of violent crime beyond the

Mexican context, and incite more detailed data collection and empirical study of youth opportunities and violence elsewhere. The developmental consequences of political and criminal violence are vast (World Bank, 2011) and to this end, failing to invest in human capital among young people may represent a double development challenge.

Table II.1: Effect of youth bulge and youth opportunity on youth crime
Dependent variable: Federal youth crime incidents per capita (log)

	(1) OLS-FE	(2) OLS-FE	(3) OLS-FE	(4) OLS-FE	(5) SGMM
Constant	-15.35***	-10.75***	-9.995***	-11.91***	-2.098**
	(3.485)	(3.627)	(3.815)	(3.777)	(0.956)
Lagged Dependent Variable		0.357***	0.345***	0.331***	0.400***
		(0.0572)	(0.0564)	(0.0560)	(0.0915)
State Per capita GDP (log) t-1	0.654**	0.546*	0.397	0.515	-0.126
	(0.329)	(0.306)	(0.339)	(0.333)	(0.0902)
State GDP growth t-1	-0.00303	-0.00554	-0.00405	-0.00450	-0.00841*
	(0.00509)	(0.00462)	(0.00473)	(0.00466)	(0.00486)
State Population t-1	8.06e-08	4.70e-08	5.27e-08	3.96e-08	-7.95e-08***
	(5.11e-08)	(5.07e-08)	(5.06e-08)	(4.80e-08)	(2.51e-08)
Urbanization t-1	0.0339***	0.0202*	0.0204*	0.0291**	0.0164***
	(0.0125)	(0.0119)	(0.0119)	(0.0122)	(0.00582)
Rate of Urbanization t-1	0.0428	0.0317	0.0246	0.0275	0.126**
	(0.0364)	(0.0358)	(0.0366)	(0.0362)	(0.0495)
Timing of State Governor Elections	-0.0875**	-0.117***	-0.118***	-0.118***	-0.168***
	(0.0397)	(0.0359)	(0.0361)	(0.0361)	(0.0361)
Male Youth Bulge t-1	**-0.120****	**-0.0789**	**-0.0714**	**-0.0307**	**-0.114***
	(0.0556)	**(0.0531)**	**(0.0531)**	**(0.0524)**	**(0.0643)**
Male Youth Unemployment Rate t-1			**0.0393**	**0.0345**	**0.0730***
			(0.0298)	**(0.0297)**	**(0.0409)**
Male Youth Secondary School Attainment t-1				**-0.0230****	**-0.0508*****
				(0.0100)	**(0.0150)**
R-squared	0.906	0.919	0.919	0.921	
Hausman test (p-value)	0.87	0.00	0.00	0.00	
Arellano-Bond test for AR(2): p-value					0.21
Hansen Statistic (p-value)					0.20
Number of Instruments					29
State specific dummies	YES	YES	YES	YES	YES
Time specific dummies	YES	YES	YES	YES	NO
Number of States	32	32	32	32	32
Observations	448	448	448	448	448

Notes: Robust standard errors in parentheses *** p<0.01, **p<0.05, * p<0.1. Results in bold reflect relationships that are central to the theoretical argument (main independent variables).

Table II.2: Effect of youth unemployment rate by education category on youth crime
Dependent variable: Federal youth crime incidents per capita (log)

	(1)	(2)	(3)	(4)
	OLS-FE	**OLS-FE**	**SGMM**	**SGMM**
Constant	-9.665**	-10.23***	5.052	27.53**
	(3.829)	(3.845)	(13.68)	(12.41)
Lagged Dependent Variable	0.340***	0.350***	0.656***	0.0221
	(0.0563)	(0.0564)	(0.130)	(0.324)
State Per capita GDP (log) t-1	0.357	0.453	-0.434	-1.847***
	(0.336)	(0.342)	(0.771)	(0.699)
State GDP growth t-1	-0.00324	-0.00468	-0.0154**	0.00195
	(0.00470)	(0.00472)	(0.00747)	(0.0114)
State Population t-1	5.47e-08	5.11e-08	-3.47e-08	-2.16e-07**
	(5.04e-08)	(5.05e-08)	(5.53e-08)	(9.05e-08)
Urbanization t-1	0.0203*	0.0198*	0.00298	0.0276***
	(0.0119)	(0.0119)	(0.00794)	(0.00774)
Rate of Urbanization t-1	0.0248	0.0274	0.232	0.0471
	(0.0360)	(0.0368)	(0.159)	(0.159)
Timing of State Governor Elections	-0.118***	-0.117***	-0.165***	-0.148***
	(0.0361)	(0.0360)	(0.0392)	(0.0379)
Male Youth Bulge t-1	**-0.0748**	**-0.0750**	**-0.323**	**-1.111*** **
	(0.0533)	**(0.0530)**	**(0.393)**	**(0.382)**
Youth Unemployment Rate in Low Education Stratum (Males) t-1	**0.0498***		**0.338***	
	(0.0282)		**(0.191)**	
Youth Unemployment Rate in High Education Stratum (Males) t-1		**0.0234**		**0.137**
		(0.0295)		**(0.242)**
R-squared	0.920	0.919		
Hausman test (p-value)				
Arellano-Bond test for AR(2): p-value			0.36	0.34
Hansen Statistic (p-value)			0.99	0.99
Number of Instruments			51	51
State specific dummies	YES	YES	YES	NO
Time specific dummies	YES	YES	YES	YES
Number of States	32	32	32	32
Observations	448	448	448	448

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Results in bold reflect relationships that are central to the theoretical argument (main independent variables).

Table II.3: Effect of youth unemployment rate by education category on youth crime
Dependent variable: Federal youth crime incidents per capita (log)

	(1) OLS-FE	(2) OLS-FE	(3) SGMM	(4) SGMM
Constant	-9.913***	-9.994***	-7.351	-1.121
	(3.686)	(3.819)	(6.051)	(4.403)
Lagged Dependent Variable	0.337***	0.348***	0.163	0.353
	(0.0546)	(0.0567)	(0.381)	(0.427)
State Per capita GDP (log) t-1	0.691*	0.546	0.151	-0.0337
	(0.359)	(0.349)	(0.302)	(0.287)
State GDP growth t-1	-0.00506	-0.00506	-0.00350	-0.00717
	(0.00458)	(0.00467)	(0.00746)	(0.00841)
State Population t-1	3.72^{e-08}	4.62^{e-08}	-9.95^{e-08}**	-7.58^{e-08}
	(5.08^{e-08})	(5.04^{e-08})	(4.88^{e-08})	(5.65^{e-08})
Urbanization t-1	0.00995	0.0158	0.0149*	0.0109
	(0.0122)	(0.0123)	(0.00829)	(0.00876)
Rate of Urbanization t-1	0.0245	0.0299	-0.0430	0.0478
	(0.0357)	(0.0372)	(0.0932)	(0.109)
Timing of State Governor Elections	-0.116***	-0.116***	-0.100**	-0.136***
	(0.0364)	(0.0361)	(0.0507)	(0.0496)
Male Youth Bulge t-1	**-0.161****	**-0.110***	**-0.105**	**-0.266***
	(0.0632)	**(0.0623)**	**(0.128)**	**(0.147)**
Unemployment Rate in Low Education Stratum (Males) t-1	**-0.581****		**-0.772**	
	(0.267)		**(0.483)**	
Unemployment Rate in Low Education Stratum (Males) t-1 × Youth Bulge t-1	**0.0301****		**0.0380***	
	(0.0124)		**(0.0220)**	
Unemployment Rate in High Education Stratum (Males) t-1		**-0.178**		**-0.797**
		(0.210)		**(0.673)**
Unemployment Rate in High Education Stratum (Males) t-1 × Youth Bulge t-1		**0.00979**		**0.0418**
		(0.0100)		**(0.0338)**
R-squared	0.922	0.919		
Hausman test (p-value)				
Arellano-Bond test for AR(2): p-value			0.40	0.84
Hansen Statistic (p-value)			1.00	1.00
Number of Instruments			60	60
State specific dummies	YES	YES	YES	NO
Time specific dummies	YES	YES	YES	YES
Number of States	32	32	32	32
Observations	448	448	448	448

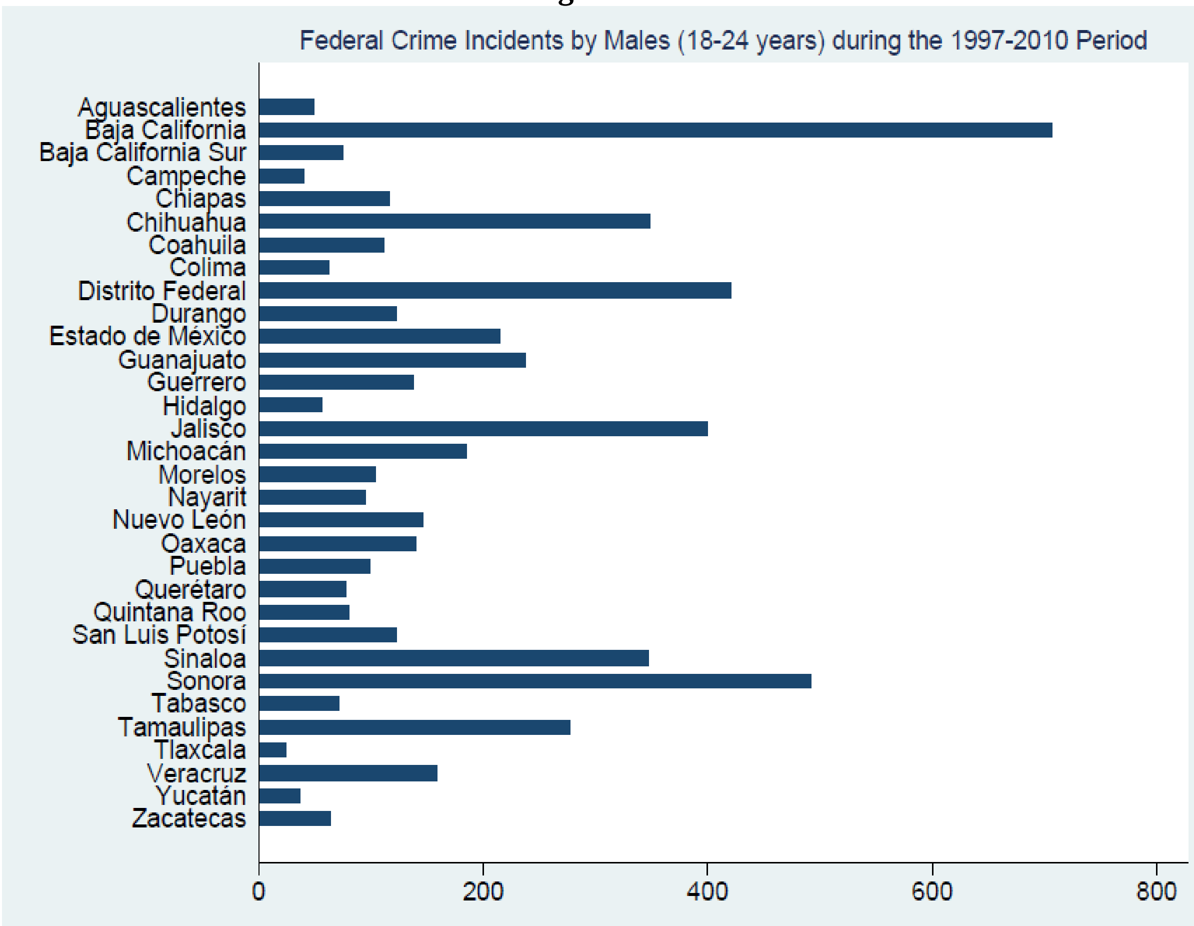
Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Results in bold reflect relationships that are central to the theoretical argument (main independent variables).

Table II.4: Effect of the density of low-opportunity cost youth on youth crime
Dependent variable: Federal youth crime incidents per capita (log)

	(1) OLS-FE	(2) SGMM	(3) OLS-FE	(4) SGMM
Constant	-9.144**	-3.054*	-10.71***	-0.157
	(3.803)	(1.587)	(3.718)	(2.357)
Lagged Dependent Variable	0.336***	0.533***	0.342***	0.701***
	(0.0564)	(0.202)	(0.0518)	(0.185)
State Per capita GDP (log) t-1	0.342	-0.00818	0.700**	0.0431
	(0.324)	(0.0574)	(0.345)	(0.0387)
State GDP growth t-1	-0.00289	-0.0103**	-0.00343	-0.0104**
	(0.00481)	(0.00492)	(0.00468)	(0.00491)
State Population t-1	5.73e-08	-4.92e-08*	2.34e-08	-2.99e-08*
	(5.08e-08)	(2.52e-08)	(5.21e-08)	(1.73e-08)
Urbanization t-1	0.0188	0.00840*	0.0199*	0.00530**
	(0.0119)	(0.00434)	(0.0120)	(0.00232)
Rate of Urbanization t-1	0.0254	0.0745*	-0.00202	0.0543*
	(0.0360)	(0.0424)	(0.0345)	(0.0300)
Timing of State Governor Elections	-0.116***	-0.161***	-0.116***	-0.202***
	(0.0359)	(0.0460)	(0.0367)	(0.0522)
Male Youth Bulge t-1	**-0.0909***	**-0.0969***	**-0.160****	**-0.174****
	(0.0547)	**(0.0527)**	**(0.0566)**	**(0.0711)**
Density of Low-Opportunity Cost Youth (Males) t-1	**0.178****	**0.188***	**-2.266****	**-2.827***
	(0.0788)	**(0.116)**	**(0.801)**	**(1.666)**
Density of Low-Opportunity Cost Youth (Males) t-1 × Youth Bulge t-1			**0.116****	**0.146***
			(0.0373)	**(0.0774)**
R-squared	0.920		0.923	
Hausman test (p-value)	0.20		0.00	
Arellano-Bond test for AR(2): p-value		0.21		0.15
Hansen Statistic (p-value)		0.20		0.12
Number of Instruments		28		31
State specific dummies	YES	NO	YES	NO
Time specific dummies	YES	YES	YES	YES
Number of States	32	32	32	32
Observations	448	448	448	448

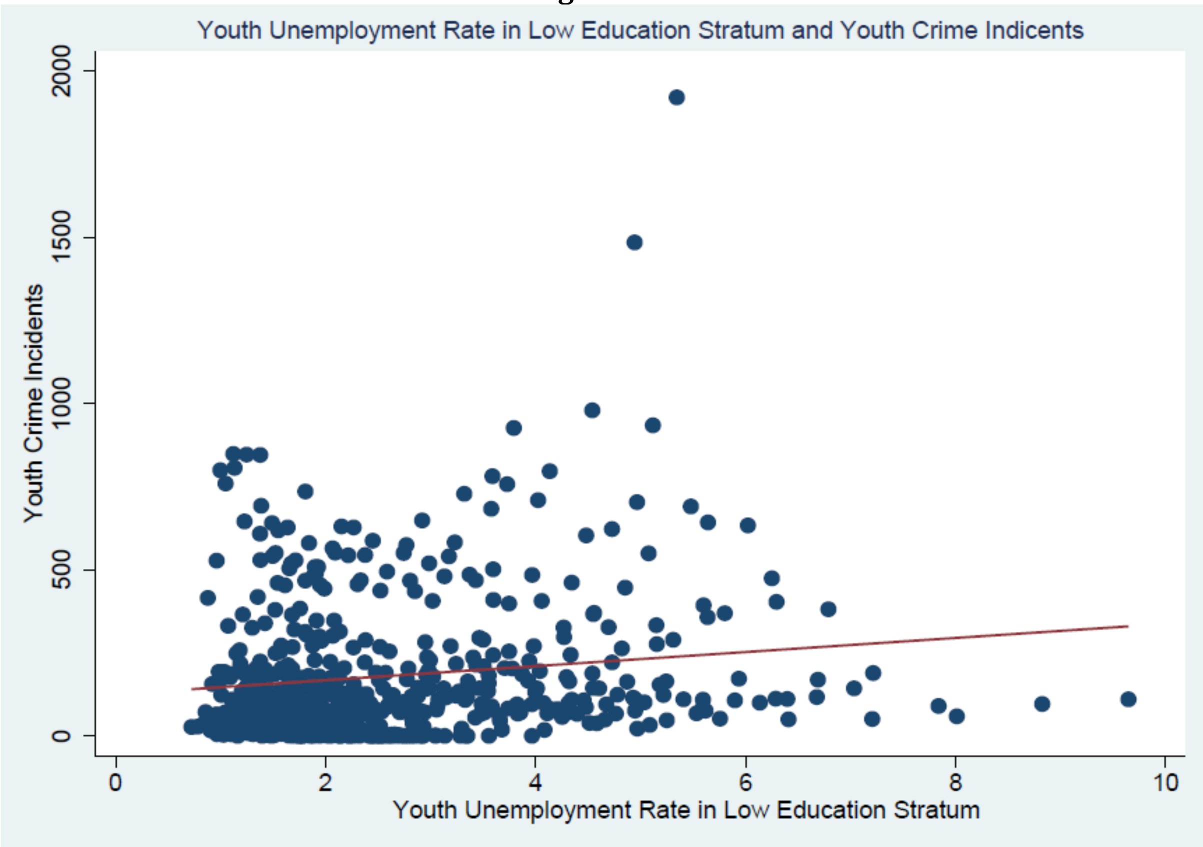
Notes: Robust standard errors in parentheses *** p<0.01, **p<0.05, * p<0.1. Results in bold reflect relationships that are central to the theoretical argument (main independent variables).

Figure II.1



Federal Crime Incidents by Males (18-24 years) during the 1997-2010 Period
Aguascalientes
Baja California
Baja California Sur
Campeche
Chiapas
Chihuahua
Coahuila
Colima
Distrito Federal
Durango
Estado de México
Guanajuato
Guerrero
Hidalgo
Jalisco
Michoacán
Morelos
Nayarit
Nuevo León
Oaxaca
Puebla
Querétaro
Quintana Roo
San Luis Potosí
Sinaloa
Sonora
Tabasco
Tamaulipas
Tlaxcala
Veracruz
Yucatán
Zacatecas
0
200
400
600
800

Figure II.2



Note: Lineal regression of Youth Crime Incidents on Youth Unemployment Rate in Low Education Stratum.

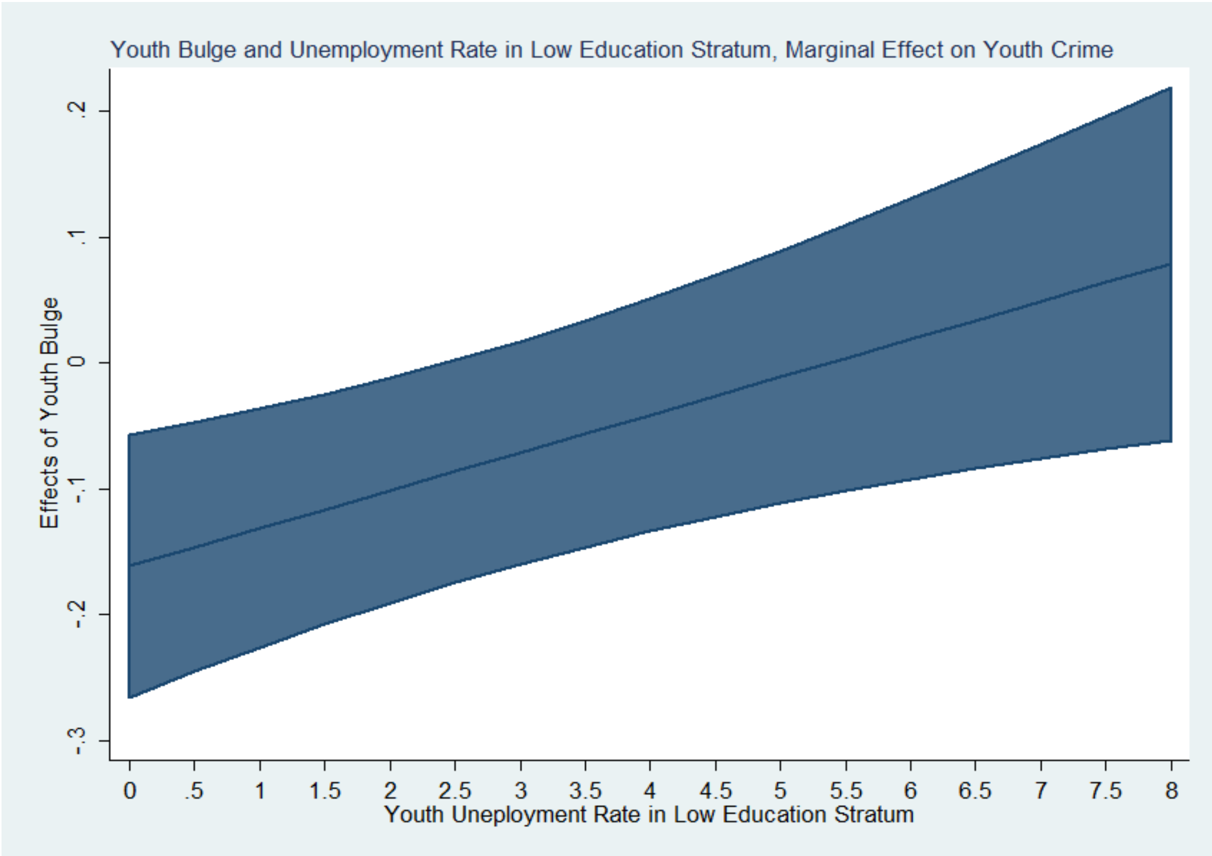


Figure II.3

Note: Youth bulges increase violent crime if the youth unemployment rate in the low education stratum increases. The positive effect is found in states with an unemployment rate in the low education stratum higher than 3.5%.

Appendices

Appendix II.1: Mexican States

Aguascalientes	Distrito Federal	Morelos	Sinaloa
Baja California	Durango	Nayarit	Sonora
Baja California Sur	Estado de México	Nuevo León	Tabasco
Campeche	Guanajuato	Oaxaca	Tamaulipas
Chiapas	Guerrero	Puebla	Tlaxcala
Chihuahua	Hidalgo	Querétaro	Veracruz
Coahuila	Jalisco	Quintana Roo	Yucatán
Colima	Michoacán	San Luis Potosí	Zacatecas

Appendix II.2: Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Observations
Youth Crime Incidents (Male)	182.15	216.31	1.00	1921.00	553
Homicides (Number of cases)	407.69	546.50	1.00	6234.00	672
State Per capita GDP (log) t-1	9.06	0.68	7.76	11.96	640
State GDP Growth t-1	3.03	4.21	-13.41	15.77	608
State Population t-1	3014547	2608974	317764	15000000	640
Urbanization t-1	72.53	14.95	39.45	99.76	640
Rate of Urbanization t-1	2.31	1.28	0.24	11.00	608
Timing of Governor Elections	0.12	0.29	0.00	1.00	672
Youth Bulge (Male) t-1	23.38	2.41	17.93	29.73	640
Male Youth Unemployment Rate t-1	2.82	1.37	1.04	8.30	640
Male Youth Secondary School attainment t-1	30.38	4.29	18.95	39.22	640
Unemployment Rate in Low Education Stratum (Males) t-1[42]	2.50	1.19	0.72	8.83	640
Unemployment Rate in High Education Stratum (Males) t-1	3.09	1.42	1.21	8.38	640
Density of Low-Opportunity Cost Youth (Males) t-1	1.02	0.43	0.36	2.84	640

[42] The lack of unemployment insurance explains the relatively low Mexican unemployment rate in general and among the youth. The high informal employment is still a policy challenge in Mexico (OECD 2012).

Appendix II.3: Data Definitions and Sources

Variables	Definitions and data sources
Youth Federal Crimes	Total number of federal crimes committed by young males in the cohort 18-24 and 18-30 in state *i* in year *t*. The data were obtained from the Penal Judicial Statistics provided by INEGI. The log of this variable is used in the OLS and System-GMM models.
Homicides	Total number of homicides in state *i* in year *t*. The data were obtained from the Mortality Statistics provided by INEGI. The variable used is Homicide per 100,000 inhabitants logged.
Youth Bulge (male)	Males in the cohort 18-24 as a share of all males aged 18 years above. The same definition applies when we expand the cohort to 18-30. The data are from the 1990, 2000 and 2010 population censuses, and from the 1995 and 2005 population surveys carried out by INEGI.
Youth Unemployment (male)	Own construction using the number of males under the age group of 18-24 years who are reportedly unemployed divided by the total male labor force under the age group of 18-24 years. The unemployment and labor force data are made available from the population censuses of INEGI. The same definition applies when we expand the cohort to 18-30.
Youth Education (male)	Own construction using the total number of males under the age group of 18-24 years with completed secondary education normalised by the total male population under the age group of 18-24 years. The data on youth secondary schooling attainment is available from the 1990, 2000, and 2010 population censuses, and from the 2005 population survey. All data are from INEGI.
Unemployment rate in low education stratum youth (male)	Own construction using the number of males under the age group 18-24 years who are unemployed and have low or no education (incomplete primary school, primary school only, and incomplete secondary school) divided by the male population under the age group 18-24 years with low education. The data is available from the 1990, 2000, and 2010 population censuses carried out by INEGI. The same definition applies when we expand the cohort to 18-30.
Unemployment rate in high education stratum youth (male)	Own construction using the number of males under the age group 18-24 years who are unemployed and have high education (at least completed secondary school) divided by the male population under the age group 18-24 years with high education. The data is available from the 1990, 2000 and 2010 population census carried out by INEGI. The same definition applies when we expand the cohort to 18-30.
Urbanization	Share of the total population living in urban areas in state *i* in year *t-1*. The data was own construction based on the information data from the population censuses 1990, 2000, 2010 and population surveys 1995, 2005 provided by INEGI.
Urbanization Rate	Growth rate of the share of people living in urban areas areas in state *i* in year *t-1*. The data is based on information from the 1990, 2000, 2010 population censuses, and the1995 and 2005 population surveys provided by INEGI.
Timing of Governor Elections	Indicator for the timing of state level Governor elections that varies between 0 and 1. It takes smaller values the later the election takes place within the calendar year of the election year and is 0 for all other years. We follow Schneider (2013) and make use of the following measure: $(12 - (Mn - 1))/12$, wherein Mn is the month in which the state Governor election took place. The data on the exact date on which the elections are held in each state are obtained from the state elections results and

	information published by Institute of Marketing and Opinion (IMO) in Jalisco, Mexico.
State per capita GDP (log)	Own calculation using data on state-level GDP and population. Values are in U.S. dollars, constant prices 2003. The data on State GDP are form the National Accounting System and the population data are from the 1990, 2000, 2010 population censuses, and population surveys 1995, 2005. All data are provided by INEGI.
State GDP Growth	Rate of growth of each State GDP. The data on State GDP are from the National Accounting System and are provided by INEGI.
Population	Population of each State and the Federal District. All data are from the 1990, 2000, 2010 population censuses, and the 1995 and 2005 population surveys done by INEGI.

Appendix II.4: Collection and categorization of the federal crime data

The criminal procedure system in Mexico classifies crimes to be recorded under two broad categories namely, federal crimes and common crimes. The federal crimes include criminal activities associated with drug violence and other forms of organized crime; homicide; blocking of roads; possession, use and sale of weapons; piracy; illegal migrant and other human trafficking; falsification of documents; and kidnapping. Common crimes on the other hand include such crimes as sexual harassment; stealing of animal livestock; property expropriation; theft; rape; and domestic violence. While federal crimes are prosecuted in Mexico under the Federal Penal Code, the common crimes are adjudicated under the Penal Code of the respective states in which the offence took place.[43] The focus of this study is federal crimes only, which are typically associated with large-scale organized crime.

The criminal procedure system in Mexico specifies that when a crime incident occurs the investigative agencies decide whether the particular crime committed falls under the category of federal or common crime. If the crime is identified as a federal crime, the agents of the Federal Public Ministry together with the judiciary police start a preliminary investigation into the incident. The incident is then and there recorded as a federal crime. The investigative agencies are then required to investigate the crime, and maintain detailed records of the progress of the investigation. During such investigation, they may question or arrest any suspects. Based on the preliminary investigation and evidence gathered, the agencies decide to either approach the judiciary court or dismiss the case (typically due to lack of sufficient evidence against the suspect(s)). If the investigative agencies decide to approach the judiciary court, all arrested

[43] On December 2nd, 2012, the incoming Mexican President together with the two principal opposition political parties PAN and PRD, signed a document called "Pact for Mexico" as a part of larger judiciary reforms. One of the main features of this pact included the introduction of a single Penal Code and a single Penal Procedures Code for the entire country.

individuals must be produced before a judiciary court and charged with a specific federal crime within 48 hours of the decision, or be released. The investigative agencies must submit a report to the judge which details the results of the investigation. Based on this report, the judge makes a decision about whether there are sufficient grounds for proceeding with a criminal case. If s/he so rules, a formal ruling is announced, detailing the offence with which the accused is charged. If the judge on the other hand concludes that the report from the investigative agencies does not provide sufficient reasons to frame a charge, the case is dismissed. Our dependent variable captures the number of incidents at the state level recorded as federal crimes for which at least one young male aged 18-24 is suspected of the crime, and has been arrested.

The state level crime data are collected by the Instituto Nacional de Estadística y Geografía (The National Institute for Statistics and Geography, INEGI). INEGI was formed in 1983 as a part of Ministry of Finance. In 2005, it was separated from the Ministry of Finance and became an autonomous institution. Its main task is to conduct regular population and economic censuses across Mexican states and municipalities. INEGI also collect and process all forms of crime data on a monthly basis based on input from the courts at the state level. Through its website, it provides data on crime incidents by suspected perpetrators for different age groups, from 1990 to 2010. The reported categories changed somewhat between 2008 and 2009. For both periods, there is a distinction between the "register year" and the "occurrence year". The former represents the year in which a crime was registered by the court of justice and the latter records the year in which the crime actually took place. The count based on 'register year' includes crimes dating back before 1990, hence we have relied on the 'occurrence year' data only. For this category we observed a sudden jump in crime figures across all age groups in 1997, and assume that data prior to 1997 has been subject to significant under-reporting.[44] Therefore, we only consider crime data starting in 1997.

[44] While data prior to 1997 appears to be significantly under-reported, INEGI recognizes that not every crime is reported, hence there could be a bias due to under-reporting for the period covered by this analysis (Síntesis Metodológica. Estadísticas Judiciales en Materia Penal, p. 6). However, we have no information suggesting that such underreporting could systematically bias the relationships that we are studying. Furthermore, systematic time period or geographical biases should in principle be picked up by the time and state specific dummy variables respectively.

Chapter III

13 Years Later: The Spread of Drug Crime in Mexico

Acknowledgements: I am grateful to Axel Dreher, Maya Schmaljohann, Hannes Öhler and Krishna C. Vadlamannati for their helpful comments. Special thanks to the last two for the lively discussion on the spatial lag weighting matrix. The kind support from INEGI in Aguascalientes for all questions about the data at the state level is acknowledged. All errors are mine.

III.1 INTRODUCTION

Drug trafficking in Mexico is nothing new, nor are the deterrent policies implemented by the local authorities. As documented in Camp (1992), Toro (1995), Turbiville (1997), Flores Pérez (2009) and Moloeznik (2009) over the last thirty years Mexican authorities have relied heavily on the armed forces in the fight against drug trafficking by deploying troops for crop eradication, drug seizures and other counter-narcotics operations. This deterrence strategy accelerated greatly during the Fox and Calderón administrations.[45] As is well documented, by the end of 2006 and start of 2007 the Mexican federal government initiated an unprecedented frontal fight against the criminal organizations operating across the Mexican territory. Following this deployment, violence started to become one of the main concerns for Mexican society and authorities. The severity of this situation caused several scholars to start to analyze why Mexico became so violent. For instance, Rios (2012) argues that the main source of violence in the country stems from both drug trafficking organizations (henceforth DTO´s) fighting each other for the control of the drug market routes to the United States and authorities fighting the DTO´s using the police and military. According to Ríos (2012), in the short run an uprising of violence is expected which is predicted to decline in the long run. In the long run only the strongest DTOs would survive this turmoil.

This strategy has been largely criticized by scholars, the media, prominent personalities such as former U.N. General Secretary Koffi Annan, as well as NGOs in Mexico and abroad who question whether it was the best strategy available to authorities (HRW 2012, 2013).

These critics argue that by solely implementing deterrent policies violent crime would not stop. Rather, they claim that as a result of these policies drug-related conflicts spread to regions

[45] This corresponds to the 2000-2006 period for the Fox administration and to the 2006 to 2012 period for the Calderón administration.

which were previously unaffected. Within the literature on the economics of crime, geographical space has gained importance since crime in general is affected not only by local factors but also by the characteristics of neighboring areas (Ratcliffe, 2010). Thus, it might be the case that one deterrence policy could represent a gain to one region but a cost to another by displacing criminal offenders to other regions.

Some authors have sought to explain changes in overall crime levels. For instance, Klann (2012) investigates the effect of drug enforcement on overall crime levels in Mexico for the 1998-2008 period. However, no assessment exists to date which analyses whether drug crime has spread throughout Mexico and whether this spillover effect is caused by the deterrent measures of the Mexican authorities. To fill this gap in the literature, I collect data specifically on drug crimes at the state level for the 1997-2010 period for the 31 Mexican federal states and Mexico City. Assessing whether drug crime in Mexico shows any spillover effect from one region to another is important in terms of public security policy planning and police force coordination. Applying spatial econometrics techniques, this paper empirically investigates whether drug related crime in a given Mexican state shows a diffusion effect to the neighboring states and whether there is a spillover or contagion effect from one state to its neighbors. I find a positive and significant effect of a diffusion of drug crimes after controlling for political and socio-economic characteristics of regions. These findings take into account the endogeneity inherent to the spatial autoregression implementing 2SLS estimation and are robust to the selection of the spatial lag weighting matrix. Furthermore, I find weak evidence of a spillover effect of drug crime as a response to the authorities' deterrence measures.

The rest of the paper is organized as follows: Section 2 provides a review of the literature and develops the hypotheses of the paper. Section 3 discusses the data and identification strategy, and the empirical results. Section 4 presents robustness checks and section 5 concludes.

III.2 LITERATURE REVIEW

Following the seminal work by Becker (1968) the literature on economics of crime has mainly attempted to determine its empirical validity. A large body of this research examines deterrence which is the idea that crime can be reduced by increasing the expected cost to felons of committing a crime. In particular, this research focuses on arrest and incarceration rates, policing levels and harsh punishments like death penalty.[46] Parallel to this research, there is an array of literature considering hypotheses derived from economic models. These hypotheses include, for instance the roles of gun laws, guns, drug prohibition, and abortion legalization in causing crime.[47]

Additional to the previous research, there is a growing strand of literature concerned within the field of crime economics that highlights the importance of local geography as a determinant of crime, (Andresen 2006; Ratcliffe 2010). The underlying idea is that crime in one region is partly influenced by crime in a neighboring region. For example, a drug gang may sell drugs in one area and their presence may influence the growth of a drug market in a neighboring location. Similarly, the crime deterrence policies implemented by the authorities in one region might have implications for its neighboring regions. In this sense, Tabarrock and Helland (2009) examine whether harsher laws in California contribute to the displacement of criminals from that location

[46] Dezhbakhsh et al. 2006; Webster et al. 2006; Di Tella and Schargrodsky 2004; Kuziemko and Levitt 2004; Shepherd 2004; Dezhbakhsh et al. 2003; Mocan et al 2006; Mocan et al 2003; Katz et al 2003; McCrary, J. 2002; Kessler 1999; Levitt 1996; Levitt 1997; Ehrlich 1996; Moody and Marvell 1996; Ehrlich 1975; Ehrlich 1977.
[47] Dobkin and Nicosia 2009; Levitt 2004; Plassmann et al 2003, Donohue and Levitt 2008; Donohue and Levitt 2004; Donohue and Levitt 2001; Foote and Goetz 2008; Grogger and Willis 2000; Joyce 2003; Joyce 2009; Miron 2001; Miron 1999; Levitt 1997.

to other states in the U.S. They find that these types of laws do not generate significant criminal spillovers.

Arguably, there might be different types of crime and it is right to ask whether the type of crime affects the rate or presence of spillover. Thus, disaggregating crime into murders, thefts, frauds and squeezes, Cracolici and Uberti (2008) explore the spatial structure and distribution of crime in Italian provinces for the years 1999 and 2003 and find some evidence of spatial spillover in four areas of crime. Cohen and Tita (1999) use spatial econometric techniques to analyze whether homicides in the city of Pittsburg exhibit a contagion effect across neighborhoods during the 1991 to 1995 period. They do find contagious diffusion between neighborhoods.

What is more, Buonanno et al. (2011) not only analyze whether crime shows a diffusion effect from one region to another but they also provide evidence that social sanctions represent a very strong deterrent to a specific type of crime: property crime. They develop an exogenous and reliable measure for the density of social interactions and by implementing spatial panel model GMM estimation for all 103 Italian provinces during the period 1996-2003 they find that areas with denser social interactions display significantly and substantially lower rates of property crime. Further examples of articles applying spatial econometric techniques to understand the crime phenomenon are Cahill and Mulligan (2007), Fotheringham et al. (2002), Andresen (2006), Martin (2002) and Mencken and Barnett (1999).

Within this body of literature, spatial econometrics studies on crime-related topics in Latin American and in particular in Mexico are scare. Dills et al. (2010) mention that this limitation is in part due to the scarcity of crime statistics and data on its possible determinants for countries other than the U.S. One such prominent study by Formisano (2002) applies spatial econometrics techniques to a cross section of 563 neighborhoods in Bogota, Colombia, for the year 1999 in order to investigate the spatial diffusion of homicides. He finds that, on average, the rate of homicides in one neighborhood spreads by 14% to surrounding neighborhoods. Extending the study period from 1995 to 2000 also reveals a contagion effect of 56% of homicides to the neighboring localities. A further finding is that homicides in Bogota are highly concentrated in a few zones, which are home to criminal groups and known drug selling locations.

III.2.1 Drug Crime in Mexico

Astorga (2009) documents that the Mexican drug trafficking organizations date back to the early twentieth century, when U.S. and worldwide laws began to prohibit the production, distribution, and consumption of alcohol and psychotropic substances. At that time Mexico was a low-level supplier of drugs and Mexican smugglers mainly trafficked in homegrown marihuana and opiates grown in areas that remain important production zones today. Since the year 1929 the country was ruled by the political party PRI (Institutional Revolutionary Party) till the year 2000. During these seven decades there was a type of peaceful operation of drug trafficking in Mexico since powerful traffickers and PRI government officials maintained relatively predictable relationships (Morris 2012). Kenny and Serrano (2012) explain that the modern Mexican State and organized crime have a mutual evolution and thus it finds itself fighting parts of itself when fighting the criminals. Similarly, Morris (2012) argues that rampant corruption in Mexico makes it difficult at times to distinguish law violators from enforcers. Accordingly, Astorga (2007), Flores Pérez (2009) and Synder and Duran Martinez (2009) point out that the centralized power structure during the PRI ruling years was at the same time permissive and protective of organized criminal activities.

This mutual evolution of the state and organized crime shaped a remarkable underlying pattern of corruption in Mexico in the kind of a revolving door, whereby state security officials leave government service to work for the DTOs and DTOs members infiltrate and work within the government (Morris 2012).

During the last three decades three broad changes altered the patterns and influence of corruption and its relation to drug trafficking and organized crime: Mexico´s political transformation (Morris 2012), changes within the drug trafficking sector itself manifested through the alliance between the Colombian and Mexican DTOs as a result of the U.S. government´s efforts to upset the Colombian supply chain through South Florida (Chabat 2002) and the confrontational policies of former President Calderón (Morris 2012).

Mexico´s political transformation occurred with the dismantling of the PRI-led authoritarian regime during the last three decades and the control of state and local governments by opposition parties. The political change of this period weakened the informal rules of operation and old bargains. This left DTOs without the state sponsored protection they had once enjoyed and forced them to acquire their own means of protection and to create their own paramilitary structures (Snyder and Duran-Martínez 2009). Consequently, drug crime in Mexico is the result of a complex system of different political economy players.

Hence, my base expectation is that:

Hypothesis 1: *Given the political and socio-economic conditions throughout regions in Mexico, drug crime spreads from one region to another, everything else being equal*.

The literature about deterrence and crime contains mixed results. For instance, many studies find that increasing deterrence reduces crime.[48] Decker and Kohfeld (1985) and Benson et al. (1994), however, suggest that while deterrence may reduce crime rates, it is more likely that arrests follow from an increase in crime as police reallocate enforcement resources to combat the increase in crime. Additionally, Cornwall and Trumbull (1994) find that labor market and criminal justice strategies are important in deterring crime, but that the effectiveness of law enforcement incentives has been greatly overstated. Tabarrok and Helland (2009) have shown that criminal sanctions in California displace criminals rather than deterring criminal activity; implying that a benefit to California represents a cost to other states.

Similarly, it has also been documented that pressure placed on drug growers is not sufficient to reduce drug crop production significantly. For instance in Bolivia, enforcement efforts against producers and traffickers have brought down the price of coca leaves, leading to a slight drop in the amount of coca produced since 1989. On the contrary, in Peru, coca production increased between 1989 and 1992 by an amount equivalent to 73 percent of Bolivia´s reduction. It is feasible that one country`s success in reducing production will simply be another´s problem as criminals migrate to places of least resistance and most opportunity, creating demand for drug crop production. This phenomenon is referred to as the "balloon or spillover effect" in the literature. In other words, what is pushed down in one place simply springs up in another (UNRISD, 1994). However, it can also be the case that the measures implemented by the authorities in one country or region inhibit the activities of criminal organizations in such a way that crime incidents in the neighboring countries or regions are also reduced.

For the case of Mexico, since December 2007 the federal Mexican authorities, by means of the federal police and the military implemented random checkpoints on highways throughout

[48] Levitt (1997, 1998), Lee and McCrary (2005), Klick and Tabarrol (2005), Evans and Owens (2007).

Mexico to hinder the flow of drugs from one state to another. Unfortunately there are no public records available which show the intensity and location of this deployment of federal forces.[49]

However, with the available data, which will be explained in the next section, I test the hypothesis that:

Hypothesis 2: *Deterrence measures from the authorities in state i could have either a negative or a positive impact on the level of drug crime incidents in the neighboring states.*

III.3 DATA AND METHOD

This paper uses a panel dataset across 32 Mexican states (including the Federal district, also known as Mexico City) during the 1997–2010 period. The following specification estimates the change in the log of drug crimes ($\ln DC_{it}$), in state *i* in year *t* as a function of a vector of control variables Z_{it} which are drawn from the existing literature and the drug crimes in other states in year *t*, a variable known in the literature as the spatial lag.

$$\ln DC_{it} = \beta Z_{it} + \delta \sum_{j \neq i} s_{ij} DC_{jt} + \nu_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

Furthermore, ν_i denotes state-fixed-effects to control for unobserved state-specific heterogeneity in the panel dataset, λ_t is a time-specific dummy and ε_{it} is the error term. For the dependent variable I use the log number of all sorts of crime events related to drugs: production, transport, trafficking, commerce and possession in each of the 31 Mexican states and the federal district. The use of panel data helps to eliminate spatial error dependence, which arises through spatial autocorrelation of omitted variables (Brueckner, 2003).

[49] According to the Mexican Secretary of Defense (SEDENA), the number and location of these check points in the Mexican highways is classified and not revealed to the public (SEDENA 2011).

The spatial lag, $\sum_{j \neq i} s_{ij} DC_{jt}$ is the weighted sum of the inverse distance in kilometers from the capital city of each Mexican state and the Federal District to the other capital cities.[50] The coefficient of the spatial lag δ depicts the degree to which changes in drug crimes in a given state are correlated with changes in the drugs crimes in its neighboring states, all else being equal. In other words, this variable captures the spillover effect of crime. That is, if a state experiences an increase in the level of crime in a given year, then the neighboring states should also experience increasing crime levels. From Figure III.1 and Figure III.3 it can be seen that the drug crimes in Mexico follow an upward trend from 1994, reach a peak in 2007 and fall thereafter. This coincides with the full-scale military campaign launched by former president Calderón's administration against DTOs across Mexico. In order to test the second hypothesis, I use data on marihuana seizures collected from the Office of the General Prosecutor Attorney General as a proxy for drug control policy and construct a spatial lag variable. Similarly to the above, this spatial lag depicts the extent to which changes in marihuana seizures in a given state affect changes in the drug crimes in its neighboring states, all else being equal. This data registers the tons of marihuana seized by the authorities in each and every state for the period 1994 through 2010. As can be seen from Figure III.2, the tons of marihuana seized show an upward trend previous to the year 2000 and from there onwards both ups and downs are frequent. Disentangling the data across states, Figure III.6 shows that the bulk of the tons of marihuana seized in the 1994-2010 period was in the states of Sinaloa, Sonora and Durango. The details of the variable definitions and data sources are reported in Appendix III.4.

[50] As in Blonigen and Davies (2004) I specify model in log-linear form because this model leads to well-behaved residuals given the skewness in the drug crime data.

Spatial econometric theory suggests that the weights used in the construction of the spatial lag should be declining in distance but it does not propose a specific form (Davies and Naughton 2013). Basically, the specification of the weights is a matter of considerable discretion and the literature offers a wide range of suggestions (Anselin and Bera, 1998). I specify the spatial weights as: $s_{ij} = \frac{1}{d_{ij}}$.

Setting s_{ij} in this way gives less weight to the states which are further away from state *i*. The rationale for using the inverse distance as a weight has been documented in the economics of crime literature since crime in general is affected not only by local factors but also by the characteristics of neighboring areas. Thus, it might be the case that one policy could represent a gain to a region by displacing criminal offenders to other regions. In other words, the cost of a region represents the gain of another (Tabarrock and Helland, 2009).

An issue of concern in the estimation of (1) pertains to the potential endogeneity of the drug crimes of other states. This is a problem which is inherent to spatial autoregression: DC_{it} depends on DC_{jt} and DC_{jt} on DC_{it}. In other words, there may be unobservable regional or national shocks which are correlated with the drug crimes of multiple states. However, even with the inclusion of time fixed effects, the issue of reverse causation and spatially correlated idiosyncratic shocks would still persist. Thus estimating equation (1) using OLS would provide biased estimates due to this endogeneity.

According to Kelejian and Prucha (1998), instrumental variables estimation (IV) yields consistent estimates even in the presence of spatial error dependence (Saavedra, 2000; Brueckner, 2001). In order to instrument for the spatial lag, I implement a 2SLS estimation procedure. The instruments for the drug crime spatial lag are the weighted sums of the control variables: log state per capita GDP; population; and the unemployment rate. To make this calculation I use the same weights as those used to calculate the spatial lag itself.

$$\sum_{j\neq i} s_{ij} DC_{jt} = a_t + b\sum_{j\neq i} s_{ij} x_{jt} + \beta x_{it} + \nu_i + \lambda_t + \varepsilon_{it} \qquad (2)$$

In the second stage, the fitted values of equation (2) are used in the estimation of equation (1) in place of $\sum_{j\neq i} s_{ij} DC_{jt}$. The vector of control variables (Z_{it}) includes other potential determinants of drug crime incidents (log) in state *i* during year *t*, which I obtain from the extant literature on the subject. This follows earlier studies by Buonanno, Pasini and Vanin (2011), Corman and Mocan (2005), Formisano (2002), Gould, Weinberg and Mustard (2002), Raphael, and Winter-Ebmer (2001) and Cornwall and Trumbull (1994). Accordingly, I include state per capita GDP (logged) in Mexican pesos $ 2003 constant prices to proxy for income. The income data are available from the National Accounts System of INEGI.[51] Likewise, I use state population, which is drawn from the population census data compiled by INEGI. The Mexican population censuses are carried out by INEGI across all the 32 Mexican states (including the Federal District) once every 10 years. Once every five years INEGI also conducts surveys known as population counts. Thus, the data used to interpolate the population variable comes from the censuses of 1990, 2000, and 2010 (INEGI, 1990; 2000; 2010), and from the population surveys of 1995 and 2005 (INEGI, 1995; 2005). Similarly, the Mexican census files for 1990, 2000 and 2010 only (INEGI, 1990; 2000; 2010) and the population survey of 2005 (INEGI 2005) register interstate migration. The unemployment and labor force data are available from the Mexican census files for 1990, 2000 and 2010 only (INEGI, 1990; 2000; 2010). The data on crime reporting agencies are taken from the Penal Judicial Statistics provided and published on an annual basis by INEGI. Additionally, I

[51] For more details see: www.inegi.org.mx

include three political dummy variables which take the value of one if the state governor in state *i* during year *t* belonged to either one of the three governing political parties, PRI, PAN, PRD.[52] As is well documented, and mentioned above, for many decades Mexico had in place a highly centralized power structure which was permissive and protective of organized criminal activities (Astorga Almanza 2007; Flores Pérez 2009; Synder and Duran Martinez 2009). The data on the exact governing period for each of these political parties in each state are obtained from the information published by the Institute of Marketing and Opinion (Instituto de Mercadotecnia y Opinión 2012).

III.4 EMPIRICAL RESULTS

Column 1 of Table III.1 represents the baseline model in which only the spatial lag of drug crimes is considered together with control variables drawn from the literature. Column 2 includes the spatial lag of marihuana seizures and excludes the spatial lag for drug crimes. Columns 3 and 4 consider both spatial lags but employ both different external instruments. For this first set of estimations I use the inverse distance of each of the capital of each state to all other capital cities as a weighting matrix. As introduced above, this allows me to give more weight to the drug crime incidents taking place in the neighboring states of state *i*. The weight of drugs crimes is thus decreasing with increased distance.

Turning to the coefficient of interest in Column 1 the results show a positive and significant spatial lag of drug crimes. Thus, keeping all other variables constant, an increase of one standard deviation in the drug crimes incidents from state i's neighboring states leads to an increase of

[52] I leave the three political dummy variables in the model estimations since the states Chiapas 2001-2006 and Nayarit 2000-2005 experienced a government coalition involving the parties PAN and PRD.

29.7[53] percent in state i. This value is positive and significant at the 10% level. For this estimation I implement the spatial lags of GDP per capita logged, unemployment rate, population and crime reporting agencies of other states.

As highlighted above, first, the spatial lag of the drug crimes is regressed on the spatial lags of GDP per capita logged, unemployment rate, population and crime reporting agencies of other states and all other regressors. In this way the predicted values of the spatial lag of drug crimes are obtained which then enter the second stage regression to obtain an unbiased estimator for the drug crime incidents variable. Staiger and Stock (1997) argue that in order to reject the null hypothesis that the selected instruments are not relevant, the first stage F-statistic should show a value larger than 10. As can be seen at the bottom of Table III.1, Column 1 the specification shows an F-statistic far above 10, thus rejecting the null hypothesis that the selected instruments are not relevant. Furthermore, the Hansen J-statistic with a p-value of 0.18 shows that the null-hypothesis of exogeneity cannot be rejected at conventional levels of significance. Next, in Column 2, I account for the effect of drug control policy by including the spatial lag of marihuana seizures as a deterrence measure. The coefficient of this spatial lag shows a negative and significant coefficient at the 5% level. Again, for its interpretation I proceed in the same way as before. Thus, holding all other control variables constant, an increase of one standard deviation in the tons of marihuana seized in the neighboring states of state *i* leads to a reduction in drug crime incidents by 75.8%. This could be interpreted as a success of the drug control policy of the Mexican authorities. Since the dependent variable measures the drug crimes due to production, transport, trafficking, commerce and possession of drugs in state *i* at time *t*, the tons

[53] For the sake of interpretation of all results presented in this section, I perform the following calculation: $(e^{\beta * SD} - 1) * 100$, where β is the estimated coefficient from each model and *SD* is one standard deviation from the estimated sample.

of marihuana seized in state *i* at time *t* exert variation in the drug crimes incidents variable.[54] Thus, I exclude the marihuana seizures variable in state *i* at time *t* in the second specification.[55] Again, the F-statistic provides support for the relevance of external instruments and the Hansen J-statistic with a p-value of 0.87 shows that the null-hypothesis of exogeneity cannot be rejected at conventional levels of significance.

Column 3 considers both spatial lags, namely for drug crime incidents and for marihuana seizures. By doing so, I intend to control for the spillover of crime when drug enforcement operations are being carried out. Although the coefficient on the spatial lag of drug crime incidents shows a positive and significant coefficient and an F statistic above the threshold level of 10, the Hansen J-statistic does not render support for the exogeneity of the set of external instruments used, - the spatial lags of GDP per capita, unemployment rate, population and crime reporting agencies per capita. Consequently and based on the results of the first stage estimation, I exclude the spatial lag of the GDP per capita and again perform the 2SLS estimation with the remaining external instruments. The results of this estimation are shown in Column 4.

In this case, holding all other controls constant, a one standard deviation increase in drug crime incidents in the neighboring states to state *i* at time *t* leads to an increase of drug crime incidents of 80% in state *i* at time *t*. Contrary to the previous estimation in Column 3, the F-statistic now shows a value above 10 for both of the spatial lags, which provides support for the relevance of the external instruments and the Hansen J-statistic with p-value of 0.86 exhibits support for their exogeneity. This result shows a higher spillover effect of drug crime from one

[54] Arguably, marihuana is not the only illicit drug produced, consumed and trafficked in Mexico; however due to data availability I use only the tons of marihuana seized in each state *i* at time *t*.

[55] The inclusion of the marihuana seizures variable in state *i* does not qualitatively change the results. These estimations are not shown due to space limitations but are available upon request.

state to another when controlling for drug enforcement in neighboring states to state *i* through the spatial lag of marihuana seizures.

Coming now to the control variables and as shown in table 1, the variable for crime reporting agencies is positive and significant at the 1% level in the first two specifications and positive and significant at the 10% level in the Columns 3 and 4. It could be argued that more crime reporting agencies are assigned to those regions with more crime incidents leading to a potential endogeneity problem in this variable. However, the distribution of crime reporting agencies throughout Mexico is not attached to the incidence of crime in its different regions. There are states in Mexico for which the distribution of crime reporting agencies does not correspond to the levels of crime activity in those regions. The number of crime reporting agencies assigned to regions is more an issue of financial costs (Fondevila 2012). Next, the type of government controls do not show any significance and no conclusions from these variables can be drawn. Further, I also control for income differences throughout states by including the state per capita GDP. Since the impact of the additional controls is not my primary focus, I do not delve further into these aspects in the interest of space.

III.4.2 Robustness Checks

As a robustness check of the previous findings in this section I present the estimations of the above-mentioned models using a different weighting matrix in the construction of the spatial lags. In line with Buonanno et al. (2011), Bode et al. (2007) and Gumprecht (2005) I model the spatial weights as inverse exponential distances as: $e^{-\tau(Dis_{ij})}$ where Dis_{ij} denotes the distance between states *i* and *j*, and τ is a constant distance decay parameter that determines the percentage-diffusion-loss per unit of distance. In other words, it accounts for the degree of how strong the drug crimes lose weight with increasing distance. Following Bode et al. (2007), I arbitrarily assume three different values for τ = 0.005, 0.01 and 0.001. Tables 2, 3 and 4 present the results considering this weighting scheme with the three different corresponding values for τ.

First, in all three tables in Column 1 it can be seen that regardless of the value assigned to τ the spatial lag of the drug crime incidents variable remains significant and positive at the 5% and 10% level. Here I use the same external instrument set as in Table 1. Thus, for all three tables, the F statistic and the Hansen J-statistic lend support to the relevance and exogeneity of the external instruments in Column 1. Looking now at Table 2, we see that by assigning τ the intermediate value of 0.005, the F statistics of the spatial lag for the marihuana seizures variable in Columns 2 to 4 are less than 10, while the Hansen-J statistic renders support to the three specifications. Based on this, in Table 3 I choose the smaller value of 0.01 for τ. The results are similar to those in Table 2 in terms of the F statistic for the marihuana seizures variable being less than 10. Next, in Table 4, I choose the smallest value of the three selected for τ, namely 0.001. We see that all four specifications observe the same behavior as in Table 1, however the spatial lag of the marihuana seizures variable now shows no significance. In terms of interpretation, Column 1 Table 4 shows that, everything else constant, an increase of one standard deviation in drug crime incidents in the neighboring states of state *i* leads to an increase of 34.2% in drug crimes in state *i*. I obtain this value in a similar way as in Table 1. Furthermore, holding all other controls constant, in Columns 3 and 4, an increase of one standard deviation in drug crime incidents in the neighboring states of state *i* lead to an increase of the drug crimes in state *i* by 41% and 42%, respectively.

As can be seen in Table 4 Column 2, the spatial lag of the marihuana seizures is no longer significant. Given the availability of data, this does not necessarily mean that by seizing drugs the authorities do not exert an impact on organized crime and hence on crime derived from illegal drug activities. Certainly the literature on the crime-deterrence relationship has found mixed results with the contributions of Ehrlich (1975), Witte (1980), Layson (1985), Grogger (1991), and Levitt (1997) finding that increases in criminal-justice sanctions reduce criminal activity. On the other hand, the papers of Myers (1983), Cover and Thistle (1988) and Cornwell and Trumbull (1994) find either a weak relationship, or none at all.

One reason for the vanishing of significance in the spatial lag of marihuana seizures could be the frequency of the data. In the literature on the economics of crime, this has been highlighted by Corman and Mocan (2000), who by employing high frequency data, find a strong support for the deterrence hypothesis.

III.5 CONCLUSION

This article investigates whether there is a spillover effect of drug crime across Mexican states or whether there is a deterrent effect from drug control policy on drug crimes across Mexican states. Building on the historical background of a highly centralized, permissive and protective power structure towards organized criminal activities, I initially hypothesize that drug crime in Mexico should vary not only with local socio-economic factors but that geographical space also plays an important role in this variation. Applying spatial econometrics techniques and accounting for the inherent endogeneity in a spatial regression, I find that drug crime incidents show a diffusion effect from one region of Mexico to another. This effect is robust to different weighting schemes of the weighting matrix used in the computation of the spatial lag variable. I further hypothesized that deterrence measures from the authorities in state *i* could have either a negative or a positive impact on the level of drug crime incidents in the neighboring states.

It can be the case that DTOs move to neighboring locations as a result of a harsh deterrence policy in state *i* thereby increasing drug crime incidents in the former locations. On the contrary it can also be the case that the measures implemented by the authorities in state *i* inhibit the activities of the DTOs in such a way that drug crime incidents in the neighboring states get reduced. In practice there is a wide array of deterrence measures from the authorities as suggested in the economics of crime literature. For instance, the number of police and military forces deployed, effective arrests and stricter sentences for those arrested on drug charges, seizures of arms and drugs etc. Given the scarce availability of this kind of data, which would allow me to construct a reasonable sub-national panel dataset, I use tons of marihuana seizures as a proxy for deterrence, i.e., drug control policy. I find weak evidence for this last expectation; a result which is not borne out by the robustness checks of the empirical models. As argued above, this does not necessarily mean that deterrence measures from the authorities do not imply a re-structuration of the DTOs when a leading kingpin gets arrested or big seizures of drugs, weapons and money take place.

This study provides evidence of a diffusion effect of drug crimes from one region in Mexico to another. The findings reported here may have implications for our understanding on whether drug crime in Mexico spreads from one state to another and whether a drug crime deterrent measure in one region coincides with a cost or a benefit for another. In terms of public security policy this has implications for a better coordination among the several police forces across Mexico.

Furthermore, the findings presented here may have implications for regions beyond the Mexican context experiencing a similar situation and may motivate more detailed data collection on crime statistics. Further research might look at the effects of different drug crime deterrence measures by the authorities and at which level of deterrence, if any, a turning point exists.

Table III.1: Drug Crimes (1997-2010): 2SLS estimations.
Weighting Scheme: Inverse Distance

VARIABLES	(1) Drug Crimes (log)	(2) Drug Crimes (log)	(3) Drug Crimes (log)	(4) Drug Crimes (log)
Spatial Lag Drug Crimes	**0.00499***		**0.00528***	**0.00805****
	(0.00286)		(0.00305)	(0.00388)
Spatial Lag Marihuana Seizures		**-0.00169****	-4.96e-05	0.000182
		(0.000754)	(0.000791)	(0.000841)
GDP pc (log)	-0.546	0.806	-0.446	-0.602
	(0.575)	(1.108)	(0.831)	(0.897)
Unemployment Rate	-0.119	0.0426	-0.116	-0.170*
	(0.0966)	(0.119)	(0.0999)	(0.102)
Population (log)	1.550	-0.835	1.611	2.317
	(1.161)	(1.243)	(1.967)	(2.099)
Crime Reporting Agencies pc (log)	**0.255*****	**0.354*****	**0.255***	**0.234***
	(0.0987)	(0.136)	(0.133)	(0.139)
Migration Rate	-0.0584	-0.0603	-0.0546	-0.0594
	(0.0921)	(0.0979)	(0.0947)	(0.107)
Marihuana Seizures (log)			**0.0332***	**0.0450****
			(0.0178)	(0.0188)
PRI Governor ruling years	-0.0253	-0.0973	-0.0290	-0.00123
	(0.258)	(0.428)	(0.255)	(0.278)
PAN Governor ruling years	0.0435	0.153	0.0453	0.0184
	(0.150)	(0.311)	(0.175)	(0.183)
PRD Governor ruling years	-0.161	-0.356	-0.161	-0.0911
	(0.186)	(0.273)	(0.195)	(0.226)
F-statistic (spatial lag Drug Crimes)	52.3		53.12	19.97
F-statistic (spatial lag Marihuana Seizures)		11.3	12.13	12.6
Hansen J (p-value)	0.1885	0.8798	0.0874	0.8654
Time specific dummies	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES
Number of States	32	32	32	32
Number of Observations	455	455	453	453
R-squared	0.545	0.229	0.542	0.500
Method	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS

Robust standard errors clustered by state in parentheses *** p<0.01, ** p<0.05,*p<0.1.

Note: Column 3 uses the spatial lags of GDP per capita logged, unemployment rate, population and crime reporting agencies. Column 4 uses the spatial lags of unemployment rate, population and crime reporting agencies.

Table III.2: Drug Crimes (1997-2010): 2SLS estimations
Weighting Scheme: Exponential Function Inverse Distance (0.005)

VARIABLES	(1) Drug Crimes (log)	(2) Drug Crimes (log)	(3) Drug Crimes (log)	(4) Drug Crimes (log)
Spatial Lag Drug Crimes	**6.65e-05****		0.000123	**0.000145***
	(3.30e-05)		(7.66e-05)	(7.56e-05)
Spatial Lag Marihuana Seizures		-3.48e-06	3.87e-06	5.52e-06
		(2.14e-06)	(5.27e-06)	(5.70e-06)
GDP pc (log)	-0.497	-0.468	-0.564	-0.621
	(0.542)	(0.536)	(0.679)	(0.722)
Unemployment Rate	-0.116	0.0336	-0.263	-0.325
	(0.0844)	(0.130)	(0.207)	(0.234)
Population (log)	**1.715***	-0.197	3.558	4.280
	(0.904)	(1.292)	(2.493)	(2.719)
Crime Reporting Agencies pc (log)	**0.235*****	**0.287*****	**0.187***	0.168
	(0.0784)	(0.106)	(0.0993)	(0.105)
Migration Rate	-0.0557	-0.0647	-0.0430	-0.0392
	(0.0760)	(0.0753)	(0.0923)	(0.102)
Marihuana Seizures (log)			-0.00681	-0.0235
			(0.0545)	(0.0601)
PRI Governor ruling years	-0.0571	0.0477	-0.176	-0.224
	(0.233)	(0.257)	(0.292)	(0.319)
PAN Governor ruling years	0.0468	0.120	-0.0243	-0.0534
	(0.141)	(0.156)	(0.184)	(0.197)
PRD Governor ruling years	-0.207	-0.242	-0.187	-0.179
	(0.154)	(0.151)	(0.161)	(0.163)
F-statistic (spatial lag Drug Crimes)	28.96		27.36	36.35
F-statistic (spatial lag Marihuana Seizures)		4.17	3.17	4.17
Hansen J (p-value)	0.5219	0.2017	0.5458	0.7527
Kleibergen Paap LM test	16.75	8.038	3.784	3.79
Time specific dummies	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES
Number of States	32	32	32	32
Observations	455	455	453	453
R-squared	0.659	0.541	0.599	0.522
Method	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS

Robust standard errors clustered by state in parentheses *** p<0.01, ** p<0.05,*p<0.1.
Note: Column 3 uses the spatial lags of GDP per capita logged, unemployment rate, population and crime reporting agencies. Column 4 uses the spatial lags of unemployment rate, population and crime reporting agencies.

Table III.3: Drug Crimes (1997-2010): 2SLS estimations
Weighting Scheme: Exponential Function Inverse Distance (0.01)

VARIABLES	(1) Drug Crimes (log)	(2) Drug Crimes (log)	(3) Drug Crimes (log)	(4) Drug Crimes (log)
Spatial Lag Drug Crimes	**9.76e-05***		8.20e-05	9.44e-05
	(5.49e-05)		(0.000106)	(0.000107)
Spatial Lag Marihuana Seizures		-5.20e-06	-1.37e-06	-3.85e-07
		(3.36e-06)	(4.44e-06)	(4.84e-06)
GDP pc (log)	-0.373	-0.641	-0.343	-0.326
	(0.512)	(0.607)	(0.516)	(0.525)
Unemployment Rate	-0.0832	0.0607	-0.0438	-0.0700
	(0.0910)	(0.148)	(0.187)	(0.199)
Population (log)	**1.606****	-0.567	1.202	1.536
	(0.739)	(1.429)	(1.520)	(1.657)
Crime Reporting Agencies pc (log)	**0.242*****	**0.275****	**0.246*****	**0.242*****
	(0.0696)	(0.111)	(0.0720)	(0.0682)
Migration Rate	-0.0326	-0.0751	-0.0365	-0.0308
	(0.0687)	(0.0820)	(0.0558)	(0.0596)
Marihuana Seizures (log)			0.0422	0.0304
			(0.0489)	(0.0535)
PRI Governor ruling years	-0.121	0.116	-0.0720	-0.112
	(0.211)	(0.271)	(0.267)	(0.287)
PAN Governor ruling years	0.0141	0.142	0.0384	0.0182
	(0.127)	(0.162)	(0.154)	(0.160)
PRD Governor ruling years	**-0.258***	-0.222	**-0.248***	**-0.255***
	(0.131)	(0.161)	(0.135)	(0.137)
F-statistic (spatial lag Drug Crimes)	10.96		10.38	10.31
F-statistic (spatial lag Marihuana Seizures)		1.82	2.2	2.8
Hansen J (p-value)	0.8282	0.7534	0.7342	0.577
Kleibergen Paap LM test	12.06	5.012	9.02	5.002
Time specific dummies	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES
Number of States	32	32	32	32
Observations	455	455	453	453
R-squared	0.695	0.478	0.684	0.695
Method	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS

Robust standard errors clustered by state in parentheses *** p<0.01, ** p<0.05,*p<0.1.

Note: Column 3 uses the spatial lags of GDP per capita logged, unemployment rate, population and crime reporting agencies. Column 4 uses the spatial lags of unemployment rate, population and crime reporting agencies.

Table III.4: Drug Crimes (1997-2010): 2SLS estimations
Weighting Scheme: Exponential Function Inverse Distance (0.001)

VARIABLES	(1) Drug Crimes (log)	(2) Drug Crimes (log)	(3) Drug Crimes (log)	(4) Drug Crimes (log)
Spatial Lag Drug Crimes	**2.68e-05***		**3.13e-05****	**3.19e-05****
	(1.52e-05)		(1.54e-05)	(1.58e-05)
Spatial Lag Marihuana Seizures		-1.44e-06	8.06e-07	8.27e-07
		(1.56e-06)	(1.13e-06)	(1.13e-06)
GDP pc (log)	-0.690	-0.307	-0.816	-0.822
	(0.600)	(0.560)	(0.669)	(0.674)
Unemployment Rate	-0.101	0.0541	-0.160	-0.163
	(0.0922)	(0.165)	(0.122)	(0.122)
Population (log)	1.957	-0.291	2.759	2.802
	(1.282)	(1.752)	(1.853)	(1.859)
Crime Reporting Agencies pc (log)	**0.257*****	**0.289*****	**0.243****	**0.243****
	(0.0939)	(0.108)	(0.101)	(0.101)
Migration Rate	-0.0537	-0.0573	-0.0436	-0.0436
	(0.0874)	(0.0792)	(0.0973)	(0.0977)
Marihuana Seizures (log)			0.0224	0.0225
			(0.0174)	(0.0174)
PRI Governor ruling years	-0.0652	0.0219	-0.121	-0.122
	(0.223)	(0.285)	(0.262)	(0.262)
PAN Governor ruling years	0.0485	0.132	0.0106	0.00916
	(0.137)	(0.180)	(0.164)	(0.165)
PRD Governor ruling years	-0.210	-0.268*	-0.202	-0.201
	(0.155)	(0.144)	(0.155)	(0.156)
F-statistic (spatial lag Drug Crimes)	84.57		102.31	131.26
F-statistic (spatial lag Marihuana Seizures)		27.18	13.57	13.16
Hansen J (p-value)	0.2257	0.0535	0.4067	0.2007
Kleibergen Paap LM test	84.567	27.181	12.749	11.875
Time specific dummies	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES
Number of States	32	33	34	35
Observations	455	455	453	453
R-squared	0.599	0.560	0.588	0.588
Method	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS

Robust standard errors clustered by state in parentheses *** $p<0.01$, ** $p<0.05$,*$p<0.1$.

Note: Column 3 uses the spatial lags of GDP per capita logged, unemployment rate, population and crime reporting agencies. Column 4 uses the spatial lags of unemployment rate, population and crime reporting agencies.

Appendix III.1: Mexican States

Aguascalientes	Distrito Federal	Morelos	Sinaloa
Baja California	Durango	Nayarit	Sonora
Baja California Sur	Estado de México	Nuevo León	Tabasco
Campeche	Guanajuato	Oaxaca	Tamaulipas
Chiapas	Guerrero	Puebla	Tlaxcala
Chihuahua	Hidalgo	Querétaro	Veracruz
Coahuila	Jalisco	Quintana Roo	Yucatán
Colima	Michoacán	San Luis Potosí	Zacatecas

Appendix III.2: Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Observations
Drug Crime Incidents (log)	6.353096	1.118547	2.99573	9.88262	456
GDP pc (log)	9.038824	.6807205	7.75593	11.9643	672
Unemployment Rate	2.485603	1.166651	.735916	6.60365	672
Population (log)	14.61702	.7967536	12.6691	16.5368	672
Crime Reporting Agencies pc (log)	-5.845844	.6100128	-8.37109	-4.51869	541
Migration Rate	3.385281	2.306138	.56069	15.8146	672
PRI state ruling years	.7127976	.4527938	0	1	672
PAN state ruling years	.1845238	.3881997	0	1	672
PRD state ruling years	.1175595	.3223257	0	1	672
Tons of Marihuana Seizures (log)	8.4711	3.02253	-3.506558	13.44835	542
Spatial Lag Drug Crime Incidents	48.16873	51.14232	.0461443	242.2251	512
Spatial Lag Marihuana Seizures	1749.082	875.2641	180.8141	4020.006	512
Spatial Lag Unemployment Rate	.1284549	.0834982	.0093864	.4506391	672
Spatial Lag Population	174006.4	101571.6	20663.55	462146	672
Spatial Lag Crime Rep. Agencies pc	.0001542	.0000688	.0000153	.0003237	544

Appendix III.3: Descriptive Statistics of Spatial Lags for Robustness Checks

Variables	Mean	Standard Deviation	Minimum	Maximum	Observations
ROBUSTNESS of TABLE 2					
Spatial Lag Drug Crime Incidents	2979.87	3729.946	6.60e-07	24744.72	544
Spatial Lag Marihuana Seizures	96786.33	106357.5	330.3813	744577.1	544
Spatial Lag Unemployment Rate	7.605879	5.563206	.0401859	28.01068	672
Spatial Lag Population	1.07e+07	8356705	64059.5	3.27e+07	672
Spatial Lag Crime Rep. Agencies pc	.0092507	.0043306	9.37e-06	.0207834	544
ROBUSTNESS of TABLE 3					
Spatial Lag Drug Crime Incidents	1572.538	2337.871	1.83e-15	20738.42	544
Spatial Lag Marihuana Seizures	57921.23	97802.42	.6165496	695796.6	544
Spatial Lag Unemployment Rate	3.985855	2.725504	.0011553	15.62765	672
Spatial Lag Population	5538695	4911314	1789.706	2.26e+07	672
Spatial Lag Crime Rep. Agencies pc	.0049928	.0022659	1.10e-08	.0119154	544
ROBUSTNESS of TABLE 4					
Spatial Lag Drug Crime Incidents	12793.83	11306.89	4.625066	47877.76	544
Spatial Lag Marihuana Seizures	569167.3	293635.7	44457.74	1376893	544
Spatial Lag Unemployment Rate	33.39079	17.62321	1.791199	82.98112	672
Spatial Lag Population	4.38e+07	1.64e+07	2211108	7.25e+07	672
Spatial Lag Crime Rep. Agencies pc	.0425417	.0143317	.0073515	.0680854	544

Appendix III.4: Data Definitions and Sources

Variables	Definitions and data sources
Drug Crime Incidents (log)	Measure which includes drug related crimes in state *i* at time *t*. (Production, Selling, Transportation and Trafficking of illicit drugs). The data are provided by INEGI.
Unemployment Rate	Rate of unemployed people in state *i* at time *t*. The data are from the population census data and the population counting, both provided by INEGI.
Crime Reporting Agencies	Number of Crime Reporting Agencies per capita in state *i* at time *t*. The data are from the Judiciary System Statistics provided by INEGI.
Migration Rate	Rate of people migrating from one state to another. The data are from the population census data and the population counting, both provided by INEGI.
PRI state ruling years	Dummy variable which takes the value of 1 if the state governor was from the political party PRI. The data on the exact date on which a governor was ruling in each state are obtained from the state elections results and information published by Institute of Marketing and Opinion (IMO) in Jalisco, Mexico.
PAN state ruling years	Dummy variable which takes the value of 1 if the state governor was from the political party PAN. The data on the exact date on which a governor was ruling in each state are obtained from the state elections results and information published by Institute of Marketing and Opinion (IMO) in Jalisco, Mexico.
PRD state ruling years	Dummy variable which takes the value of 1 if the state governor was from the political party PRD. The data on the exact date on which a governor was ruling in each state are obtained from the state elections results and information published by Institute of Marketing and Opinion (IMO) in Jalisco, Mexico.
State per Capita GDP (log)	Own calculation using data on each State GDP and Population in each State. Values are in Mexican pesos, constant prices 2003. The data on State GDP are form the National Accounting System and the Population data are from the population censuses 1990, 2000, 2010 and population counting 1995, 2005. All data are provided by INEGI.
Tons of Marihuana Seizures (log)	Tons of Marihuana seized by the Mexican authorities in state *i* at time *t*. The data are from the Office of the General Prosecutor Attorney General.
Spatial Lag Drug Crime Incidents	Variable which registers the drug crimes in states *j-i* at time *t*. This measure was calculated implementing an inverse distance weighting matrix without row standardization.
Spatial Lag Marihuana Seizures	Variable which registers the tons of marihuana seized in states *j-i* at time *t*. This measure was calculated implementing an inverse distance weighting matrix without row standardization.
Spatial Lag Unemployment Rate	Variable which registers the unemployment rate in states *j-i* at time *t*. This measure was calculated implementing an inverse distance weighting matrix without row standardization.
Spatial Lag Population	Variable which registers the population in states *j-i* at time *t*. This measure was calculated implementing an inverse distance weighting matrix without row standardization.
Spatial Lag Crime Rep. Agencies pc	Variable which registers the crime reporting agencies in states *j-i* at time *t*. This measure was calculated implementing an inverse distance weighting matrix without row standardization.

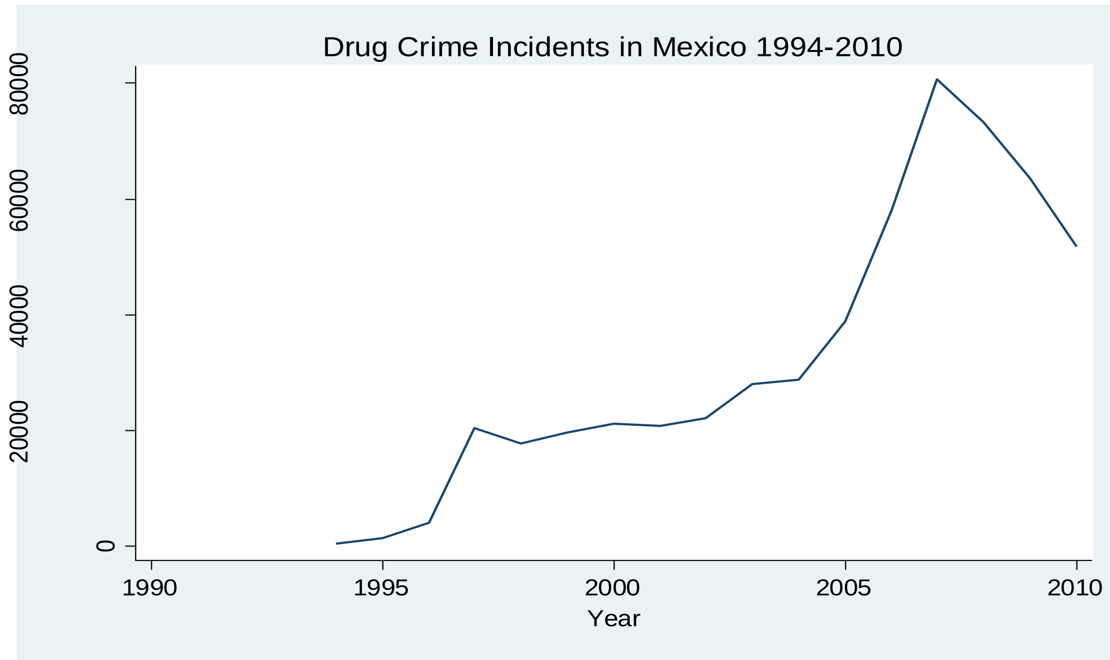


Figure III.1

Figure III.2

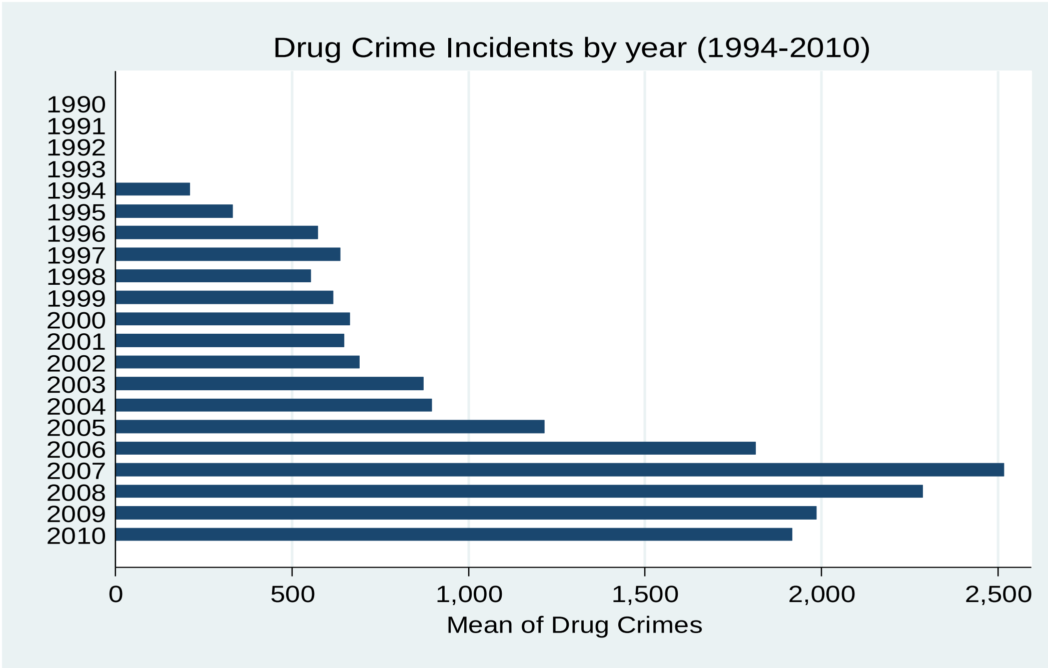


Figure III.3

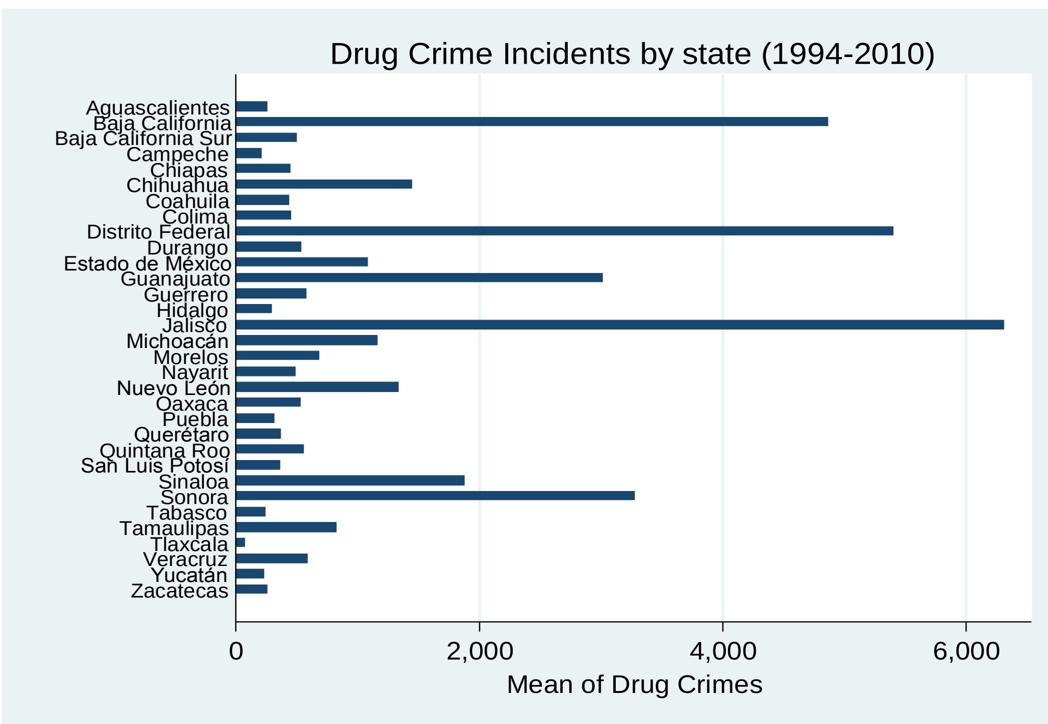


Figure III.4

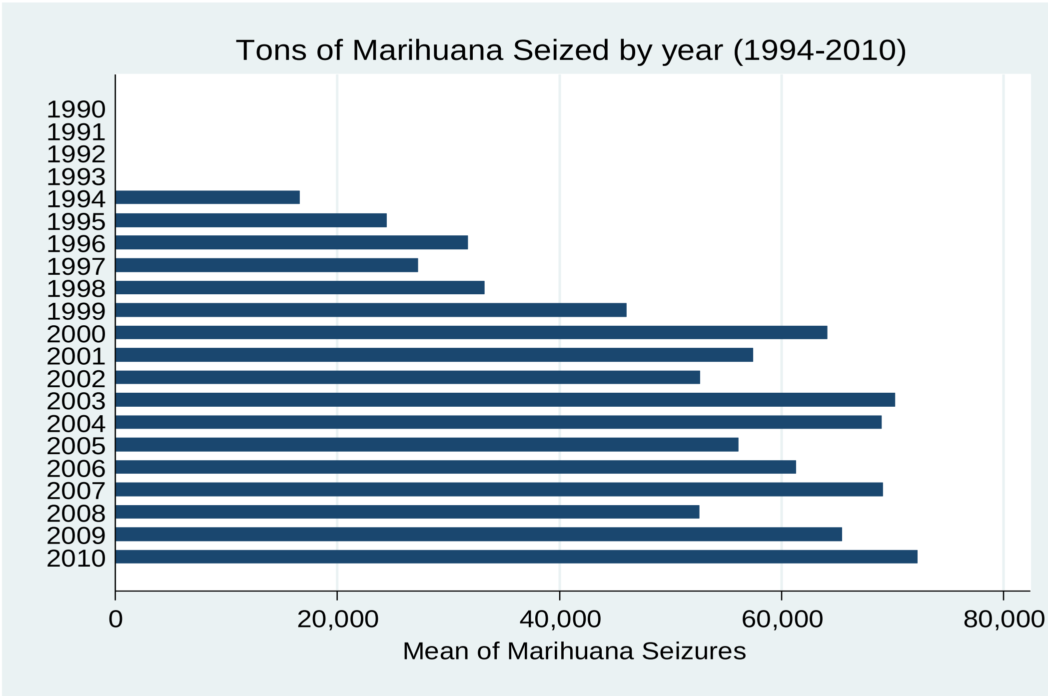


Figure III.5

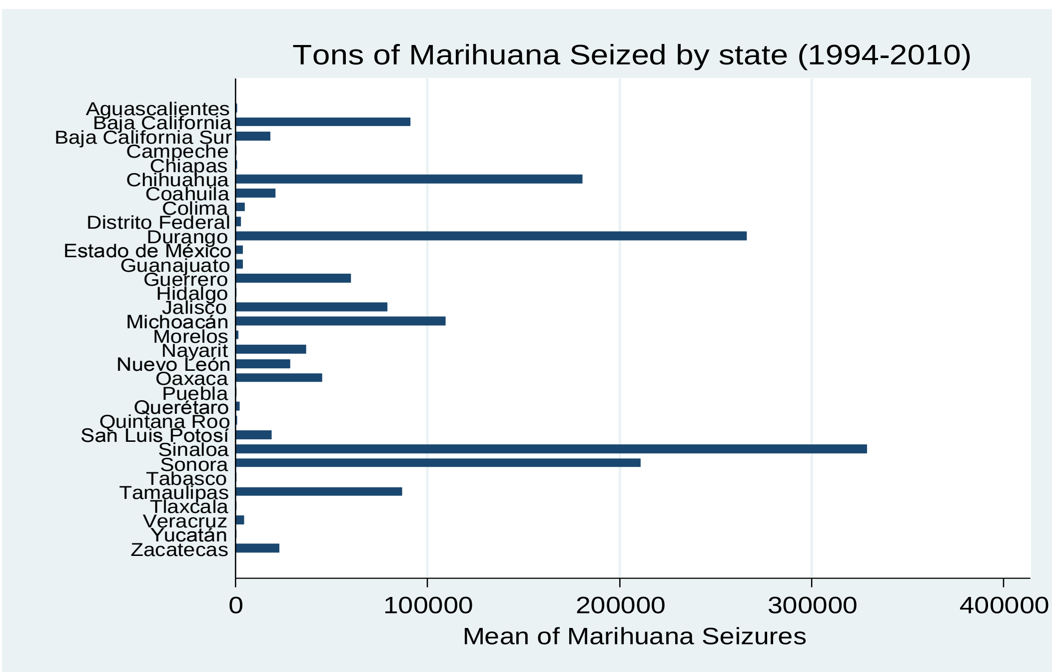


Figure III.6

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