Hidden Drivers of Violence Diffusion: Evidence from Illegal Oil Siphoning in Mexico

Ivan Lopez Cruz*
Sabanci University

Gustavo Torrens†
Indiana University

October 2019

Abstract

This paper develops a model of spatial violence diffusion when criminal organizations specialized in one illegal activity (e.g., drug trafficking) are attacked by security forces and tests its theoretical implications using the wave of violence triggered by the Mexican War on Drugs. The model predicts that violence will spread to locations with strategic value for other illegal activities (e.g., oil siphoning). We find evidence supporting this prediction. We document that the Mexican War on Drugs induced drug trafficking organizations to begin stealing oil from the Mexican oil pipeline network and this portfolio reallocation of illegal activities affected the spatial diffusion of violence. We show that violence increased in locations in the oil pipeline network with no strategic value for drug trafficking. Also aligned with the theoretical predictions of the model, we find that violence increased more in isolated branches of the oil pipeline network, which are more complicated to protect by the authorities and where simultaneously opening several illegal taps produces a severe negative externality.

JEL classification codes: D74, K42, R12

Keywords: crime, violence diffusion, war on drugs

1 Introduction

Given that the cost of fully eradicating all illegal activities in every location is usually prohibitive, it is important to understand how crime and violence react when authorities decide to intensify law enforcement efforts against some illegal activities in specific locations. Understanding the spatial diffusion of crime and violence becomes crucial when authorities must deal with relatively large and well-organized criminal organizations (e.g., drug trafficking organizations), who have the capacity to fight security forces, mobilize resources in multiple locations and restructure their operations to other illegal activities. Once criminal organizations are more intensively persecuted in some locations, do they relocate their activities elsewhere? If so, are they induced to rebalance their portfolio of illegal activities? If crime is displaced to other activities and locations, are criminal organizations likely to clash with each other for controlling new strategic spots, thereby displacing not only crime but also violence? These are core questions at the frontier of the economics of crime. The answers have also key policy implications for the deployment of law enforcement resources across illegal activities and locations.

*E-mail: ilopezcr@sabanciuniv.edu
†E-mail: gtorrens@iu.edu

This paper studies the effects of geographically focused crackdowns of criminal organizations on criminal diversification and the spatial diffusion of illicit activities and violence. To do so, we develop a simple model of crime diversification and spatial violence diffusion in the context of organized criminal activities. We use the model to derive theoretical predictions for the patterns of violence diffusion when authorities initiate a crackdown of organized crime in specific locations. In particular, we focus on modeling how violence spreads to locations with low strategic value for criminal organizations before the government intervention. Finally, we test these theoretical predictions using a major crackdown of drug trafficking organizations in Mexico.

The model is a contest game among several criminal organizations that fight to control locations with different strategic values for two illegal activities. Each organization makes two decisions. First, it chooses how much capital to allocate to each illegal activity. Second, it selects the weapon level employed to defend the profits generated in each activity and capture those of its rivals. Each location is partially controlled by one organization, who has an advantage to collect the profits from illegal activities generated in the location. The equilibrium allocation of capital and weapons by criminal organizations determine the level of violence caused by each illegal activity across locations. When the government attacks an organization in its territory, it weakens the organization's capacity to defend its location, which induces other organizations to invest more in weapons. Higher investments in weapons reduce profits from the prime illegal activity in the location, inducing criminal organizations to relocate their capital to the other illegal activity and, hence, to other locations. Thus, the equilibrium effect of the government intervention is criminal diversification and violence displacement. Moreover, under proper conditions, violence also increases in the location targeted by the government, which implies that, after the crackdown, violence spreads everywhere.

The recent escalation of drug-related violence in Mexico offers a fertile ground to test these theoretical predictions. Beginning in 2007, the Mexican government initiated the Mexican War on Drugs (hereinafter MWD), a series of military operations in selected municipalities aimed at arresting or eliminating prominent drug lords commanding large drug trafficking organizations (hereinafter DTOs). Beheaded DTOs, weakened after losing their leadership, became easy targets for rival groups who soon started launching armed incursions against them (Calderon et al. 2015). The resulting upsurge in violent conflict spread across the country, including municipalities that prior to the MWD were of little interest to DTOs and, hence, of presumably low strategic value for drug trafficking (Molzahn et al. 2012 and Osorio 2015). Simultaneously, several media outlets began documenting the link between DTOs' efforts to diversify their operations and the appearance of illegal taps along the Mexican oil pipeline network (hereinafter OPN).[1] Shortly afterwards, illegal taps reached alarming levels (for example, before 2007, the average number of detected illegal taps per year was 150, while in 2009, 2011, and 2013, the number of detected illegal taps was 500, 1000, and 2000, respectively).

We put together Mexican data on homicides, drug trafficking activities, location of the Mexican OPN, oil thefts and law enforcement efforts and find support for the hypothesis that, following the onset of the MWD in 2007, DTOs partially switched their attention to illegal oil siphoning, which triggered a series of turf wars in oil-rich municipalities. Specifically, the empirical analysis reveals four main findings. First, immediately after the MWD, there was an enormous increase in the level of illegal oil siphoning from the

[1] We use the term 'diversification' because DTOs never abandoned drug trafficking or fully switched to illegal oil. Indeed, the preeminence of Mexican DTOs as suppliers of the US market of narcotics remained largely untouched (see, for example, Beittel 2018).

Mexican OPN. Second, homicide rates rose in municipalities traversed by the OPN but with no strategic value for drug trafficking. Third, municipalities located in the dense nodes of the OPN (i.e., those close to hydrocarbon processing plants) exhibited lower increases in homicide rates than their counterparts crossed by isolated branches of the OPN. Finally, spatial econometric techniques show that the instensity of the violence spillovers that the isolated branches of the OPN generated to their neighbors, is similar to that sparked by drug-valuable municipalities.

Our empirical analysis hinges on accurately separating a set of municipalities whose violence levels are unrelated to drug-driven confrontations. To achieve identification, we exploit the exogenous location of the OPN and municipal variation in the suitability to carry out drug trafficking activities, as well as the unexpected surge in drug-related violence triggered by the MWD. Specifically, we use data on drug seizures, geographic characteristics and an index of each municipality potential for drug production, to sort out municipalities between valuable and non-valuable for drug trafficking. Municipalities crossed by the OPN but non-valuable for drug trafficking provide us with a treatment group, which we subsequently compare to a base group formed by municipalities with no oil (i.e., those not crossed by the OPN) and no value for drug trafficking.

Our outcome variable is the homicide rate, i.e., homicides per 100,000 inhabitants, measured at the municipality level. Relative to municipalities neither valuable for drug trafficking nor for oil siphoning, the presence of the OPN is estimated (on average) to have directly increased violence in 3.6 additional homicides per 100,000 inhabitants. Moreover, oil-related violence seems to be highly contagious, as the presence of the OPN is estimated (on average), to have produced 8.1 additional homicides per 100,000 inhabitants in OPN neighbors via spillover effects. Overall, the total effect on violence associated with the presence of oil pipelines was 11.8 additional homicides per 100,000 inhabitants. When we focus on municipalities traversed by the isolated branches of the OPN, the presence of the OPN increased homicides per 100,000 inhabitants by 4 and 9 through direct and spillover effects, respectively. The national homicide rate in the post MWD period was 8.27 higher than before 2007, while the median increase in the homicide rate was 3.2. Relative to municipalities neither valuable for drug trafficking nor for oil siphoning, the MWD led to an increase of 4.7 additional homicides in drug valuable municipalities and 10.5 additional homicides through spillover effects. Thus, oil-driven violence stands out as a major source of violence during the MWD, comparable to that of drug trafficking.

To confirm these results, we perform a battery of robustness and validation checks. First, estimates are robust to several alternative ways of defining the drug-valuable region, suggesting that our regressions consistently estimate the effect of the OPN on homicides. Moreover, the pre-MWD spatial distribution of violence is consistent with our definitions. For example, prior to the MWD, gun violence was far more pervasive in the drug-valuable region than elsewhere. Second, restricting the sample to OPN municipalities and their neighbors, we estimate a positive and significant effect of oil on homicides (although the estimated coefficients are lower). Such a procedure shields our results from the bias induced by violence spillovers coming from the drug-valuable region. Third, including a measure of military deployment, the most salient source of violence after 2007, does not change our results. Fourth, falsely attaching the status of OPN member to OPN neighbors and removing them from genuine OPN municipalities' leads to estimating a null effect of oil on violence. Finally, to corroborate that the violence emerging along the OPN after the MWD resulted from DTOs' actions, we show that the timing of violence increments fits very well with a substantial body of journalistic evidence identifying 2009 as the moment when several DTOs began to systematically participate in oil theft.

1.1 Related Literature

The paper is related and contributes to several bodies of literature on crime and conflict. First, although not many works have studied criminal diversification, there are a few exceptions. Bergman (2018) discusses how Latin-American DTOs became involved in other illegal activities, such as extortion, kidnapping, human trafficking and illegal extraction of natural resources. In his view, criminal diversification is associated with DTOs that failed to reach or loose an adequate scale to compete with larger organizations. Using Mexican data, Calderon et al. (2015) show that government crackdowns of DTOs during the MWD spur violence against segments of the population that rarely participate in organized crime. Moreover, they argue that the rise in the cost of long-distance drug trade caused by the MWD is the main motivation for DTOs to diversify their operations to other illegal activities. Magaloni et al. (2014), on the other hand, attribute this phenomenon to conflict financing. They argue that, during the MWD, DTOs looked for alternative sources of funds to sustain the war against rival organizations and government forces. None of these works, however, develops a formal model of crime diversification and test its theoretical implications.

Second, the paper contributes to the evaluation of the effects of place-based interventions on crime displacement. In his thorough review of the literature on crime displacement, Johnson et al. (2014) point out that most of the empirical studies on law enforcement programs consider hotspot policing interventions within a single city. These program-evaluations often focus on the program's impact on the incidence of common crime offenses, such as robberies, within a short period. One important finding of these works is that hotspot interventions do not tend to significantly displace crime.[2] On the contrary, we study the effects of a large-scale intervention on several locations across the country against well-organized criminal syndicates and find that violence spread even to municipalities with low strategic value for DTOs before the government intervention. Thus, our work suggests that, unlike individual criminals, criminal organizations might have superior mobility, enabling them to relocate their activities.

Third, although several papers have documented episodes of spatial diffusion of conflict (see, for example, Cordell and Wolff 2009, Lyall 2009 and Raleigh et al. 2010), only a few explore the mechanisms that govern it, and when they do so, they stress the role of combatants' logistic requirements. For example, Zhukov (2012) argues that road networks are often object of intense disputes given they are critical for the circulation of personnel and equipment. In a similar vein, Dell (2015) shows that the imposition of blockages on the traditional drug trafficking routes by the Mexican army forced DTOs to explore and eventually fight for controlling alternative routes to move their drug shipments. We contribute to this literature exploring the connections between crime diversification and violence dispersion. When the government partially suppress traditional sources of illegal rents, criminal organizations respond by diversifying their portfolio of criminal activities, which may cause a spatial redistribution of violence. Regarding the MWD, our paper shows that stealing oil from the OPN was a significant driver of violence propagation.

Fourth, our work is also related to the extensive literature on the 'natural resource course' (for detailed surveys, see Frankel 2010 and Van der Ploeg 2011); particularly, the papers that connect natural resources with organized crime. For example, Pinotti (2015) uses cross-country data to document a positive correlation between a country's dependency on natural resources and the presence of criminal

[2]Results could be very different when broader geographic areas are considered, as Gonzalez-Navarro (2013) has shown regarding the changes in the spatial distribution of auto theft caused by the installment of tracking devices in some Mexican states.

syndicates, conditional on high levels of corruption. Several papers relate the emergence of the Italian mafia to the exploitation of sulphur in Sicily (see Dixit 2003, Skaperdas 2011, and Buonano et al. 2015). Dube and Vargas (2013) show that violent conflict sparked by clashes between paramilitary forces soared in Colombian oil regions after a spike in oil prices between 1998 and 2005. Our research contributes to this literature showing how policy interventions that target criminal organizations could push them toward illegal extraction of natural resources, thereby spreading violence in otherwise peaceful regions.

Finally, our work highlights the difficulties of generalizing successful common-crime-control initiatives to the realm of combating organized crime. Following the work of Barr and Pease (1990), one can classify an episode of criminal displacement as either "benign" or "malign". An instance of benign (malign) displacement occurs when, due to a government intervention, offenders start committing less (more) serious crimes, in the same area or elsewhere, than prior to the program implementation. Hotspot policing interventions seems to be examples of benign or no displacement. Two examples of benign displacements involving organized crime are the crackdowns of the Italian and Italian-American mafias, which forced criminal organizations to abandon the use of violence and to pursue instead rather white-collar crimes (see, for example, Finckenauer 2001 and Paoli 2008). In both cases, one key factor leading to a successful intervention was the government systematic, prolonged and generalized attack on criminal structures, accompanied by the strengthening of the state's judicial capacities, such as the creation of investigating grand juries specialized in organized crime and in prosecuting corrupt politicians offering protection to criminals. On the contrary, this paper deals with a case of "malign" displacement, possibly attributable to the longstanding history of corruption deeply embedded in the country's law enforcement agencies.[3] Along these lines, our work warns against the danger of indiscriminate use of public force against powerful criminal organizations before counting with adequate institutions.

The rest of the paper is organized as follows. Section 2 develops a model of violence diffusion. Section 3 describes the basic facts on violence diffusion and illegal oil siphoning after the MWD. Section 4 describes the data and Section 5 the empirical strategy. Section 6 formally tests the theoretical predictions of the model employing panel data regression analysis and spatial econometric techniques. Section 7 summarizes several robustness checks. Section 8 presents the conclusions.

2 A Model of Crime Diversification and Violence Diffusion

Consider a set of locations indexed by l. Each location is characterized by $v_l = \left(v_l^D, v_l^O\right)$, the value location l has for two criminal activities (e.g., D for drug trafficking and O for illegal oil siphoning). Some locations are valuable for both criminal activities while others are only valuable for one activity. Formally, let $v_l^D > 0$ and $v_l^O \geq 0$ for $l \in N_D = \{1, ..., n\}$ and $v_l^D = 0$ and $v_l^O > 0$ for $l \in N_O = \{n+1, ..., 2n\}$, with $n \geq 2$. That is, the first n locations are valuable for drug trafficking and potentially also for oil siphoning, while the second n locations are only valuable for oil siphoning. Criminal activities are carried out by a set of criminal organizations indexed by $i \in N_D = \{1, ..., n\}$. Each organization has a primary place of operation, i.e., a location partially controlled by the organization. Specifically, assume that organization i controls location $l = i$. That is, each location valuable for activity D (drug trafficking) is under the

[3] Trejo and Ley (2018) provide a thorough description of how drug cartels penetrated law enforcement agencies in Mexico at both the national and local levels since the 80s. As we argue in section 3, it was such an environment of generalized corruption what enabled criminals to set up their oil siphoning operations too.

control of one and only one criminal organization, while locations only valuable for activity O (illegal oil siphoning) are not controlled by any organization.

Controlling location $l = i$ allows organization i to fully protect a proportion $p_l \in (0, 1)$ of the profits that activity D generates in location l. Profits from drug trafficking in location l are given by $\pi_i^D = v_i^D \left(k_i^D\right)^\alpha$, where $\alpha \in (0, 1)$ and $k_i^D \in [0, 1]$ is the proportion of its capital that organization i invests in drug trafficking. The organization also spends $g_i^D \geq 0$ (e.g., hitmen and guns) to protect the rest of its location and fight for a share of the locations controlled by other organizations. Formally, the payoff obtained by criminal organization $i \in N_D$ from its drug trafficking activities is given by:

$$V_i^D = p_i v_i^D \left(k_i^D\right)^\alpha + \gamma_i^D \left[\sum\nolimits_{l \in N_D} (1 - p_l)\, v_l^D \left(k_l^D\right)^\alpha\right] - g_i^D, \tag{1}$$

where γ_i^D is given by the following contest success function $\gamma_i^D = \left(g_i^D\right)^m / \sum\nolimits_{l \in N_D} \left(g_l^D\right)^m$ with $m \in (0, 1]$.

Let $\left(1 - k_i^D\right)$ denote the proportion of its capital that organization i invests in illegal oil siphoning. The capital invested in activity O by organization i generates profits from illegal oil siphoning in two locations: the location controlled by organization i (i.e., $l = i$) and one of the locations only valuable for oil siphoning (without lose of generality, assume that such location is $l = n + i$). Then, the profits from activity O in locations $l = i$ and $l = n + i$ are given by $\pi_i^O = v_i^O \left(1 - k_i^D\right)$ and $\pi_{n+i}^O = v_{n+i}^O \left(1 - k_i^D\right)$, respectively. Controlling location $l = i$ allows organization i to fully protect π_i^O. However, π_{n+i}^O can be disputed by other criminal organizations. To protect these profits and fight for a share of the profits generated in other locations valuable for oil siphoning, organization i spends $g_i^O \geq 0$. Formally, the payoff that criminal organization $i \in N_D$ obtains from its illegal oil siphoning activities is given by:

$$V_i^O = v_i^O \left(1 - k_i^D\right) + \gamma_i^O \left[\sum\nolimits_{l \in N_D} v_{n+l}^O \left(1 - k_l^D\right)\right] - g_i^O \tag{2}$$

where γ_i^O is given by the following contest success function $\gamma_i^O = \left(g_i^O\right)^r / \sum\nolimits_{i \in N_D} \left(g_i^O\right)^r$ with $r \in (0, 1]$.

The aggregate payoff of organization i is given $V_i = V_i^D + V_i^O$. That is, organization i chooses its capital allocation and guns levels to maximize V_i. Specifically, the timing of events is as follows:

1. All criminal organizations simultaneously and independently select $k_i^D \in [0, 1]$ for $i \in N_D$.
2. Organizations observe $k_i^D \in [0, 1]$ for $i \in N_D$ and, then, simultaneously and independently select $\left(g_i^D, g_i^O\right)$ for $i \in N_D$.

For the notion of equilibrium we employ subgame perfect Nash equilibrium.

2.1 Equilibrium

To compute the subgame perfect Nash equilibrium we proceed through backward induction. Lemmas 1 and 2 characterize the equilibrium in each illegal activity for any capital allocation. Proposition 1 characterizes the equilibrium capital allocation.

Lemma 1 ***Drug trafficking***. *Suppose that criminal organizations select $k^D = \left(k_i^D\right)_{i \in N_D}$. Then, the Nash equilibrium level of guns in the drug trafficking activity is given by:*

$$g_i^D = g^{D,*}\left(k^D\right) = \frac{m\,(n-1)}{n^2} \left[\sum\nolimits_{l=1}^{n} (1 - p_l)\, v_l^D \left(k_l^D\right)^\alpha\right] \textit{ for } i \in N_D, \tag{3}$$

while the equilibrium payoff obtains by organization $i \in N_D$ from drug trafficking is given by:

$$V_i^D = V_i^{D,*}\left(k^D\right) = p_i v_i^D \left(k_i^D\right)^\alpha + \frac{n - m\,(n-1)}{n^2}\left[\sum\nolimits_{l=1}^{n} (1-p_l)\, v_l^D \left(k_l^D\right)^\alpha\right]. \tag{4}$$

Proof: *See Appendix A.* ■

Two important remarks apply to Lemma 1. First, $g^{D,*}\left(k^D\right)$ is decreasing in p_i for all $i \in N_D$. Thus, when a criminal organization is less able to protect its location (p_i is lower), all organizations invest more in guns (g_i^D higher). The reason is that a higher proportion of the drug trafficking profits in location i can be disputed. As a consequence, the payoff of organization i from its drug trafficking activities is lower, but the payoff obtained by other organizations is higher. Formally, a reduction in p_i decreases $V_i^{D,*}\left(k^D\right)$, but increases $V_j^{D,*}\left(k^D\right)$ for $j \neq i$. Second, a change in p_i also affects the incentives to allocate capital to the drug trafficking sector. A decrease in p_i makes drug trafficking less attractive for organization i, but more attractive for other organizations.

Lemma 2 ***Oil siphoning***. *Suppose that criminal organizations select $k^D = \left(k_i^D\right)_{i\in N_D}$. Then, the Nash equilibrium level of guns in the oil siphoning activity is given by:*

$$g_i^O = g^{O,*}\left(k^D\right) = \frac{r\,(n-1)}{n^2}\left[\sum\nolimits_{l=1}^{n} v_{n+l}^O \left(1-k_l^D\right)\right] \text{ for } i \in N_D, \tag{5}$$

while the equilibrium payoff obtains by organization $i \in N_D$ from oil siphoning is given by:

$$V_i^O = V_i^{O,*}\left(k^D\right) = v_i^O\left(1-k_i^D\right) + \frac{n - r\,(n-1)}{n^2}\left[\sum\nolimits_{l=1}^{n} v_{n+l}^O \left(1-k_l^D\right)\right]. \tag{6}$$

Proof: *See Appendix A.* ■

Two important remarks apply to Lemma 2. First, as the profits from oil siphoning in locations only valuable for oil siphoning rises (v_{n+l}^O higher for $l = 1, ..., n$), criminal organizations invest more in guns. The reason is that in these locations, oil siphoning profits can be disputed. Second, the incentives to invest in oil siphoning activities are higher for organizations that have access to extracting oil in their own locations. Formally, $V_i^{O,*}\left(k^D\right)$ is increasing in v_i^O.

Proposition 1 *The equilibrium capital allocation of organization $i \in N_D$ is given by:*

$$k_i^D = k_i^{D,*} = \begin{cases} 1 & \text{if } p_i \geq \bar{p}_i \\ \left(\bar{k}_i\right)^{\frac{1}{1-\alpha}} & \text{if } p_i < \bar{p}_i \end{cases} \tag{7}$$

where $\bar{k}_i = \frac{\alpha\left[(n)^2 p_i + (1-p_i)(n-mn+m)\right]v_i^D}{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O}$ *and* $\bar{p}_i = \frac{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O - \alpha v_i^D (n-mn+m)}{\alpha v_i^D\left[(n)^2 - (n-mn+m)\right]}$. *Moreover,* $\bar{p}_i \in (0,1)$ *if and only if* $\frac{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O}{\alpha (n)^2} < v_i^D < \frac{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O}{\alpha(n-mn+m)}$. ***Proof***: *See Appendix A.* ■

Proposition 1 combined with Lemmas 1 and 2 fully characterizes the subgame perfect Nash equilibrium. Note that if the proportion of protected drug trafficking profits in location l is high enough

($p_l \geq \bar{p}_l$), then criminal organization $i = l$ is fully specialized in drug trafficking. For $p_l < \bar{p}_l$, the organization also allocates capital to oil siphoning. Indeed, as p_l decreases, the organization invest more in oil siphoning activities and less in drug trafficking. Formally, the elasticity of k_l^D with respect to p_l is given by:

$$\frac{\partial \ln k_l^{D,*}}{\partial \ln p_l} = \eta_l = \begin{cases} 0 & \text{if } p_l \geq \bar{p}_l, \\ \frac{p_l}{1-\alpha} \frac{(n)^2 - (n - mn + m)}{(n)^2 p_l + (1-p_l)(n - mn + m)} > 0 & \text{if } p_l < \bar{p}_l. \end{cases}$$

2.2 Government Intervention and Violence Diffusion

Disputed profits induce criminal organizations to invest in guns. Indeed, the aggregate level of guns associated with drug trafficking and oil siphoning are $\sum_{j=1}^n g_j^D$ and $\sum_{j=1}^n g_j^O$, respectively. Next we specify how these investments translate into violence in each location. We define the number of homicides in locations valuable for drug trafficking as follows:

$$H_l = \mu_l \sum_{j=1}^n g_j^D = \left[\lambda \frac{(1-p_l)\,\pi_l^D}{\sum_{j=1}^n (1-p_j)\,\pi_j^D} + (1-\lambda) \frac{g_j^D}{\sum_{j=1}^n g_j^D} \right] \sum_{j=1}^n g_j^D \; \textit{for } l = 1, ..., n. \tag{8}$$

That is, we assign to location l a share $\mu_l \in [0,1]$ of aggregate violence associated with drug trafficking (i.e., $\sum_{j=1}^n g_j^D$), where μ_l is a weighted average between the proportion of unprotected drug profits in location l ($(1-p_l)\,\pi_l^D / \sum_{j=1}^n (1-p_j)\,\pi_j^D$) and the proportion of drug related guns investments in location l ($g_j^D / \sum_{j=1}^n g_j^D$). Similarly, we define the number of homicides in locations only valuable for oil siphoning as follows:

$$H_l = \mu_l \sum_{j=1}^n g_j^O = \left[\lambda \frac{\pi_l^O}{\sum_{j=1}^n \pi_{n+j}^O} + (1-\lambda) \frac{g_{l-n}^O}{\sum_{j=1}^n g_j^O} \right] \sum_{j=1}^n g_j^O \; \textit{for } l = n+1, ..., 2n. \tag{9}$$

That is, we assign to location l a share $\mu_l \in [0,1]$ of aggregate violence associated with oil siphoning (i.e., $\sum_{j=1}^n g_j^O$), where μ_l is a weighted average between the proportion of unprotected oil profits in location l ($\pi_l^O / \sum_{j=1}^n \pi_{n+j}^O$) and the proportion of oil related guns investments in location l ($g_{l-n}^O / \sum_{j=1}^n g_j^O$).

Employing Lemmas 1 and 2 and Proposition 1, the equilibrium number of homicides in location l is given by:

$$H_l^* = \begin{cases} \frac{m(n-1)\left[\lambda n (1-p_l) v_l^D \left(k_l^{D,*}\right)^\alpha + (1-\lambda) \sum_{j=1}^n (1-p_j) v_j^D \left(k_j^{D,*}\right)^\alpha\right]}{n^2} & \textit{for } l = 1, ..., n, \\ \frac{r(n-1)\left[\lambda n v_l^O \left(1-k_l^{D,*}\right) + (1-\lambda) \sum_{j=1}^n v_{n+j}^O \left(1-k_j^{D,*}\right)\right]}{n^2} & \textit{for } l = n+1, ..., 2n, \end{cases} \tag{10}$$

where $k_i^{D,*}$ is given by (7).

Using (10) we can explore the effects of several government interventions on homicides in each location. First, consider an intervention that changes p_l. For example, suppose that the government attacks drug trafficking activities in location l. This will reduce p_l, the proportion of drug trafficking profits in location

l that organization $i = l$ can fully protect. A reduction in p_l will change the incentives of each organization to invest in guns as well as its capital allocation. Both changes will affect the level of violence in each location. Formally, taking the derivative of H_l^* with respect to p_l, we obtain:

$$\frac{\partial H_l^*}{\partial p_l} = \frac{m\,(n-1)\,[\lambda n + (1-\lambda)]\, v_l^D \left(k_l^{D,*}\right)^{\alpha}}{n^2} \left[\frac{\alpha\,(1-p_l)\,\eta_l}{p_l} - 1\right]$$
$$\frac{\partial H_j^*}{\partial p_l} = \frac{m\,(n-1)\,(1-\lambda)\, v_l^D \left(k_l^{D,*}\right)^{\alpha}}{n^2} \left[\frac{\alpha\,(1-p_l)\,\eta_l}{p_l} - 1\right] \textit{ for } j = 1,...,n,\ j \neq l$$
$$\frac{\partial H_{n+l}^*}{\partial p_l} = \frac{-r\,(n-1)\,[\lambda n + (1-\lambda)]\, v_{n+l}^O k_l^{D,*} \eta_l}{n^2 p_l}$$
$$\frac{\partial H_j^*}{\partial p_l} = \frac{-r\,(n-1)\,(1-\lambda)\, v_{n+l}^O k_l^{D,*} \eta_l}{n^2 p_l} \textit{ for } j = n+1,...,2n,\ j \neq n+l$$

$\partial H_l^*/\partial p_l$ is the marginal change in homicides in the location attacked by the government; $\partial H_j^*/\partial p_l$ for $j = 1, ..., n$ and $j \neq l$ are the marginal changes in homicides in other locations valuable for drug trafficking; $\partial H_{n+l}^*/\partial p_l$ is the marginal change in homicides in the location valuable for oil siphoning where criminal organization l has its oil investments; and, finally, $\partial H_j^*/\partial p_l$ for $= n+1, ..., 2n$ and $j \neq n+l$ are the marginal changes in homicides in locations where other criminal organizations have their oil investments. The following proposition signs these derivatives for different parameter values.

Proposition 2 ***Government intervention (change in*** p_l***).*** *Suppose that* $\alpha\,(n)^2 > (n - mn + m)$ *and let* $\hat{p}_l = \frac{\alpha(n)^2 - (n-mn+m)}{(n)^2 - (n-mn+m)}$.

1. *Suppose that* $\frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha (n)^2} < v_l^D < \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha^2 (n)^2}$. *Then:*
   (a) *If* $p_l \leq \hat{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} \geq 0$, $\frac{\partial H_j^*}{\partial p_l} \geq 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} < 0$ *and* $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.
   (b) *If* $\hat{p}_l < p_l < \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} < 0$, $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} < 0$ *and* $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.
   (c) *If* $p_l \geq \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} < 0$, $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} = 0$ *and* $\frac{\partial H_j^*}{\partial p_l} = 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.

2. *Suppose that* $\frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha^2 (n)^2} \leq v_l^D < \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha (n-mn+m)}$. *Then:*
   (a) *If* $p_l < \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} > 0$, $\frac{\partial H_j^*}{\partial p_l} > 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} < 0$ *and* $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.
   (b) *If* $p_l \geq \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} < 0$, $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} = 0$ *and* $\frac{\partial H_j^*}{\partial p_l} = 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$. ***Proof****: See Appendix A.* ■

The most interesting scenario is case 1.b. In such a case, when the government attacks the drug trafficking activities of organization l, there is a reduction in p_l that triggers a rise in homicides in all locations (formally, $\partial H_j^*/\partial p_l < 0$ for all $j = 1, ..., 2n$). That is, the government intervention induces a wave of violence that diffuses across the territory. The logic behind this result is as follows. A reduction in p_l makes drug trafficking profits in location l less protected, which induces criminal organizations to invest more in guns associated with their drug trafficking activities. As a consequence, violence rises in all locations valuable for drug trafficking. The organization attacked by the government also reacts changing its capital allocation. Since drug trafficking becomes less profitable for the organization, it moves capital from drug trafficking to oil siphoning, which increases oil siphoning profits in location $l + n$. Since these profits can be disputed by other organizations, this triggers an increase in guns-investments related to oil siphoning activities, which rises violence in locations only valuable for oil siphoning. For this chain of events to occur a key condition is required, namely, $\hat{p}_l < p_l < \bar{p}_l$.[4] $p_l < \bar{p}_l$ assures that oil siphoning is attractive enough for organization l, so a reduction in p_l leads to a capital reallocation from drug trafficking to oil siphoning (formally, $\eta_l > 0$). This is crucial to induce more violence in locations only valuable for oil siphoning. $\hat{p}_l > p_l$ assures that this capital reallocation is not too drastic, so a reduction in p_l always increases $(1 - p_l)\, v_l^D \left(k_l^{D,*}\right)^\alpha$, i.e., disputed drug trafficking profits in location l (formally, $\alpha\eta_l < p_l/\,(1 - p_l)$). This is crucial to induce more violence in locations valuable for drug trafficking.

The changes in violence triggered by a reduction in p_l are not homogeneous across locations.

Proposition 3 ***Government intervention (change in*** p_l***).*** *Suppose that* $0 < \hat{p}_l < p_l < \bar{p}_l < 1$. *Then:*

1. *Drug-valuable locations:* $\left|\frac{\partial H_l^*}{\partial p_l}\right| > \left|\frac{\partial H_j^*}{\partial p_l}\right|$ *for* $j = 1, ..., n$ *and* $j \neq l$.
2. *Oil-valuable locations:* $\left|\frac{\partial H_{n+l}^*}{\partial p_l}\right| > \left|\frac{\partial H_j^*}{\partial p_l}\right|$ *for* $j = n + 1, ..., 2n$ *and* $j \neq n + l$.
3. *Oil abundance:* $\frac{\partial}{\partial v_l^O}\left|\frac{\partial H_l^*}{\partial p_l}\right| < 0$ *and* $\frac{\partial}{\partial v_{n+l}^O}\left|\frac{\partial H_{n+l}^*}{\partial p_l}\right| > 0$. ***Proof****: See Appendix A.* $\blacksquare$

$|\partial H_l^*/\partial p_l| > \left|\partial H_j^*/\partial p_l\right|$ for $j = 1, ..., n$ and $j \neq l$ states that the rise in violence induced by a reduction in p_l is more intense in the location attacked by the government than in other drug valuable locations. The reason of this result is that a higher proportion of the drug trafficking profits in location l become disputable. $\left|\partial H_{n+l}^*/\partial p_l\right| > \left|\partial H_j^*/\partial p_l\right|$ for $j = n + 1, ..., 2n$ and $j \neq n + l$ means that the increase in violence induced by a reduction in p_l is more intense in the location valuable for oil siphoning where criminal organization l has its oil investments (i.e., location $n+l$) than in other locations only valuable for oil siphoning. Intuitively, when attacked by the government, organization l responds reallocation capital to oil siphoning activities in location $n+l$, which increases the proportion of disputed oil siphoning profits in location $n + l$. Finally, the change in violence is also affected by the abundance of oil in a location. The effect of oil abundance, however, is not the same in all locations. As location l has more oil, the government intervention leads to a more moderate rise in violence (formally, $\partial \left|\partial H_l^*/\partial p_l\right| /\partial v_l^O < 0$). On the contrary, as location $n + l$ has more oil, the government intervention induces a more intense rise in

[4] $\alpha\,(n)^2 > (n - mn + m)$ assures that $\hat{p}_l > 0$ and $\left[(n)^2 v_l^O + (b - rn + r)\, v_{n+l}^O\right]/\alpha\,(n)^2 < v_l^D < \left[(n)^2 v_l^O + (b - rn + r)\, v_{n+l}^O\right]/\alpha^2\,(n)^2$ that $\hat{p}_l < \bar{p}_l < 1$.

homicides (formally, $\partial \left|\partial H^*_{n+l}/\partial p_l\right| / \partial v^O_{n+l} > 0$). The difference comes from how disputable oil profits are in each location. While in location l, oil siphoning profits are perfectly protected, in location $n+l$ profits can be disputed by other criminal organizations. Thus, in location l, more oil leads to less capital allocated to drug trafficking (the disputed activity), while in location $n+l$, more oil implies more capital allocated to oil siphoning (the disputed activity).

3 Background

This section provides some basic historical background on drug trafficking and illegal oil siphoning in Mexico. First, we show that after the Mexican War on Drugs (MWD) there was a sudden rise in violence in municipalities valuable for drug trafficking, but also in municipalities with no strategic value for drug trafficking. Second, we document that after the MWD there was a sharp increase in illegal oil siphoning from the oil pipeline network (OPN). Third, we show that the OPN affected the spatial diffusion of violence across the country triggered by the MWD. Finally, we show that the structure of the OPN (local density and distance to urban centers) also influenced how violence spread to municipalities in the OPN.

3.1 The Mexican War on Drugs and Violence

Figure 1 shows homicide rates (measured by the number of homicides per 100,000 inhabitants) in Mexican municipalities from 2000 to 2017. Note that homicide rates were falling from 2000 to 2007. Moreover, before 2007, the evolution of homicides rates in drug-valuable municipalities is indistinguishable from the evolution of homicides rates in the remaining municipalities.[5] In December 2006, President Felipe Calderón took office after winning a highly contested election whose results were plagued by accusations of fraud. Allegedly, with the intention of gaining legitimacy, he decided to launch a war on drug trafficking organizations (DTOs), which in the government's view was unavoidable to regain control over territories ruled by criminals and to curve drug violence. To that end, the government organized a series of military campaigns aimed to arrest or eliminate drug lords. As many authors have documented (see, for example, Jones 2013 and Calderón et al. 2015), beheading DTOs resulted in more violence among and within cartels and triggered a wave of violence that spread across the country. Indeed, Figure 1 shows that homicide rates experienced a sharp increase immediately after the beginning of the Mexican War on Drugs in 2007.

Several mechanisms have been considered to explain how the MWD caused a rise in violence. First, cartels attacked by the government resorted to violence to defend its position (see, for example, Dell 2015). Second, when the authorities succeeded in beheading or weakening an organization that controlled a location valuable for drug trafficking, a vacuum emerged, which triggered a violent fight to conquer the location (see, for example, Calderón et al. 2015). Finally, in some cases, after the government intervention, criminal syndicates fragmented into smaller cells, which also competed for territorial control (see, for example, Osorio 2015). None of these mechanisms, however, are well equipped to explain why violence also increased in municipalities with no strategic value for drug trafficking (see Figure 1). One possible explanation is that after the Mexican War on Drugs, DTOs began to diversify their sources of income. Since drug trafficking became very dangerous and, sometimes, really complicated due to the militarization of the Mexican-US border, criminal syndicates looked for profits in other illicit activities

[5] In Section 4 we explain how we determine which municipalities are valuable for drug trafficking.

such as kidnapping, extortion, human trafficking and, more importantly, oil theft. The path followed by Los Zetas and El Cartel del Golfo (two of the most prominent Mexican cartels) illustrates this diversification process. After 2007, the government targeted both organizations and inflicted severe damages on their drug trafficking operations. As a result, both DTOs almost fully switched to hydrocarbon crimes, leaving drug trafficking as a secondary activity (see, for example, Montero 2016).

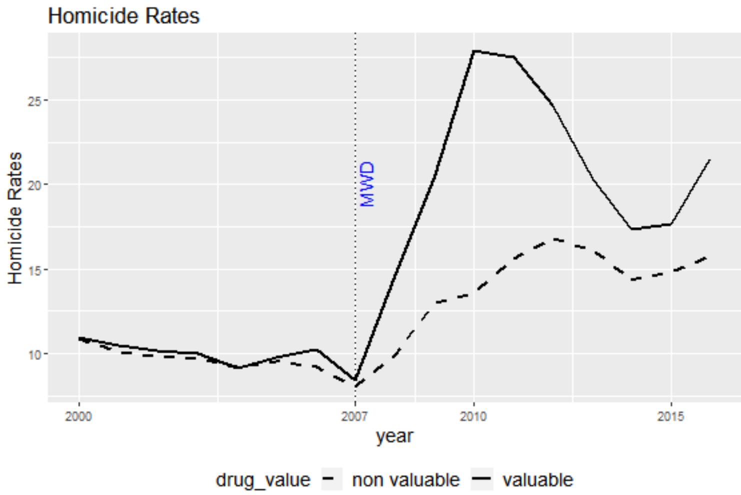


Fig. 1 : Annual homicide rate (per 100,000 inhabitants). *Note*: This graph shows the annual homicide rate at the national level. *Source*: INEGI (2016).

3.2 The National Oil Pipeline Network and Illegal Oil Siphoning

Mexico is a major oil producer that counts with verified reserves equivalent to ten million barrels (Ralby 2017). Until very recently, Petroleos Mexicanos (PEMEX), the Mexican publicly owned oil company, held a legal monopoly on the Mexican hydrocarbon sector. In addition to extracting oil, PEMEX supplies gasoline and other refined fuels to major urban areas and industries. The company stores fuels in its storage and distribution terminals and dispatches them through the national oil pipeline network (OPN), which extends along 17,000 kilometers (PEMEX website). The OPN is primarily dedicated to supply local markets. Only the segment connecting Reynosa, Juarez and El Paso carries exported or imported fuel shipments.

Since the 1990s, PEMEX has been aware of occasional illegal tapping of the pipelines in some regions (Perez 2012). However, before 2007, illegal tapping was rare and did not represent significant losses for the company. Nevertheless, in 2000, PEMEX installed a 300 million USD security system named SCADA (System of Control and Data Acquisition) to monitor and protect the OPN (Luege 2019). The system can obtain immediate information on abrupt changes in the pressure levels inside the tubes, enabling PEMEX to timely detect possible leakages and illicit extractions. Figure 2 depicts the number of illegal taps detected in the Mexican OPN from 2000 to 2014. Although oil theft was on the rise before 2007, it was not until the onset of the MWD that PEMEX's records on illegal taps escalated exponentially, which suggests that the upsurge in illegal oil siphoning was triggered by the MWD.

Most likely, large-scale oil theft resulted from a series of blows that the Mexican government was able to inflict to some DTOs, forcing them to look for alternative sources of income other than drug trafficking (see, for example, Correa-Cabrera 2017). Several DTOs realized that tapping the OPN was very lucrative and also safer than smuggling drugs because the stolen oil could be sold to local buyers as opposed to drugs, which must be transported across the Mexican-US border. Los Zetas monopolized illegal oil siphoning in the states of Puebla and Veracruz. El Cartel del Golfo took control of illegal extraction in the pipelines running in the northern state of Tamaulipas. In north east Mexico, El Cartel de Sinaloa monopolized oil siphoning. Finally, in central Mexico (specifically in the state of Guanajuato), the cartel Santa Rosa de Lima took control of local pipelines (see, Monroy 2017 and Asmann 2018).

PEMEX began suffering significant economic losses due to illegal oil siphoning. Although we are not aware of publicly available estimations of these losses, there are several signs that the problem is serious. For example, Montero (2018), based on information collected by Etellekt, a consulting firm expert in hydrocarbon crime, reports that 20% of the Mexican market of fuels is under the control of DTOs. Illegal taps also generate interruptions of oil flows through the OPN, creating fuel shortages in some locations. For instance, Montero (2016) documents that in 2015, the pipeline connecting Minatitlan and Puebla suffered numerous robberies, leading many gas stations in Puebla and Tlaxcala to suspend their services. In some cases, when availability of legal fuel falls, gasoline prices in the black market rise and criminals compete more intensively for it (Asman, 2018).

To counter the rise in oil theft, authorities reacted with a series of measures. They increased military protection to specific sections of the pipelines, mostly located close to refining centers. They augmented penalties associated with oil theft. Finally, PEMEX tried to reduce the transportation of ready-to-use hydrocarbons throughout the OPN. Despite these measures, reducing oil theft has proved to be a difficult mission for at least three reasons (the number of illegal taps continued to grow, as Figure 2 indicates). First, cartels have designed effective methods of extraction. Usually, they hire a group of PEMEX engineers that provide them with maps revealing the exact location of the pipelines and the required equipment to install the taps (Ferri 2019). PEMEX employees also provide DTOs with timely alerts on when to expect fuel to be flowing. Second, surveilling specific spots of the OPN is extremely costly since the pipelines go through isolated territories comprising deserts and mountains. Third, there is a substantial demand for stolen fuel, which is sold to a variety of costumers, ranging from taxi drivers to factories and even legal gas stations (Ralby 2017).

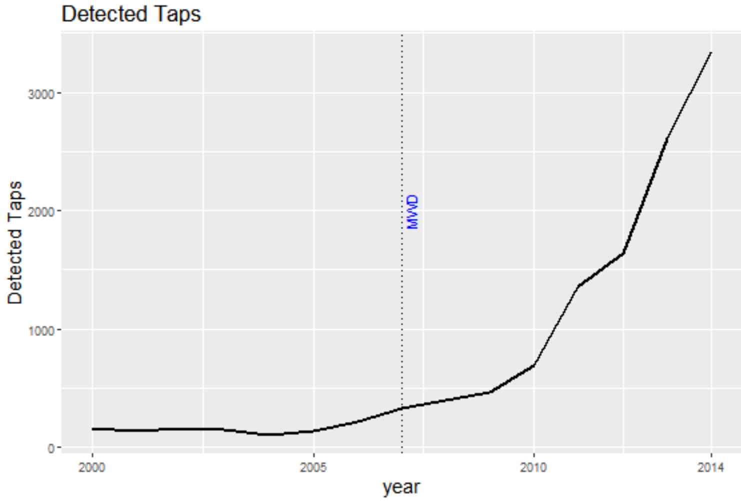


Fig. 2 : Illegal taps in the Mexican oil pipeline network. *Note*: This graph plots the national annual number of illegal taps that the Mexican authorities recorded between 2000 and 2014. *Source*: El Universal (2015).

3.3 Illegal Oil Siphoning and the Spatial Diffusion of Violence

As we already have argued, the MWD induced drug trafficking organizations to look for alternative sources of income; in particular, they began stealing oil from the national oil pipeline network. Since municipalities suitable for oil siphoning do not necessarily coincide with municipalities valuable for drug trafficking, this shift in illegal activities affected the spatial diffusion of violence.[6] Areas with access to the OPN got infected with violence in part because drug trafficking organizations began to fight for strategic spots to install and exploit illegal taps. Los Zetas challenged El Cartel del Golfo's control over the state of Tamaulipas, and in turn, a new group called Los Bucanans gained ground in the state of Veracruz at the expense of Los Zetas. A major new player, a powerful cartel known as Jalisco Nueva Generación, started an open war against Santa Rosa de Lima, Los Zetas and Los Bucanans (see, for example, Asmann 2018).

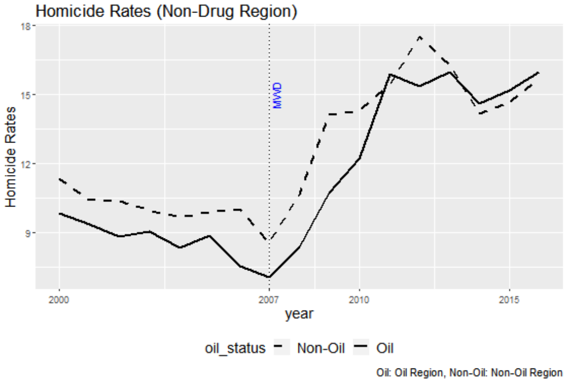
In municipalities valuable for drug trafficking and oil siphoning it is complicated to disentangle if a rise in violence can be attributed to conflicts over drugs or oil. However, if we focus on municipalities with no strategic value for drug trafficking it is possible to isolate the effect of the OPN on the diffusion of violence. Figure 3.a depicts homicide rates for municipalities with no value for drug trafficking. Note that before the beginning of the MWD municipalities with oil pipelines had on average lower homicide rates than municipalities with pipelines. However, after the MWD and especially from 2010, homicides rates for both groups are indistinguishable. Thus, after the MWD on average violence rose more in municipalities with access to the OPN, suggesting that the presence of oil pipelines attracted DTOs, who began to fight for the control of illegal oil extraction in these locations. One potential concern with this interpretation is that municipalities with oil pipelines could be systematically closer to municipalities valuable for drug trafficking, making them more prone to get infected with drug related violence. To deal with this issue, Figure 3.b shows homicide rates for municipalities with no oil pipelines neighboring municipalities with pipelines. Note that both groups of municipalities have on average very similar and

[6] In Section 4 we explain how we determine which municipalities are valuable for illegal oil siphoning.

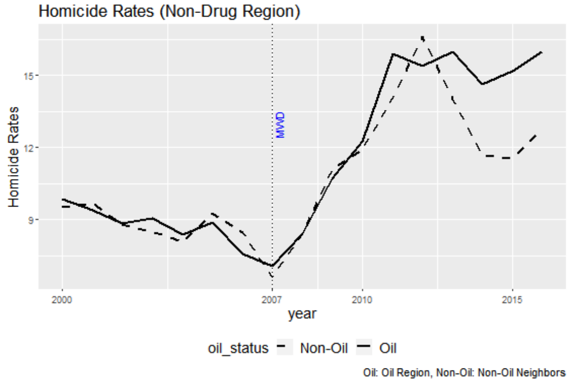
declining homicide rates in the 2000-2007 period and experienced a sharp increase in violence after 2007. However, in municipalities with oil pipelines homicide rates stayed high even after violence began to fall in neighboring municipalities with no oil pipelines.

The structure and location of the OPN seems to have also affected the spread of violence. In branches of the OPN closer to refining plants, DTOs have less incentives to use violence for at least two reasons. First, closer to refining plants the OPN is denser and, hence, there are parallel pipelines that can be simultaneously exploited by different criminal organizations. On the contrary, in isolated branches of the OPN, there is only one pipeline and, hence, oil siphoning in one spot negatively affects oil siphoning opportunities downstream the pipeline. As a result, DTOs fierily compete to monopolize the whole pipeline. Second, refining plants are better protected by security forces and usually closer to urban areas, where the army and police forces maintain a greater presence. Thus, in branches of the OPN closer to refining plants, violent clashes would trigger a much faster response by the authorities. Indeed, the rise in homicide rates was particularly severe in municipalities located in isolated branches of the OPN. Figure 3.c depicts the evolution of homicide rates for the same groups in Figure 3.b, except that we restrict the sample to isolated branches of the OPN. Comparing with Figure 3.b, we observe that, after the beginning of the MWD, municipalities with isolated branches of the OPN experienced higher increases in homicide rates (relative to neighboring municipalities with no oil) than all municipalities with oil (also, relative to neighboring municipalities with no oil). Finally, Figure 3.d depicts homicide rates for municipalities with isolated branches of the OPN and their synthetic controls with no oil pipelines, following the method proposed by Abadie, Diamond and Hainmueller (2015), and controlling for socioeconomic indicators. As the figure shows, a significant gap in homicides rates between municipalities with oil pipelines and their synthetic controls emerged after 2010, the year in which several DTOs including Los Zetas, became massively involved in illegal hydrocarbon extraction. The annual average effect of the treatment after 2010 entails 3.22 additional homicides per 100,000 inhabitants, with a maximum increase of 6.24 additional homicides per 100,000 inhabitants in 2011 and a minimum of 0.71 in 2014.

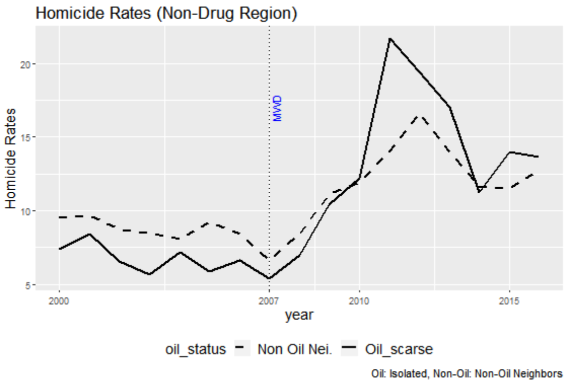
Summing up, immediately after the MWD there was a sharp increase in the level of illegal oil siphoning from the OPN (measured by the number of illegal taps detected). The MWD also triggered a wave of violence that spread across the country (measured by homicide rates). Municipalities in the OPN and, specifically, those in isolated branches of the OPN experienced more intense increases in violence.



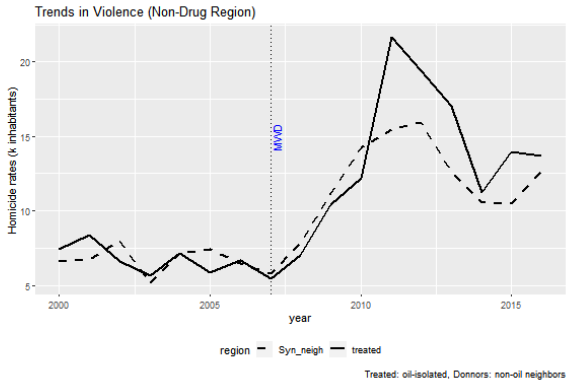
Panel A: Oil versus non-oil



Panel B: Oil versus non-oil neighbors



Panel C: Isolated branches of the OPN versus non-oil neighbors



Panel D: Isolated branches of the OPN versus synthetic controls

Fig. 3 : Homicide rates in municipalities with no value for drug trafficking. *Notes*: *Panel A*. This graph shows the annual homicide rate of municipalities outside the drug region distinguishing between members and non-members of the OPN. *Panel B*. This graph replicates that of Panel A but restricting the sample to OPN members and their neighbors. *Panel C*. This graph replicates that of Panel B but restricting the sample to OPN members that are not contiguous to municipalities hosting a hydrocarbon processing plant. *Panel D*. This graph employs Abadie, Diamond and Heinmueller (2014) synthetic controls method to compare the homicide rates of oil municipalities, outside the drug region and far away from hydrocarbon processing plants and that of the synthetic control unit formed with their non-oil neighbors. *Sources*: Insight Crime (2010), El Universal (2015), Osorio (2015), INEGI (2015, 2016), and Carto Critica (2017).

4 Data

Our data-set tracks 2,455 Mexican municipalities between the years 2000 and 2016. For each municipality we count with annual information on violence and socioeconomic controls. We also incorporate various municipal time-invariant characteristics that capture the presence and structure of the OPN. Next, we briefly explain our main variables and the corresponding data sources. Tables B.1 and B.2 in Appendix B provide a list of the corresponding sources of information and summary statistics of all the variables.

4.1 Violence

We measure violence in a municipality as its homicide rate, i.e., the number of homicides per 100,000 inhabitants at the municipality level as reported by the National Institute of Geography and Statistics (INEGI) from 1990 to 2016. INEGI's data identify the occupation of every homicide victim and the device that provoked the person's death. This allows us to construct the number of murdered military personnel by a firearm (and by any other weapon), a variable that serves as a proxy of the clashes involving the army and criminal organizations. INEGI's (2016) data also identify the place of residence of each murder victim, which allows us to sort homicides in two categories: imports and the rest. An import occurs in municipality m when a person residing somewhere else is murdered in m. We interpret an increase in the ratio of imports to total homicides as reflecting greater conflict between DTO's, since only these organizations are capable of mobilizing militias around different territories.

4.2 Socioeconomic Controls

Unfortunately, standard measures of economic development such as GDP per capita, are not available at the municipality level. To proxy for municipal level of development we employ the following socioeconomic controls (available from 2001 to 2015): the number of vehicles registered per capita, females' deaths per capita from any cause linked to or aggravated by pregnancy or its handling, doctors per capita, doctors' offices and beds per capita. The first three variables as well as population levels come from INEGI (2016), while the last three from the National System of Health Information (SINAIS 2016).

4.3 Geographic Information and the OPN

All the cartographic information for municipalities comes from INEGI (2015). INEGI cartographic information allows us to measure distances and areas across the Mexican territory. To spatially locate the OPN, we employ two sources of information. An important Mexican newspaper, El Universal initiated a transparency requirement and obtained from PEMEX the annual number of detected illegal oil taps in each municipality from 2000 to 2014. We use this dataset to identify municipalities across the OPN. To complement El Universal's dataset, we also incorporate the spatial information contained in a map of the OPN reported by Insight Crime (2010). We define a municipality as belonging to the OPN if there has been at least one illegal oil tap according to the El Universal's dataset or if it belongs to the map reported by Insight Crime. Finally, from Carto Critica (2017), a Mexican think tank dedicated to the collection and analysis of cartographic data, we obtain the exact location of the most important hydrocarbon processing plants across the OPN. Figure C.1 in Appendix C shows a map displaying the full set of oil municipalities and the location of hydrocarbon plants across the OPN.

4.4 Municipalities Valuable for Drug Trafficking

From Osorio's (2015) data-set, we obtain information on the annual number of drug seizures occurring at each municipality between 2000 and 2010. From INEGI's cartographic information we identify the municipalities that belong to the Mexican coastal line. We define a municipality as valuable for drug trafficking if it satisfies at least one of the following criteria. First, the number of drug seizures in the municipality, as reported by Osorio (2015), must exceed 12.5 events (the fourth quintile of the distribution of drug seizures).[7] Second, the municipality must belong to the Mexican coastal line. The rationale behind the first criterion is that a municipality exhibiting a meaningful number of drug seizures must belong to a drug-trafficking route. The second criterion draws on the fact that drugs entering the Mexican territory must do so somewhere along the south Mexican border or the Pacific/Gulf coast; and that controlling the municipalities along the US-Mexico border line is critical for smuggling purposes. Figure C.1 in Appendix C shows a map displaying the municipalities valuable for drug trafficking.

In addition to the preceding considerations, and to count with a direct manner of pinning down those municipalities along the drug trafficking routes, we employ a measure of connectivity introduced by Calderon et al. (2015). This variable identifies which locations belong to the national transportation network. Indeed, a municipality belongs to the transportation network if it comprises at least one of the following facilities: an airport, an aerial landing field, a seaport, a freight train crossing, or a Mexico-US border crossing. This classification constitutes an alternative definition of the drug region.

5 Empirical Strategy

This section discusses two empirical approaches to estimate the role of the OPN on the spatial diffusion of violence after the MWD. First, we employ a difference-in-differences strategy, which implicitly relies on the assumption that the observations in our data set are independent. Second, to explicitly deal with spatial spillovers, we use a spatial econometric approach.

5.1 Difference-in-differences

The difference-in-differences (DID) strategy can be implemented estimating the following regression model:

$$\begin{aligned} Hom\_rate_{m,t} = {} & \alpha_t + \gamma_m + \beta' Sec_{m,t} + \delta_1(Oil_m \times MWD_t) \\ & + \delta_2(Drug_m \times MWD_t) + \delta_3(Oil_m \times Drug_m \times MWD_t) \\ & + \delta_6(Gov\ Violence)_{m,t} + u_{m,t} \end{aligned} \tag{11}$$

where the outcome variable $Hom\_rate_{m,t}$ is the homicide rate (homicides per 100,000 inhabitants) for municipality m in year t. Year effects and municipality fixed effects are denoted by α_t and γ_m, respectively; $Sec_{m,t}$ are socioeconomic covariates (population, the number of vehicles registered per capita, females' deaths per capita from any cause linked to or aggravated by pregnancy or its handling, doctors per capita, doctors' offices and beds per capita.); the dummy variable $Drug_m$ adopts the value 1 when municipality m is valuable for drug trafficking activities and 0 otherwise; the dummy variable Oil_m adopts the value 1 when municipality m belongs to the OPN and 0 otherwise; and MWD_t adopts the value 1 for the years after the beginning of the MWD (i.e., 2007-2016) and 0 for the years before the MWD (i.e., 2000-2006). Finally, $Gov\ Violence_{m,t}$ captures the intensity of the government intervention in municipality m and year t. We proxy $Gov\ Violence_{m,t}$ by the clashes between DTOs and the army and the clashes among DTOs. $u_{m,t}$ is an error term.

The parameter of interest in equation (11) is δ_1, which reflects the change in the average homicide rate due to the presence of oil pipelines, taking the set of municipalities with neither value for drug trafficking

[7] The distribution of the total number of detected seizures between 2000 and 2010 is highly concentrated in a small group of municipalities.

nor for illegal oil siphoning as the base group with respect to which all comparisons are made. Thus, δ_1 (which can be estimated by OLS) results from comparing homicide rates between municipalities that belong to the OPN with municipalities in the base group.

One source of concern that could bias the estimation of δ_1 is that the MWD triggered a wave of violence. As the government attacked some of the most important DTOs, there was a rise in violence between DTOs and security forces as well as among and within DTOs. Therefore, it could be that municipalities that belong to the OPN were systematically receiving more government-initiated violence than their non-oil counterparts. To shield our estimates from this omitted variable bias, (11) includes $Gov\ Violence_{m,t}$, i.e., different proxies for DTOs-army clashes and clashes among DTOs.

Another source of bias estimating δ_1 is the distance between municipalities with and without oil and the region valuable for drug trafficking. It is possible that the MWD sparked violence to drug valuable municipalities and their neighbors. If municipalities in the OPN are systematically closer to the drug-valuable region, then violence along the OPN would be mistakenly associated to DTO's struggles to control oil flows. Moreover, variations in the intensity of drug-related conflicts across the drug-valuable region imply that the contagion of drug-related violence to the OPN territory could also vary over time, making municipality fixed effects incapable of controlling for this confounder. To address this problem, we estimate (11) restricting the sample to OPN municipalities and their neighbors. Intuitively, if municipalities containing oil were systematically closer to territories infected with drug violence, their neighbors would also suffer the same fate.

We also explore the role that the structure of the OPN had on the spatial diffusion of violence. As we discussed in Section 3, we expect that after the beginning of the MWD, oil municipalities closer to refining plants should exhibit a relatively lower escalation of violence than oil municipalities in isolated branches of the OPN. To test this hypothesis, we modify (11) to distinguish between oil municipalities neighboring a hydrocarbon processing plant, and those oil municipalities that are farther away. Specifically, we split Oil_m into Oil_c_m and Oil_f_m, which indicate whether m is a municipality close or far away to a refining plant, respectively.

5.2 Spatial Regressions

The difference-in-differences model (11) assumes that the observations in our data set are spatially independent. However, the statistical analysis of violence outbreaks often reveals some degree of spatial correlation among locations, which in turn constitutes a potential source of bias.[8] To account for spatial spillovers, we extend our econometric specification to admit the presence of a spatial lag with respect to the outcome variable, and a spatial autoregressive component in the error term. Specifically, we resort to the following SARAR specification to capture potential spatial dependence:[9]

$$\begin{aligned} Hom\_rate_{m,t} &= \lambda \sum_{m \neq \ell} w_{m,\ell} Hom\_rate_{\ell,t} + \gamma_m + \beta' Sec_{m,t} + u_{m,t} \\ u_{m,t} &= \rho \sum_{m \neq \ell} w_{m,\ell} u_{\ell,t} + \varepsilon_{m,t} \end{aligned} \tag{12}$$

[8]See Hill and Rotchild (1986), Sieverson and Star (1990) and Forshberg (2014).

[9]In Appendix C, we discuss a series of tests we applied to our data which support the use of SARAR instead of simpler versions such as SEM or SAR.

where λ captures the spatial correlation in the outcome variable and ρ the extend to which unobservable shocks affecting municipality m interact with shocks taking place in neighboring municipalities. $\sum_{m\neq\ell} w_{m,\ell} Hom\_rate_{\ell,t}$ is a weighted average of the violence exhibited by municipality m's neighbors and the exogenous weights $w_{m\ell}$ regulate the intensity of the relationship between municipality m and each one of its neighbors.[10] Analogously, $\sum_{m\neq\ell} w_{m,\ell} u_{\ell,t}$ is a weighted average of the error terms in municipality m's neighbors, using the same weights employed to compute $\sum_{m\neq\ell} w_{m,\ell} Hom\_rate_{\ell,t}$. γ_m is a municipality fixed effect and $Sec_{m,t}$ are socioeconomic covariates. The parameters λ and ρ in model (12) can be estimated by maximum likelihood.

6 Results

This section presents the main empirical results. First, we estimate the effect of the presence of oil on the increase in violence after the MWD. Second, we explore the role played by the structure of the pipeline network on the diffusion of violence.

6.1 Oil and Violence

6.1.1 Difference-in-differences

Table 1 shows the estimations of several alternative specifications of the regression model (11). Overall, the estimates in Table 1 indicate that the effect of having oil pipelines across a municipality significantly increased violence following the onset of the drug war. Columns 1 to 3 show that, when we include the full set of municipalities in our sample, having oil pipelines across a municipality increased homicide rates in approximately 6 homicides of civilians per 100,000 inhabitants. Column 1 shows the estimates when no covariates are included; column 2 includes the full list of socioeconomic controls discussed in Section 4; and column 3 includes all the socioeconomic controls plus a measure of government-induced violence, namely, the number of military personnel killed by a firearm. Note that the estimate of the coefficient of $Oil_m \times MWD_t$ remains relatively stable and highly significant for the first three columns of Table 1. In particular, including the number of military personnel killed by a firearm (a measure of military deployment) does not affect the estimated effect of $Oil_m \times MWD_t$; which suggests that the OPN represented a genuine source of violence.

Columns 4-6 in Table 1 report the estimates of the same specifications in columns 1-3 but restricting the sample to OPN municipalities and their non-oil neighbors. As we discussed in Section 5, the purpose of these specifications is to control for a potential confounder coming from the distance that each oil municipality has with respect to the drug-valuable region. For example, if municipalities crossed by the OPN were systematically closer to the drug valuable region than municipalities not crossed by the OPN, differences in the variations in violence could be caused by differential spatial spillover effects. Such a concern, however, vanishes when we focus exclusively on neighboring municipalities. Although of a lower magnitude than in columns 1-3, the estimated coefficient of $Oil_m \times MWD_t$ in columns 4-6 remains statistically and economically significant. Having oil pipelines across a municipality is associated with an increase in approximately 4 extra homicides per 100,000 inhabitants relative to neighboring municipalities

[10] For instance, if $w_{m\ell} = 0$, then there is no spatial connection between violence taking place in m and violence takin place in l. See De Bellefon, Loonis and Le Gleut (2018) for a thourgh discussion on spatial weigths. The exogenous weights can be properly collected in a spatial weight matrix W.

with no oil. To some extent, the lower estimates of $Oil_m \times MWD_t$ in columns 4-6 in comparison to those in columns 1-3 are foreseeable since the violence linked to oil-driven conflicts may have generated spatial spillover effects on non-oil neighbors.

Finally, Table 1 also shows three important results. First, as expected, for all specifications, drug trafficking was the main source of violence. Indeed, being located within the valuable drug region is associated with approximately 9 additional homicides per 100,000 inhabitants after 2007. Second, for all specifications, the triple interaction coefficient $Oil_m \times Drug_m \times MWD_t$ is negative, but statistically non-significant. Third, as columns 3 and 6 indicate, the murder of an additional soldier by a firearm is associated with approximately 5 additional homicides per 100,000 inhabitants, suggesting that military interventions were a crucial trigger of violence during the period.

Table 1: Effect of oil on homicide rates (DID model)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	9.50***	9.81***	9.71***	8.97***	8.57***	8.72***
	(1.56)	(1.53)	(1.52)	(2.69)	(2.56)	(2.56)
oil.MWD	5.38***	6.01***	6.07***	3.55*	4.40**	4.42**
	(1.95)	(1.99)	(1.99)	(2.14)	(2.18)	(2.18)
oil.drug.MWD	−4.54	−4.07	−3.82	−4.01	−2.74	−2.81
	(2.89)	(2.82)	(2.81)	(3.63)	(3.50)	(3.49)
gov_violence			5.89***			4.47***
			(1.41)			(1.70)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	43.73***	35.60***	36.86***	27.32***	22.56***	22.54***

Notes: This table reports the results of estimating model (11). The dependent variable is homicide rate per 100,000 inhabitants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

6.1.2 Spatial Regressions

One source of biased estimates (commonly present in quantitative studies of violence) comes from the possibility that violence in one municipality may directly or indirectly trigger violence in other municipalities. Specifically, in relation to oil-driven violence, one can argue that DTOs may not only fight for the control of OPN municipalities, but also try to extend their rule to neighboring territories; for example, to secure the transportation of stolen oil. It may also be the case that rival DTOs intercept shipments of stolen oil in areas surrounding the OPN inducing an increase in violence in non-oil neighbors. Indeed, the estimations in Table 1 suggest that there could be violence contagion from OPN municipalities to adjacent areas.[11] Moreover, several works have found spatial violence diffusion during the MWD (Guerrero, 2011; Molzhan, Rodiguez-Ferrer and Shirik, 2012; and Osorio, 2015). Thus, we consider critical to introduce spatial econometric techniques into our analysis.

In order to estimate model (12), we need to specify the weight matrix W. To do so, we define municipality m's neighbors employing a contiguity criterion.[12] More precisely, we use the Queen-contiguity rule, which states that two spatial entities are neighbors if they share one common boundary point.[13] In addition of defining neighbors, we must specify the intensity of the spatial relationship between neighbors; i.e., we must specify the weights embedded in matrix W.[14] In particular, we assume that W is exogenous and, to facilitate interpretations, employ a binary, row-standardized version of W.[15,16]

Table 2 shows maximum likelihood estimates of model (12). The first two rows of Table 2 indicate that both spatial parameters, λ and ρ are statistically significant, although there is stronger evidence of a spatial lag in the outcome variable than a spatial auto-regressive term in the error. More importantly, the coefficient associated to the effect of oil on violence is significant. However, as Le Sage and Dominguez (2012) have pointed out, the interpretation of a coefficient from a spatial regression is not straightforward.[17] Thus, we resort to the method introduced by Le Sage and Pace (2009) to compute the so called average direct effects, average indirect effects and average total effects for each regressor. The "direct effect" refers to the change in violence in municipality m triggered by a change in an independent variable in municipality m. The "indirect effect" refers to the change in violence in municipality m produced by a change in a regressor in other municipalities.[18] The results are also shown in Table 2.

The estimated direct effect of switching on the treatment status for an oil-municipality is 3.7 additional homicides per 100,000 inhabitants. The estimated indirect effect brought by a change in the treatment status of some other municipality is 8.2 additional homicides per 100,000 inhabitants. Overall, the estimated total effect on violence after the onset of the MWD associated with the presence of oil was 11.7 additional homicides per 100,000 inhabitants. These figures are comparable to the effect of drugs on violence. Indeed, the estimated direct, indirect and total affects of belonging to the drug valuable region

[11] Recall that the estimated coefficient of oil.MWD is smaller when we restrict our sample to the members of the OPN and their neighbors.

[12] De Bellefon, Loons and Le Gleut (2018) argue that when the spatial data refers to a partition of an entire territory, as is the case of our paper, the concept of distance between observational units can become ambiguous. For this reason, we employ a contiguity criterion rather than a distance-based rule to determine the neighbors of a municipality.

[13] For robustness, we have also performed our analysis using the Rook criterion. Estimates do not change. Results are available upon request.

[14] In Anselin and Griffith (1998) words W establishes "the formal expression of spatial dependency between observations".

[15] Hill and Rotchild (1986) and Sieverson and Starr (1990) equate violence diffusion to the spread of a disease, while Dell (2011), Zhukov (2012) and Forshberg (2014) consider violence contagion as the consequence of choices made by rational agents, rather than an exogenous process.

[16] In line with Le Sage and Pace (2010) we found that using other common alternative specifications of W do not alter our main conclusions. Results are available upon request.

[17] The problem is that a variation of a regressor occurring in municipality m, does not only impact the value of the outcome variable in m, but also in municipalities neighboring m.

[18] See Golgher and Voss (2016) for a detailed discussion on how to interpret the direct and indirect effects introduced by Le Sage and Pace (2009).

are 4.7, 10.5, and 15.2 additional homicides per 100,000 inhabitants, respectively.

Summing up, Tables 1 and 2 show that oil represented a major source of violence during the MWD. Moreover, as it was the case with drug-related violence, oil-related violence was highly contagious to neighboring municipalities.

Table 2: Effect of oil on homicide rates (SARAR model)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.74	0.01	97.22	0.00
rho	-0.59	0.01	-39.31	0.00
drug.MWD	4.02	0.68	5.86	0.00
oil.MWD	3.12	0.82	3.81	0.00
oil.drug.MWD	-2.72	1.44	-1.89	0.06
gov_violence	3.77	0.54	7.03	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	4.67	0.00	10.49	0.00	15.16	0.00
oil.MWD	3.62	0.00	8.14	0.00	11.76	0.00
oil.drug.MWD	-3.16	0.04	-7.11	0.04	-10.27	0.04
gov_violence	4.39	0.00	9.86	0.00	14.24	0.00

Notes: This table reports maximum likelihood estimations of model (12). The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The upper panel shows the coefficients resulting from the maximum likelihood estimation of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

6.2 Violence and the Structure of the OPN

In order to further explore the relationship between oil and violence across municipalities, Table 3 presents the results of estimating an extended version of model (11). In particular, we split our oil indicator into two subcategories. Oil_c_m (Oil_f_m) adopts the value 1 if municipality m belongs to the OPN and it is (not) a neighbor of a municipality in which a hydrocarbon plant is located. Table 3 shows that oil municipalities far away from hydrocarbon plants exhibit relatively higher increases in violence than those closer to hydrocarbon plants. Indeed, oil municipalities far away from hydrocarbon plants exhibit approximately 6 additional homicides per 100,000 inhabitants, while oil municipalities far away from hydrocarbon plants exhibit approximately 3 to 4 additional homicides per 100,000 inhabitants (Table 3, columns 1-3).

It is worth noticing that the magnitude of the effect that oil has on violence becomes lower upon restricting the sample to OPN members and their neighbors (Table 3, columns 4-6). Once again, this may indicate the presence of spillover effects, which suggests the use of spatial weights. Table 4 shows the results of estimating an extended version of model (12) in which the oil indicator is split between Oil_c_m and Oil_f_m. Both spatial parameters, λ and ρ, are statistically significant. Moreover, the estimated effect of oil on violence in OPN municipalities far away from hydrocarbon plants is quite high. Specifically, the estimated total effect on violence associated to the oil region located far away from hydrocarbon plants was 13 additional homicides per 100,000 inhabitants. Such estimate is only 14% lower than the effect stemming from being located in the drug-valuable region.[19]

Summing up, the results in Tables 1-4 support the hypothesis that disputes over oil territories were a significant trigger of violent conflict upon the onset of the MWD. Moreover, they also support the idea that the structure of the OPN shaped the intensity of violence.

Table 3: Effect of the structure of the OPN on homicide rates (DID model)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	9.50***	9.81***	9.71***	8.97***	8.57***	8.72***
	(1.56)	(1.53)	(1.52)	(2.69)	(2.56)	(2.56)
oil_c.MWD	2.89**	3.96***	3.98***	1.07	2.35	2.32
	(1.40)	(1.44)	(1.45)	(1.66)	(1.68)	(1.68)
oil_c.drug.MWD	−0.68	−0.64	−1.01	−0.14	0.59	0.06
	(3.55)	(3.48)	(3.51)	(4.17)	(4.05)	(4.08)
oil_f.MWD	5.81**	6.37***	6.44***	3.99	4.76*	4.79**
	(2.26)	(2.30)	(2.29)	(2.43)	(2.45)	(2.44)
oil_f.drug.MWD	−5.31*	−4.76	−4.36	−4.78	−3.42	−3.37
	(3.23)	(3.15)	(3.14)	(3.90)	(3.77)	(3.75)
gov_violence			5.88***			4.46***
			(1.41)			(1.71)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	39.19***	33.00***	34.26***	24.49***	20.91***	20.95***

Notes: This table reports the results of estimating model (11), after incorporating indicators for municipalities neighboring or not municipalities hosting hydrocarbon plants. The dependent variable is homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon plants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

[19]Mexico is integrated by municipalities of different sizes. Thus, it is important to verify whether our results hold for alternative definitions of "being close" to a processing plant. In Appendix C, we repeat the estimations in Tables 3 and 4 reclassifying the municipalities close to hydrocarbon plants as those intersecting an 80 kilometers buffer around hydrocarbon plants. Tables C.1 and C.2 show that our results do not significantly change after such a reclassification.

Table 4: Effect of the structure of the OPN on homicide rates (SARAR model)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.74	0.01	107.72	0.00
rho	-0.59	0.01	-41.77	0.00
drug.MWD	4.01	0.68	5.85	0.00
oil_c.MWD	1.52	2.02	0.76	0.45
oil_c.drug.MWD	-1.68	3.14	-0.53	0.59
oil_f.MWD	3.43	0.89	3.85	0.00
oil_f.drug.MWD	-2.85	1.58	-1.80	0.07
gov_violence	3.79	0.54	7.04	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	4.66	0.00	10.47	0.00	15.14	0.00
oil_c.MWD	1.77	0.42	3.98	0.42	5.75	0.42
oil_c.drug.MWD	-1.95	0.52	-4.38	0.52	-6.33	0.52
oil_f.MWD	3.98	0.00	8.96	0.00	12.94	0.00
oil_f.drug.MWD	-3.31	0.09	-7.44	0.10	-10.75	0.10
gov_violence	4.40	0.00	9.89	0.00	14.30	0.00

Notes: This table reports maximum likelihood estimations of model (12), after incorporating indicators for municipalities neighboring or not municipalities hosting hydrocarbon plants. The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon plants. The upper panel shows the coefficients resulting from the maximum likelihood estimation of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

7 Robustness Checks and Additional Results

In this section we perform several robustness checks. First, we consider alternative definitions for our spatial variables. Second, we explore the temporal evolution of violence before and after the MWD. Finally, we present additional evidence supporting the hypothesis that the increase in homicide rates in municipalities crossed by the OPN is linked to the activities of DTOs.

7.1 Spatial Definitions

7.1.1 Oil Region

Omitted spatial characteristics may introduce a bias in our estimations. Specifically, one potential concern is that municipalities in the OPN are systematically closer to the drug valuable region than municipalities outside the OPN. To deal with this issue, in Tables 1 and 3 we have also reported the results when we restrict the sample to OPN municipalities and their non-oil neighbors. To confirm our results, we have also conducted a falsification test. Specifically, we have assigned the oil-status to municipalities neighboring OPN members and gave the non-oil status to the latter. Thus, the underlying base group of the analysis comprises a combination of oil and non-oil municipalities. Tables C.3 and C.4 in Appendix C report the corresponding estimations. The falsified oil status does not have a significant effect on violence, reinforcing the hypothesis that being a member of the OPN is a legitimate source of conflict.

7.1.2 Drug Region

Our definition of a drug-valuable region encompasses municipalities satisfying at least one of the following two criteria. The first criterion consists of a geographic characteristic, namely, that the municipality belongs to the Mexican coastal line or the Mexico-US/Central America borders. The second criterion relies on drug seizures records. A municipality belongs to the drug-valuable region if it exhibits a notably high number of drug seizures. We have repeated the estimations in Tables 1-3 using only one if these criteria to define the drug-valuable region. In Appendix C we present the results. Tables C.5-C.7 show the estimations when the drug-valuable region is defined using only the geographic criterion; while Tables C8-C10 show the results when only drug seizures are employed to determine if a municipality is valuable for drug trafficking. As Tables C.5-C.10 indicate, our results are robust to both definitions of the drug-valuable region.

Yet another way of defining the set of municipalities valuable for DTOs' activities is to employ an index constructed by the National Defense Secretariat (SEDENA) and reported by Osorio (2015). This index reflects whether a municipality has proper conditions for drug production. It includes four categories labeled as 0, 1, 2, and 3, where 0 (3) indicates null (maximum) suitability. We employ this information to construct an alternative drug region encompassing all the municipalities for which the SEDENA index is different from zero. Tables C.11-C.13 in Appendix C show that our results are also robust to this alternative specification of the drug-valuable region.

Finally, as we mentioned in Section 4.4, one potential determinant of a municipality value for drug trafficking is its location in the transportation network.[20] Indeed, Calderon et al. (2016) estimate that, upon the outbreak of criminal violence in 2007, homicide rates rose 51.8 percent in municipalities hosting major transportation infrastructures. If the OPN were also part of the transportation network, our results could be biased. However, when we define the drug-valuable region employing the measure of connectivity used by Calderon et al. (2016), our results remain unaltered (see Tables C.14-C.16 in Appendix C).

7.2 Temporal Evolution

Consistently estimating the effect of the OPN on homicide rates using model (11) requires that, in the absence of the MWD, homicide rates in municipalities located in the region with no strategic value for drug trafficking share a common time trend. Figure 4 shows annual homicide rates for municipalities with no value for drug trafficking and crossed by OPN and municipalities with no value for drug trafficking and outside the OPN. Note that before the onset of the MWD, the trends in homicide rates were very similar for both groups of municipalities. Before 2007, in municipalities with no value for drug trafficking, homicide rates were systematically lower if they were crossed by the OPN. However, after 2007 homicide rates in municipalities crossed by the OPN quickly converged to the level of those outside the OPN.

In Section 3, we mentioned that various media reports identify 2009 as the year when DTOs began to systematically engage in illegal oil siphoning. Thus, it is interesting to explore the temporal pattern of the effects of oil availability and drug trafficking suitability on violence. To do so, we extended model

[20]Municipalities closer to the transportation network participate in the logistics of international trade flows and, hence, are vital for smuggling operations and more prone to be the object of turf wars.

(11) to include the interactions between the year effects and indicators for municipalities with no value for drug trafficking and crossed by OPN; municipalities with no value for drug trafficking and outside the OPN; and municipalities with value for drug trafficking and outside the OPN. This procedure delivers a series of estimated coefficients that capture the temporal evolution of the yearly effect of oil and drugs on homicide rates relative to the base year (2001). Figure 5 plots these estimates. In line with media reports, the "oil effect" began to gain steam after 2009.

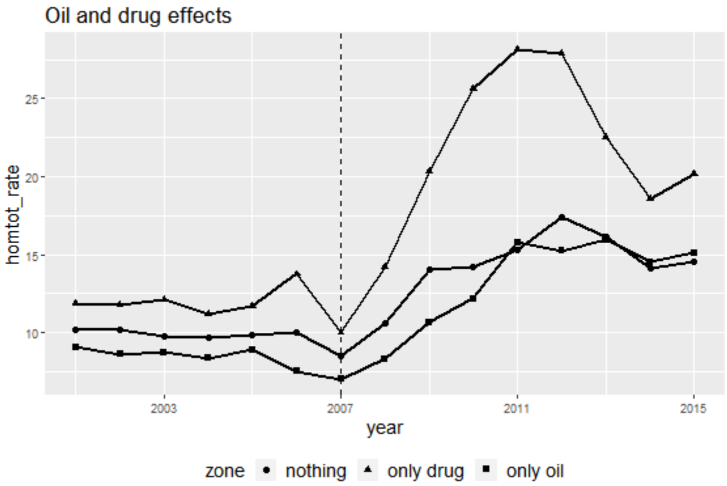


Fig. 4 : Trends in homicide rates. *Notes*: This graph plots the annual homicide rates for municipalities with no value for drug trafficking and crossed by OPN; municipalities with no value for drug trafficking and outside the OPN; and municipalities valuable for drug trafficking and outside the OPN. *Source*: INEGI (2015, 2016).

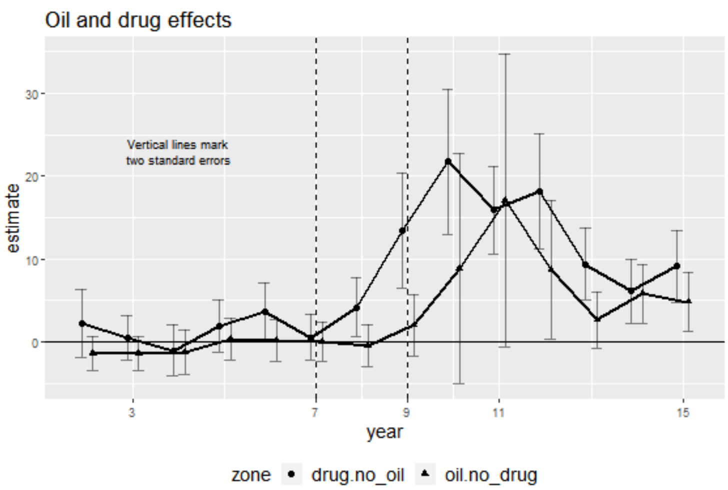


Fig. 5 : Time evolution of the effects of oil and drugs on homicides rates. *Notes*: This graph shows the estimated coefficients of the interactions between time dummies and Oil_m and $Drug_m$. The discontinuous vertical lines mark the beginning of the MWD in 2007 and the year 2009 when DTOs bbegan to systematically engage in illegal oil siphoning. *Source*: INEGI (2016).

7.3 Sources of Violence

Available data do not allow us to verify whether a specific homicide resulted from DTOs' direct actions. The data, however, can shed some light on the characteristics of these homicides. In particular, as we mentioned in Section 4, we can identify the place of residence of each murder victim, which allows us to separate homicides in two categories: imports and the rest. An import occurs in municipality m when a person residing somewhere else is murdered in m. Since only large-scale criminal organizations such as DTOs are capable of mobilizing militias between distant territories, an increase in the ratio of imports to total homicides suggests that the rise in violence is linked to DTOs rather than to local criminal bands. Thus, we estimated models (11) and (12) using imports/total homicides as the outcome variable.[21] Tables C.17-C.19 in Appendix C show the results.

The effects of $Drug_m \times MWD_t$ and $Oil_m \times MWD_t$ on $Imports_{m,t}/Homicides_{m,t}$ are both positive and statistically significant, supporting the hypothesis that the rise of violence after the MWD in municipalities valuable for drug trafficking as well as in those containing oil pipelines was primarily due to turf wars between DTOs. Moreover, the estimated coefficient of $Oil_m \times MWD_t$ more than doubles that of $Drug_m \times MWD_t$, which supports the hypothesis that DTOs began to diversify their criminal activities toward illegal oil siphoning after the onset of the MWD. The idea is that back in 2006, DTOs were not engaged in the oil-siphoning and, hence, their presence in municipalities with no value for drug trafficking was negligible. After 2007, some DTOs started considering oil siphoning a profitable alternative activity and they sent militias to municipalities along the OPN to gain territorial control. The resulting clashes among rival DTOs increased the number of imported homicides in the oil region.

8 Conclusion

In this paper, we have studied criminal diversification and spatial diffusion of illicit activities and violence in the presence of organized criminal syndicates when authorities initiate a crackdown of organized crime in specific locations. We have developed a simple model that predicts that the equilibrium effect of this type of government intervention is criminal diversification and violence displacement. In particular, the model predicts that violence spreads to locations with low strategic value for criminal organizations before the government intervention, but ex post high strategic value to diversify their operations to other criminal activities. Using data from a major crackdown of DTOs in Mexico, we have shown that after the government intervention violence spread to municipalities valuable for illegal oil siphoning and that oil-driven violence (as drug-driven violence) was highly contagious. We have also found that the structure of the OPN also played an important role to explain the diffusion of violence in the oil region. Indeed, municipalities closer to hydrocarbon plants experienced lower increases in violence than those located far away from hydrocarbon plants, suggesting that DTOs strategically employed less violent means to compete for territories where law enforcement agencies had a greater presence (which is the case of areas close to hydrocarbon processing plants). Finally, to support that the rise of violence across the OPN was linked to the operations of DTOs, we have shown that after the MWD, municipalities across the OPN experienced a rise in the ratio of homicides where the victim was not a local resident.

[21] That is, the outcome variable is $Imports_{m,t}/Homicides_{m,t}$. $Imports_{m,t}$ is the number of homicides in the municipality m in the year t when the victim is a legal resident of a municipality different from m. $Homicides_{m,t}$ is the total number of homicides in the municipality m in the year t.

There are several ways to further develop our line of analysis. Here we will mention just two of them. First, illegal oil siphoning was the major alternative activity for many Mexican DTOs, but by no means it was the only one. Kidnapping, extorsion and human trafficking were also part of their portfolio of criminal activities. Thus, it would be interesting to extend our analysis also to these activities. Second, our work suggests the importance of properly understanding how the equilibrium among criminal organizations will be affected after a government intervention. Otherwise, unintended consequences will be pervasive. For example, if the government affects the most profitable activity of a criminal organization, then the organization will presumably redirect its operations toward the second most profitable activity, which may trigger a spatial relocation of crime and violence and may not be less violent than the activity targeted by the government.

References

[1] Abadie, A., Diamond, A. and Hainmueller, J. 2015. Comparative politics and the synthetic control method. *American Journal of Political Science* 59(2):495-510.

[2] Anselin, L. and Griffith, D. 1988. Do spatial effects really matter in regression analysis? *Papers in Regional Science* 65(1):11–34.

[3] Anselin, L., Bera, A.K., Florax, R. and Yoon, M.J. 1996. Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics* 26(1):77-104.

[4] Asmann, P. 2018. Lucrativa industria de robo de combustible recrudece violencia criminal en México. *Insight Crime.* Accessed on September 13, 2019 from: https://es.insightcrime.org/noticias/noticias-del-dia/lucrativa-industria-robo-combustible-mexico-recrudece-violencia-criminal/

[5] Arellano, M. 1987. Computing Robust Standard Errors for Within-Groups Estimators. *Oxford Bulletin of Economics and Statistics* 49:431-434.

[6] Barr, R. and Pease, K. 1990. Crime placement, displacement, and deflection. *Crime and Justice* 12:277-318.

[7] Beittel, J. 2018. Mexico: organized crime and drug trafficking organizations. Congressional Research Service. Report R41576. Accessed on September 13, 2019 from: https://fas.org/sgp/crs/row/R41576.pdf

[8] Bergman, M. 2018. Criminal diversification and corruption in the drug business. In *Illegal drugs, drug trafficking and violence in Latin America.* New York, NY: Springer.

[9] Bouayad, S., Le Gallo, J. and Vedrine, L. 2018. Spatial econometrics on panel data. In *Handbook of spatial analysis, theory and practical application with R.* Coordinated by Loonis, V. and De Bellefon M., INSEE-Eurostat, 180-200.

[10] Buonanno, P., Durante, R., Prarolo, G. and Vanin, P. 2015. Poor institutions, rich mines: resource curse in the origins of the Sicilian mafia. *Economic Journal* 125(586):175-202.

[11] Correa-Cabrera, G. 2017. *Los Zetas INC: criminal corporations, energy, and civil war in Mexico*. Austin, Texas: University of Texas Press.

[12] Calderón, G., Robles, G., Díaz-Cayeros, A. and Magaloni, B. 2015. The beheading of criminal organizations and the dynamics of violence in Mexico. *Journal of Conflict Resolution* 59(8):1455–1485.

[13] Cordell, K. and Wolff, S. 2009. *Ethnic conflict: causes, consequences, and responses*. Malden, MA: Polity Press.

[14] De Bellefon, M., Loonis, V. and Le Glout R. 2018. Codifying the neighborhood structure. In *Handbook of spatial analysis, theory and practical application with R*. Coordinated by Loonis, V. and De Bellefon M., INSEE-Eurostat, 31-47.

[15] Debarsy, N. and Ertur, C., 2010. Testing for spatial autocorrelation in a fixed effects panel data model. *Regional Science and Urban Economics* 40(6):453–470.

[16] Dell, M. 2015. Trafficking networks and the Mexican Drug War. *American Economic Review* 105(6):1738-79.

[17] Dixit, A. 2003. On modes of economic governance. *Econometrica* 71(2):449-81.

[18] Dube, O., and Vargas, J. 2013. Commodity price shocks and civil conflict: evidence from Colombia. *The Review of Economic Studies* 80(4):1384–1421.

[19] Ferri P. 2019. Antes como policía, ganaba 270 dólares al mes. Ahora con el combustible, puedo sacar hasta 50,0000. *El País*. Accessed on September 13, 2019 from: https://elpais.com/internacional/2017/05/23/mexico/1495496778_273384.html.

[20] Forsberg, E. 2014. Diffusion in the study of civil wars: a cautionary tale. *International Studies Review* 16(2): 188–198.

[21] Frankel, J. 2010. The natural resource curse: a survey. Working Paper No. 15836, National Bureau of Economic Research.

[22] Finckenauer, J. 2001. La cosa nostra in the United States. National Institute of Justice. Accessed on Septermber 13 2019, from http://www.ojp.usdoj.gov/nij/international/lcn.html.

[23] Guerrero, E. 2011. 2011: La dispersion de la violencia. *Nexos*. Accessed on February 17, 2019. http://www.nexos.com.mx/?p=14705.

[24] Golgher, A. and Voss, P. 2016. How to interpret the coefficients of spatial models: spillovers, direct and indirect effects. *Spatial Demography* 4:175– 205.

[25] Gonzalez-Navarro, M. 2013. Deterrence and geographical externalities in auto theft. *American Economic Journal: Applied Economics* 5(4):92-110.

[26] Hill, S. and Rothchild, D. 1986. The contagion of political conflict in Africa and the World. *Journal of Conflict Resolution* 30(4):716-735.

[27] Johnson, S.D., Guerette, R.T. and Bowers, K. 2014. Crime displacement: what we know, what we don't know, and what it means for crime reduction. *Journal of Experimental Criminology* 10(4):549–571.

[28] Jones, N., 2013. The unintended consequences of kingpin strategies: kidnap rates and the Arellano-Félix organization. *Trends in Organized Crime* 16(2):156–76.

[29] LeSage, J. and Dominguez, M. 2012. The importance of modeling spatial spillovers in public choice analysis. *Public Choice* 150(3-4):525–545.

[30] LeSage, J. P., and Pace, R. K. 2009. *Introduction to spatial econometrics*. Boca Raton: Florida: CRC Press.

[31] LeSage J. and Pace R. 2014. The biggest myth in spatial econometrics. *Econometrics* 2(4):217-249.

[32] Luege, J., 2019. SCADA y los ductos de PEMEX. *El Universal*. Accessed on September 13, 2019 from https://www.eluniversal.com.mx/columna/jose-luis-luege-tamargo/metropoli/scada-y-los-ductosde-pemex.

[33] Lyall, J., 2009. Does indiscriminate violence incite insurgent attacks? evidence from Chechnya. *Journal of Conflict Resolution* 53(2).

[34] Magaloni B., Matanock A., Romero V. and Díaz-Cayeros A. 2014. Living in fear: the dynamics of extortion in Mexico's criminal insurgency. Center for International Development Working Paper No. 557.

[35] Molzahn, C., Rios, V., and Shirk, D. 2012. Drug violence in Mexico: data and analysis through 2011. Trans Border Institute Joan B. Kroc School of Peace Studies, University of San Diego.

[36] Montero, J. 2016. El robo de combustible en México en el contexto del narcotráfico: una vía alternativa de financiación. Documento de Opinión IEEE 55/2016. Accessed on September 13, 2019 from http://www.ieee.es/Galerias/fichero/docs_opinion/2016/DIEEEO55-2016_Robo_Combustible_Mejico_MonteroVieira.pdf.

[37] Montero, J. 2018. Expansión del robo de combustible en México: de actividad delictiva a fenómeno criminal. Documento de Opinión IEEE 119/2018. Accessed on September 13, 2019 from http://www.ieee.es/Galerias/fichero/docs_opinion/2018/DIEEEO119_2018JIGMON-Mexico.pdf

[38] Monroy, J. 2017. Huachicol extendido por casi todo el país. *El Economista*. Accessed on Spetember 13, 2019 from: https://www.eleconomista.com.mx/politica/Huachicol-extendido-por-casi-todo-el-pais-20170522-0059.html

[39] Osorio, J. 2015. The contagion of drug violence: spatiotemporal dynamics of the Mexican War on Drugs. *Journal of Conflict Resolution* 5(8):1403-1432 (Special issue on Mexican drug violence).

[40] Paoli, L. 2008. The decline of the Italian mafia. In Siegel, D. and Nelen, H. (eds), *Organized crime: culture, markets and policies*. The Netherlands: Springer.

[41] Pérez A. 2012. *El cártel negro*. Mexico City: Grijalbo.

[42] Pinotti, P. 2015. The causes and consequences of organised crime: preliminary evidence across countries. *The Economic Journal* 125(586):158–174.

[43] Ralby, I., 2017. Downstream oil theft: global modalities, trends, and remedies. *Atlantic Council*. Accessed on September 13, 2019 from www.jstor.org/stable/resrep03694.

[44] Raleigh, C., Linke, A., Hegre, H. and Karlsen, J. 2010. Introducing ACLED: an armed conflict location and event dataset. *Journal of Peace Research* 47(5):651-660.

[45] Siverson, R. and Starr, H. 1990. Opportunity, willingness, and the diffusion of war. *American Political Science Review* 84(1):47-67.

[46] Skaperdas, S. 2011. The costs of organized violence: a review of the evidence. *Economics of Governance* 12:1-23.

[47] Trejo, G. and Ley., S. 2018. Why did drug cartels go to war in Mexico? Subnational party alternation, the breakdown of criminal protection, and the onset of large-scale violence. *Comparative Political Studies* 51(7):900-937.

[48] Van der Ploeg, F. 2011. Natural resources: curse or blessing? *Journal of Economic Literature* 49(2):366-420.

[49] Zhukov, Y., 2012. Roads and the diffusion of insurgent violence: The logistics of conflict in Russia's North Caucasus. *Political Geography* 31(3):144-156.

Appendix to "Hidden Drivers of Violence Diffusion: Evidence from Illegal Oil Siphoning in Mexico"

A Theoretical Results

This appendix presents the proofs of all the lemmas and propositions in Section 2.

A.1 Lemmas 1 and 2 and Propositions 1, 2 and 3

Lemma 1 ***Drug trafficking***. *Suppose that criminal organizations select $k^D = \left(k_i^D\right)_{i \in N_D}$. Then, the Nash equilibrium level of guns in the drug trafficking activity is given by:*

$$g_i^D = g^{D,*}\left(k^D\right) = \frac{m\left(n-1\right)}{n^2}\left[\sum_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha}\right] \text{ for } i \in N_D,$$

while the equilibrium payoff obtains by organization $i \in N_D$ from drug trafficking is given by:

$$V_i^D = V_i^{D,*}\left(k^D\right) = p_i v_i^D\left(k_i^D\right)^{\alpha} + \frac{n-m\left(n-1\right)}{n^2}\left[\sum_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha}\right].$$

Proof. Restrict the set of feasible guns choices for criminal organization i to $g_i^D \in G^D = [\epsilon_L, \epsilon_H]$ with $\epsilon_L > 0$ arbitrarily small and $\epsilon_H = \sum_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha}$ Note that G^D is a compact and convex set. The payoff of criminal organization i is $V_i^D = p_i v_i^D\left(k_i^D\right)^{\alpha} + \gamma_i^D\left[\sum_{l \in N_D}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha}\right] - g_i^D$. The first and second derivatives of V_i^D with respect to g_i^D are given by:

$$\frac{\partial V_i^D}{\partial g_i^D} = \frac{m\gamma_i^D\left(1-\gamma_i^D\right)}{g_i^D}\sum_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha} - 1$$
$$\frac{\partial^2 V_i^D}{\left(\partial g_i^D\right)^2} = \frac{-\left(2m\gamma_i^D + 1 - m\right)m\gamma_i^D\left(1-\gamma_i^D\right)}{\left(g_i^D\right)^2}\sum_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha}$$

Since $\partial^2 V_i^D / \left(\partial g_i^D\right)^2 < 0$ for all $g_i^D \in G^D$, V_i^D is strictly concave in g_i^D. Thus, Glicksberg's existence theorem implies that there exists a Nash equilibrium. Moreover, note that

$$\begin{aligned}\lim_{g_i^D \to \epsilon_L}\left(\partial V_i^D / \partial g_i^D\right) &= \frac{m\left(\epsilon_L\right)^m \sum_{l \neq i}^{n}\left(g_l^D\right)^m}{\left[\left(\epsilon_L\right)^m + \sum_{l \neq i}^{n}\left(g_l^D\right)^m\right]^2}\sum_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha} - \epsilon_L \\ &> \frac{m\left(n-1\right)}{n^2}\sum_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^{\alpha} - \epsilon_L > 0\end{aligned}$$

and

$$\begin{aligned}\lim_{g_i^D \to \epsilon_H}\left(\partial V_i^D / \partial g_i^D\right) &= \frac{m\left(\epsilon_H\right)^m \sum_{l \neq i}^{n}\left(g_l^D\right)^m}{\left[\left(\epsilon_H\right)^m + \sum_{l \neq i}^{n}\left(g_l^D\right)^m\right]^2}\epsilon_H - \epsilon_H \\ &< \left(\frac{m}{4} - 1\right)\epsilon_H < 0\end{aligned}$$

Therefore, the best response function of i is given by $g_i^D = m\gamma_i^D \left(1-\gamma_i^D\right) \sum_{l=1}^n \left(1-p_l\right) v_l^D \left(k_l^D\right)^\alpha$, which implies that the set of Nash equilibrium profiles is the solution to the following system of equations:

$$g_i^D = m\gamma_i^D \left(1-\gamma_i^D\right) \sum\nolimits_{l=1}^n \left(1-p_l\right) v_l^D \left(k_l^D\right)^\alpha \text{ for } i \in N_D$$

Note that for any $i, j \in N_D$ we have $g_i^D/g_j^D = \gamma_i^D \left(1-\gamma_i^D\right)/\gamma_j^D \left(1-\gamma_j^D\right)$, which implies $\left(g_i^D/g_j^D\right)^{1-m} = \left[\sum_{l=1}^n \left(g_l^D\right)^m - \left(g_i^D\right)^m\right] / \left[\sum_{l=1}^n \left(g_l^D\right)^m - \left(g_j^D\right)^m\right]$. Suppose that $\left(g_i^D/g_j^D\right)^{1-m} > 1$. Then, it must be the case that $\left[\sum_{l=1}^n \left(g_l^D\right)^m - \left(g_i^D\right)^m\right] / \left[\sum_{l=1}^n \left(g_l^D\right)^m - \left(g_j^D\right)^m\right] > 1$, which implies $\left(g_j^D/g_i^D\right)^m > 1$, a contradiction. Thus, the unique solution to the above system of equations is $g_i^D = g^{D,*}\left(k^D\right) = \left[m\left(n-1\right)/n^2\right] \sum_{l=1}^n \left(1-p_l\right) v_l^D \left(k_l^D\right)^\alpha$ for all $i \in N_D$.

Introducing the Nash equilibrium guns choices into the payoff function of organization i we obtain the equilibrium payoff of organization $i \in N_D$ from drug trafficking:

$$\begin{aligned} V_i^D = V_i^{D,*}\left(k^D\right) &= p_i v_i^D \left(k_i^D\right)^\alpha + \gamma_i^{D,*} \left[\sum\nolimits_{l=1}^n \left(1-p_l\right) v_l^D \left(k_l^D\right)^\alpha\right] - g^{D,*}\left(k^D\right) \\ &= p_i v_i^D \left(k_i^D\right)^\alpha + \frac{n-m\left(n-1\right)}{n^2} \left[\sum\nolimits_{l=1}^n \left(1-p_l\right) v_l^D \left(k_l^D\right)^\alpha\right] \end{aligned}$$

This completes the proof of Lemma 1. ■

Lemma 2 ***Oil siphoning***. *Suppose that criminal organizations select $k^D = \left(k_i^D\right)_{i\in N_D}$. Then, the Nash equilibrium level of guns in the oil siphoning activity is given by:*

$$g_i^O = g^{O,*}\left(k^D\right) = \frac{r\left(n-1\right)}{n^2} \left[\sum\nolimits_{l=1}^n v_{n+l}^O \left(1-k_l^D\right)\right] \text{ for } i \in N_D,$$

while the equilibrium payoff obtains by organization $i \in N_D$ from oil siphoning is given by:

$$V_i^O = V_i^{O,*}\left(k^D\right) = v_i^O \left(1-k_i^D\right) + \frac{n-r\left(n-1\right)}{n^2} \left[\sum\nolimits_{l=1}^n v_{n+l}^O \left(1-k_l^D\right)\right].$$

Proof. Restrict the set of feasible guns choices for criminal organization i to $g_i^O \in G^O = [\epsilon_L, \epsilon_H]$ with $\epsilon_L > 0$ arbitrarily small and $\epsilon_H = \sum\nolimits_{l=1}^n v_{n+l}^O \left(1-k_l^D\right)$. Note that G^O is a compact and convex set. The payoff of criminal organization i is $V_i^O = \left(1-k_i^D\right) v_i^O + \gamma_i^O \left[\sum\nolimits_{l\in N_D} v_{n+l}^O \left(1-k_l^D\right)\right] - g_i^O$. The first and second derivatives of V_i^O with respect to g_i^D are given by:

$$\begin{aligned} \frac{\partial V_i^O}{\partial g_i^O} &= \frac{r\gamma_i^O \left(1-\gamma_i^O\right)}{g_i^O} \sum\nolimits_{l=1}^n v_{n+l}^O \left(1-k_l^D\right) - 1 \\ \frac{\partial^2 V_i^O}{\left(\partial g_i^O\right)^2} &= \frac{-\left(2r\gamma_i^O + 1 - r\right) r\gamma_i^O \left(1-\gamma_i^D\right)}{\left(g_i^O\right)^2} \sum\nolimits_{l=1}^n v_{n+l}^O \left(1-k_l^D\right) < 0 \end{aligned}$$

Following the same steps used to prove Lemma 1, the unique Nash equilibrium is $g_i^D = g^{D,*}$ for all $i \in N_D$, where $g^{D,*} = \left[r\left(n-1\right)/n^2\right] \sum_{l=1}^n v_{n+l}^O \left(1-k_l^D\right)$.

Introducing the Nash equilibrium guns choices into the payoff function of organization i we obtain the equilibrium payoff of organization $i \in N_D$ from drug siphoning:

$$\begin{aligned} V_i^{O,*}\left(k^D\right) &= \left(1-k_i^D\right)v_i^O + \gamma_i^{O,*}\left[\sum\nolimits_{l=1}^{n} v_{n+l}^O\left(1-k_l^D\right)\right] - g_i^O \\ &= \left(1-k_i^D\right)v_i^O + \frac{n-r\left(n-1\right)}{n^2}\sum\nolimits_{l=1}^{n} v_{n+l}^O\left(1-k_l^D\right) \end{aligned}$$

This completes the proof of Lemma 2. ■

Proposition 1 *The equilibrium capital allocation of organization $i \in N_D$ is given by:*

$$k_i^D = k_i^{D,*} = \begin{cases} 1 & \text{if } p_i \geq \bar{p}_i \\ \left(\bar{k}_i\right)^{\frac{1}{1-\alpha}} & \text{if } p_i < \bar{p}_i \end{cases}$$

where $\bar{k}_i = \frac{\alpha\left[(n)^2 p_i + (1-p_i)(n-mn+m)\right]v_i^D}{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O}$ *and* $\bar{p}_i = \frac{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O - \alpha v_i^D(n-mn+m)}{\alpha v_i^D\left[(n)^2-(n-mn+m)\right]}$. *Moreover,* $\bar{p}_i \in (0,1)$ *if and only if* $\frac{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O}{\alpha(n)^2} < v_i^D < \frac{(n)^2 v_i^O + (b-rn+r)v_{n+i}^O}{\alpha(n-mn+m)}$.

Proof. From Lemmas 1 and 2, the payoff of organization i is given by:

$$\begin{aligned} V_i\left(k^D\right) &= p_i v_i^D\left(k_i^D\right)^\alpha + \frac{n-m\left(n-1\right)}{n^2}\left[\sum\nolimits_{l=1}^{n}\left(1-p_l\right)v_l^D\left(k_l^D\right)^\alpha\right] \\ &+ \left(1-k_i^D\right)v_i^O + \frac{n-r\left(n-1\right)}{n^2}\sum\nolimits_{l=1}^{n} v_{n+l}^O\left(1-k_l^D\right) \end{aligned}$$

We must find the value of k_i^D that maximizes $V_i\left(k^D\right)$. The first and second derivatives of $V_i\left(k^D\right)$ with respect to k_i^D are given by:

$$\begin{aligned} \frac{\partial V_i\left(k^D\right)}{\partial k_i^D} &= \left[p_i + \frac{n-m\left(n-1\right)}{n^2}\left(1-p_i\right)\right]v_i^D\alpha\left(k_i^D\right)^{\alpha-1} \\ &- \left[v_i^O + \frac{n-r\left(n-1\right)}{n^2}v_{n+i}^O\right] \\ \frac{\partial^2 V_i\left(k^D\right)}{\left(\partial k_i^D\right)^2} &= -\left[p_i + \frac{n-m\left(n-1\right)}{n^2}\left(1-p_i\right)\right]v_i^D\alpha\left(1-\alpha\right)\left(k_i^D\right)^{\alpha-2} \end{aligned}$$

Since $\partial^2 V_i\left(k^D\right)/\left(\partial k_i^D\right)^2 < 0$ and $\lim_{k_i^D\to 0}\partial V_i\left(k^D\right)/\partial k_i^D = \infty$, there are two possible to consider:

1. Suppose that $p_i < \bar{p}_i = \frac{n^2 v_i^O + (n-rn+r)v_{n+i}^O - (n-mn+m)\alpha v_i^D}{n^2-(n-mn+m)}$. Then, $\partial V_i\left(k^D = 1\right)/\partial k_i^D < 0$ and, hence, the value of k_i^D that maximizes $V_i\left(k^D\right)$ is the unique solution to $\partial V_i\left(k^D = 1\right)/\partial k_i^D = 0$, which in given by:

$$k_i^{D,*} = \left\{\frac{\left[n^2 p_i + \left(n-mn+m\right)\left(1-p_i\right)\right]\alpha v_i^D}{n^2 v_i^O + \left(n-rn+1\right)v_{n+i}^O}\right\}^{\frac{1}{1-\alpha}}$$

2. Suppose that $p_i \geq \bar{p}_i$. Then, $\partial V_i\left(k^D = 1\right)/\partial k_i^D \geq 0$ and, hence, the value of k_i^D that maximizes $V_i\left(k^D\right)$ is $k_i^{D,*} = 1$.

Moreover, $0 < \bar{p}_i < 1$ if and only if $\frac{(n)^2 v_i^O + (b-rn+r) v_{n+i}^O}{\alpha(n)^2} < v_i^D < \frac{(n)^2 v_i^O + (b-rn+r) v_{n+i}^O}{\alpha(n-mn+m)}$. This completes the proof of Proposition 1. ■

Proposition 2 ***Government intervention (change in*** p_l***).*** *Suppose that* $\alpha (n)^2 > (n - mn + m)$ *and let* $\hat{p}_l = \frac{\alpha(n)^2 - (n-mn+m)}{(n)^2 - (n-mn+m)}$.

1. *Suppose that* $\frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha(n)^2} < v_l^D < \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha^2(n)^2}$. *Then:*

   (a) *If* $p_l \leq \hat{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} \geq 0$, $\frac{\partial H_j^*}{\partial p_l} \geq 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} < 0$ *and* $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.

   (b) *If* $\hat{p}_l < p_l < \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} < 0$, $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} < 0$ *and* $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.

   (c) *If* $p_l \geq \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} < 0$, $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} = 0$ *and* $\frac{\partial H_j^*}{\partial p_l} = 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.

2. *Suppose that* $\frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha^2(n)^2} \leq v_l^D < \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha(n-mn+m)}$. *Then:*

   (a) *If* $p_l < \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} > 0$, $\frac{\partial H_j^*}{\partial p_l} > 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} < 0$ *and* $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.

   (b) *If* $p_l \geq \bar{p}_l$, *then:* $\frac{\partial H_l^*}{\partial p_l} < 0$, $\frac{\partial H_j^*}{\partial p_l} < 0$ *for* $j = 1, ..., n$, $j \neq l$, $\frac{\partial H_{n+l}^*}{\partial p_l} = 0$ *and* $\frac{\partial H_j^*}{\partial p_l} = 0$ *for* $j = n+1, ..., 2n$, $j \neq n+l$.

Proof. Let $\bar{p}_l = \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O - \alpha v_l^D (n-mn+m)}{\alpha v_l^D \left[(n)^2 - (n-mn+m)\right]}$. Since $\frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha(n)^2} < v_l^D < \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha(n-mn+m)}$, then $\bar{p}_l \in (0, 1)$. Let $\hat{p}_l = \frac{\alpha(n)^2 - \alpha(n-mn+m)}{(n)^2 - \alpha(n-mn+m)}$. Since $\alpha (n)^2 > (n - mn + m)$, then $\hat{p}_l \in (0, 1)$. From the definition of η_l, we have that $\eta_l = 0$ if and only if $p_l \geq \bar{p}_l$, while $\eta_l = \frac{p_l}{1-\alpha} \frac{(n)^2 - (n-mn+m)}{(n)^2 p_l + (1-p_l)(n-mn+m)} > 0$ if and only if $p_l < \bar{p}_l$. Also note that $\alpha \eta_l = \frac{\alpha p_l}{1-\alpha} \frac{(n)^2 - (n-mn+m)}{(n)^2 p_l + (1-p_l)(n-mn+m)} > p_l / (1 - p_l)$ if and only if $p_l < \hat{p}_l$. Finally, note that $\hat{p}_l < \bar{p}_l$ if and only if $v_l^D < \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha^2(n)^2}$

1. Suppose that $\frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha(n)^2} < v_l^D < \frac{(n)^2 v_l^O + (b-rn+r) v_{n+l}^O}{\alpha^2(n)^2}$. Then, $\hat{p}_l < \bar{p}_l$, which implies that we must distinguish the following three cases:

1.a. Suppose that $p_l \leq \hat{p}_l$. Then, $\alpha\eta_l = \frac{\alpha p_l}{1-\alpha}\frac{(n)^2-(n-mn+m)}{(n)^2 p_l+(1-p_l)(n-mn+m)} \geq p_l/(1-p_l) > 0$. Therefore:

$$\begin{aligned}
\frac{\partial H_l^*}{\partial p_l} &= \frac{m(n-1)[\lambda n+(1-\lambda)]v_l^D\left(\bar{k}_l\right)^{\frac{\alpha}{1-\alpha}}}{n^2}\left[\frac{(1-p_l)\alpha\eta_l}{p_l}-1\right] \geq 0 \\
\frac{\partial H_j^*}{\partial p_l} &= \frac{m(n-1)(1-\lambda)v_l^D\left(\bar{k}_l\right)^{\frac{\alpha}{1-\alpha}}}{n^2}\left[\frac{(1-p_l)\alpha\eta_l}{p_l}-1\right] \geq 0 \text{ for } j=1,...,n,\ j\neq l \\
\frac{\partial H_{n+l}^*}{\partial p_l} &= \frac{-r(n-1)[\lambda n+(1-\lambda)]v_{n+l}^O\left(\bar{k}_l\right)^{\frac{1}{1-\alpha}}\eta_l}{n^2 p_l} < 0 \\
\frac{\partial H_j^*}{\partial p_l} &= \frac{-r(n-1)(1-\lambda)v_{n+l}^O\left(\bar{k}_l\right)^{\frac{1}{1-\alpha}}\eta_l}{n^2 p_l} < 0 \text{ for } j=n+1,...,2n,\ j\neq n+l
\end{aligned}$$

1.b. Suppose that $\hat{p}_l < p_l < \bar{p}_l$. Then, $0 < \alpha\eta_l = \frac{\alpha p_l}{1-\alpha}\frac{(n)^2-(n-mn+m)}{(n)^2 p_l+(1-p_l)(n-mn+m)} < p_l/(1-p_l)$. Therefore:

$$\begin{aligned}
\frac{\partial H_l^*}{\partial p_l} &= \frac{m(n-1)[\lambda n+(1-\lambda)]v_l^D\left(\bar{k}_l\right)^{\frac{\alpha}{1-\alpha}}}{n^2}\left[\frac{(1-p_l)\alpha\eta_l}{p_l}-1\right] < 0 \\
\frac{\partial H_j^*}{\partial p_l} &= \frac{m(n-1)(1-\lambda)v_l^D\left(\bar{k}_l\right)^{\frac{\alpha}{1-\alpha}}}{n^2}\left[\frac{(1-p_l)\alpha\eta_l}{p_l}-1\right] < 0 \text{ for } j=1,...,n,\ j\neq l \\
\frac{\partial H_{n+l}^*}{\partial p_l} &= \frac{-r(n-1)[\lambda n+(1-\lambda)]v_{n+l}^O\left(\bar{k}_l\right)^{\frac{1}{1-\alpha}}\eta_l}{n^2 p_l} < 0 \\
\frac{\partial H_j^*}{\partial p_l} &= \frac{-r(n-1)(1-\lambda)v_{n+l}^O\left(\bar{k}_l\right)^{\frac{1}{1-\alpha}}\eta_l}{n^2 p_l} < 0 \text{ for } j=n+1,...,2n,\ j\neq n+l
\end{aligned}$$

1.c. Suppose that $p_l \geq \bar{p}_l$. Then, $\alpha\eta_l = 0 < p_l/(1-p_l)$. Therefore:

$$\begin{aligned}
\frac{\partial H_l^*}{\partial p_l} &= \frac{-m(n-1)[\lambda n+(1-\lambda)]v_l^D}{n^2} < 0 \\
\frac{\partial H_j^*}{\partial p_l} &= \frac{-m(n-1)(1-\lambda)v_l^D}{n^2} < 0 \text{ for } j=1,...,n,\ j\neq l \\
\frac{\partial H_{n+l}^*}{\partial p_l} &= 0 \\
\frac{\partial H_j^*}{\partial p_l} &= 0 \text{ for } j=n+1,...,2n,\ j\neq n+l
\end{aligned}$$

2. Suppose that $\frac{(n)^2 v_l^O+(b-rn+r)v_{n+l}^O}{\alpha^2(n)^2} \leq v_l^D < \frac{(n)^2 v_l^O+(b-rn+r)v_{n+l}^O}{\alpha(n-mn+m)}$. Then, $\hat{p}_l \geq \bar{p}_l$, which implies that we must distinguish two possible cases.

2.a. Suppose that $p_l < \bar{p}_l$. Then $\eta_l = \frac{\alpha p_l}{1-\alpha}\frac{(n)^2-(n-mn+m)}{(n)^2 p_l+(1-p_l)(n-mn+m)} > p_l/(1-p_l) > 0$. Therefore:

$$\frac{\partial H_l^*}{\partial p_l} = \frac{m(n-1)[\lambda n+(1-\lambda)]v_l^D\left(\bar{k}_l\right)^{\frac{\alpha}{1-\alpha}}}{n^2}\left[\frac{(1-p_l)\alpha\eta_l}{p_l}-1\right] > 0$$

$$\frac{\partial H_j^*}{\partial p_l} = \frac{m(n-1)(1-\lambda)v_l^D\left(\bar{k}_l\right)^{\frac{\alpha}{1-\alpha}}}{n^2}\left[\frac{(1-p_l)\alpha\eta_l}{p_l}-1\right] > 0 \text{ for } j=1,...,n,\ j\neq l$$

$$\frac{\partial H_{n+l}^*}{\partial p_l} = \frac{-r(n-1)[\lambda n+(1-\lambda)]v_{n+l}^O\left(\bar{k}_l\right)^{\frac{1}{1-\alpha}}\eta_l}{n^2 p_l} < 0$$

$$\frac{\partial H_j^*}{\partial p_l} = \frac{-r(n-1)(1-\lambda)v_{n+l}^O\left(\bar{k}_l\right)^{\frac{1}{1-\alpha}}\eta_l}{n^2 p_l} < 0 \text{ for } j=n+1,...,2n,\ j\neq n+l$$

2.b. Suppose that $p_l \geq \bar{p}_l$. Then $\eta_l = 0$. Therefore:

$$\frac{\partial H_l^*}{\partial p_l} = \frac{-m(n-1)[\lambda n+(1-\lambda)]v_l^D}{n^2} < 0$$

$$\frac{\partial H_j^*}{\partial p_l} = \frac{-m(n-1)(1-\lambda)v_l^D}{n^2} < 0 \text{ for } j=1,...,n,\ j\neq l$$

$$\frac{\partial H_{n+l}^*}{\partial p_l} = 0$$

$$\frac{\partial H_j^*}{\partial p_l} = 0 \text{ for } j=n+1,...,2n,\ j\neq n+l$$

This completes the proof of Proposition 2. ■

Proposition 3 ***Government intervention (change in*** p_l***).*** *Suppose that* $0 < \hat{p}_l < p_l < \bar{p}_l < 1$. *Then:*

1. *Drug-valuable locations:* $\left|\frac{\partial H_l^*}{\partial p_l}\right| > \left|\frac{\partial H_j^*}{\partial p_l}\right|$ *for* $j=1,...,n$ *and* $j\neq l$.

2. *Oil-valuable locations:* $\left|\frac{\partial H_{n+l}^*}{\partial p_l}\right| > \left|\frac{\partial H_j^*}{\partial p_l}\right|$ *for* $j=n+1,...,2n$ *and* $j\neq n+l$.

3. *Oil abundance:* $\frac{\partial}{\partial v_l^O}\left|\frac{\partial H_l^*}{\partial p_l}\right| < 0$ *and* $\frac{\partial}{\partial v_{n+l}^O}\left|\frac{\partial H_{n+l}^*}{\partial p_l}\right| > 0$.

Proof. Suppose that $0 < \hat{p}_l < p_l < \bar{p}_l < 1$. Then, from Propositions 1 and 2:

$$\frac{\partial H_l^*}{\partial p_l} = \frac{m(n-1)[\lambda n+(1-\lambda)]v_l^D\left(k_l^{D,*}\right)^{\alpha}}{n^2}\left[\frac{\alpha(1-p_l)\eta_l}{p_l}-1\right] < 0,$$

$$\frac{\partial H_j^*}{\partial p_l} = \frac{m(n-1)(1-\lambda)v_l^D\left(k_l^{D,*}\right)^{\alpha}}{n^2}\left[\frac{\alpha(1-p_l)\eta_l}{p_l}-1\right] < 0 \textit{ for } j=1,...,n \textit{ and } j\neq l,$$

$$\frac{\partial H_{n+l}^*}{\partial p_l} = \frac{-r(n-1)[\lambda n+(1-\lambda)]v_{n+l}^O k_l^{D,*}\eta_l}{n^2 p_l} < 0,$$

$$\frac{\partial H_j^*}{\partial p_l} = \frac{-r(n-1)(1-\lambda)v_{n+l}^O k_l^{D,*}\eta_l}{n^2 p_l} < 0 \textit{ for } j=n+1,...,2n \textit{ and } j\neq n+l,$$

where $\alpha\eta_l = \frac{\alpha p_l}{1-\alpha}\frac{(n)^2-(n-mn+m)}{(n)^2 p_l+(1-p_l)(n-mn+m)} < \frac{p_l}{1-p_l}$. Therefore:

1. Drug-valuable locations. For $j = 1, ..., n$ and $j \neq l$ we have:

$$\frac{\left|\frac{\partial H_l^*}{\partial p_l}\right|}{\left|\frac{\partial H_l^*}{\partial p_l}\right|} = \frac{\lambda n + (1-\lambda)}{(1-\lambda)} > 1$$

2. Oil-valuable locations. For $j = n+1, ..., 2n$ and $j \neq n+l$ we have:

$$\frac{\left|\frac{\partial H_{n+l}^*}{\partial p_l}\right|}{\left|\frac{\partial H_j^*}{\partial p_l}\right|} = \frac{\lambda n + (1-\lambda)}{(1-\lambda)} > 1$$

3. Oil abundance. Taking the derivatives of H_l^* with respect to p_l and v_l^O we obtain:

$$\frac{\partial^2 H_l^*}{\partial v_l^O \partial p_l} = \frac{m(n-1)\left[\lambda n + (1-\lambda)\right] v_l^D \alpha \left(k_l^{D,*}\right)^{\alpha}}{n^2 k_l^{D,*}} \frac{\partial k_l^{D,*}}{\partial v_l^O}\left[\frac{\alpha(1-p_l)\eta_l}{p_l} - 1\right]$$

where $\partial k_l^{D,*}/\partial v_l^O = ... < 0$. Therefore, $\partial^2 H_l^*/\partial v_l^O \partial p_l > 0$, which implies that $\partial\left|\partial H_l^*/\partial p_l\right|/\partial v_l^O < 0$.

Taking the derivatives of H_l^* with respect to p_l and v_{n+l}^Owe obtain:

$$\frac{\partial^2 H_{n+l}^*}{\partial v_{n+l}^O \partial p_l} = \frac{-r(n-1)\left[\lambda n + (1-\lambda)\right]\eta_l k_l^{D,*}}{n^2 p_l}\left[\frac{(1-\alpha)(n)^2 v_l^O + \alpha(b-rn+r)v_{n+l}^O}{(1-\alpha)(n)^2 v_l^O + (1-\alpha)(b-rn+r)v_{n+l}^O}\right]$$

Therefore, $\partial^2 H_{n+l}^*/\partial v_{n+l}^O \partial p_l > 0$, which implies that $\partial\left|\partial H_{n+l}^*/\partial p_l\right|/\partial v_{n+l}^O > 0$. This completes the proof of Proposition 3. ■

B Data

This appendix list all the variables, all the sources of data, and provides summary statistics for the variables employed in the econometric analysis.

Table B.1: Description of variables

Variable	Availability	Linear interpolation	Source
homicide_rate	90-16	–	INEGI (2016)
EVI	90-16	–	INEGI (2016)
divorce_rate	94-13, 15	2014 for the entire sample and 2001 for the state of Oaxaca	INEGI (2019)
marriage_rate	94-13, 15	2014 for the entire sample and 2001 for the state of Oaxaca	INEGI (2019)
pregnancy_death_rate	90-16	–	INEGI (2016)
vehicles_rate	80-16	–	INEGI (2019)
hospital_beds_rate	01-15	–	SINAIS (2016)
doctor_offices	01-15	–	SINAIS (2016)
doctors_rate	01-15	–	SINAIS (2016)
population	95,00,05,10	The values for the 5 years gaps between 95-10, come from linear interpolations. The values between 10-15 come from CONAPO's population projections	CONAPO (2016) INEGI (2019)
gov_violence	90-16	–	INEGI (2016)
drug_seizures	00-10	–	Osorio (2015)

Notes: This table lists various aspects of the variables employed in the econometric analysis. The variables expressed in rates, equate the original variables divided by population and multiplied by 100,000. EVI gives the value of the external violence index.

Sources of data:

- Calderon et al. (2015): Calderón, G., Robles, G., Díaz-Cayeros, A. and Magaloni, B. 2015. The Beheading of Criminal Organizations and the Dynamics of Violence in Mexico. *Journal of Conflict Resolution* 59(8):1455–1485. Online Appendix. URL: https://journals.sagepub.com/doi/suppl/10.1177/0022002715587053

- Carto Critica (2017): Carto Critica. 2017. Ductos, ¿por dónde circulan los hidrocarburos en México? URL: http://cartocritica.org.mx/2017/ductos/

- El Universal (2015): El Universal. 2015. Se dispara ordena de gasolina en el pais. URL: https://archivo.eluniversal.com.mx/graficos/graficosanimados15/Mapa_Tomas_Clandestinas/

- INEGI (2015): Instituto Nacional de Estadística y Geografía. 2015. Marco Geoestadístico Nacional. URL: http://www.inegi.org.mx/geo/contenidos/geoestadistica/default.aspx

- INEGI (2016): Instituto Nacional de Estadística y Geografía. 2016. Estadística de defunciones generales. URL: https://www.inegi.org.mx/programas/mortalidad/default.html#Microdatos.

- Insight Crime (2010): Insight Crime. 2010. InSight Map: Oil Pipeline Theft in Mexico. URL: https://www.insightcrime.org/news/analysis/insight-map-oil-pipeline-theft-in-mexico/

- Osorio (2015): Osorio, J., 2015. The contagion of drug violence: spatiotemporal dynamics of the Mexican War on Drugs. *Journal of Conflict Resolution* 5(8):1403-1432 (Special issue on Mexican drug violence). Online Appendix. URL: https://journals.sagepub.com/doi/suppl/10.1177/0022002715587048.

- SINAIS (2016): Sistema Nacional de Información en Salud. 2016. Estadisticas. URL: http://www.dgis.salud.gob.mx/contenidos/sinais/estadisticas.html

Table B.2: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
homicide_rate	36,825	14.9	40.3	0.0	0.0	15.7	2,278.3
EVI	36,825	17.6	30.3	0.0	0.0	27.7	100.0
divorce_rate	36,825	24.6	65.4	0.0	0.0	21.9	2,354.8
marriage_rate	36,825	523.2	510.2	0.0	271.0	694.6	12,602.9
pregnancy_death_rate	36,825	0.7	4.2	0.0	0.0	0.0	353.9
vehicles_rate	36,825	6,601.1	13,876.8	0.0	0.0	0.0	175,104.2
hospital_beds_rate	36,825	15.9	83.3	0.0	0.0	0.0	4,077.8
doctor_offices_rate	36,825	46.3	50.7	0.0	18.9	57.7	2,661.3
doctors_rate	36,825	73.2	83.5	0.0	29.1	96.0	2,969.2
population	36,825	44,539.6	131,097.1	89.8	4,214.0	31,313.5	1,826,077.0
gov_violence	36,825	0.03	0.3	0	0	0	19
ssd	24,550	2.9	12.8	0.0	0.0	1.0	471.0

Notes: This table shows summary statistics of all the variables utilized in the quantitative analysis.

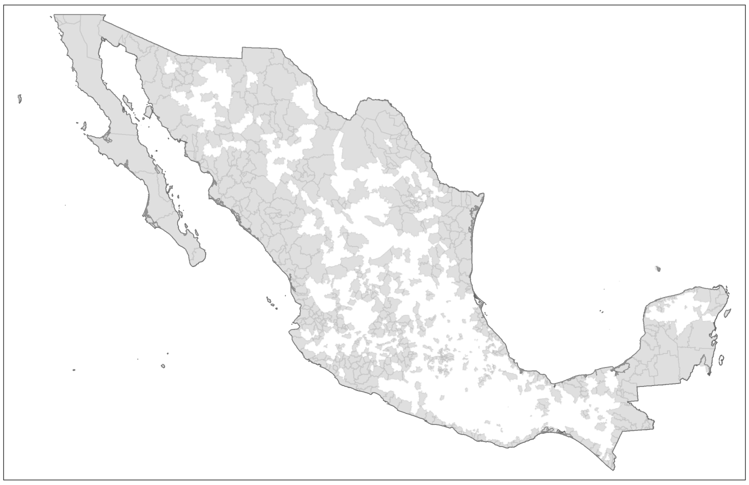
C Additional Empirical Results

This appendix presents several additional results. First, we show maps summarizing the geographic distribution of drug trafficking, the oil pipeline network and violence. Second, we present all the robustness checks and additional results discussed in Sections 6 and 7. Finally, we show the results of two specification tests for spatial models that justify the use of the SARAR model.

C.1 The Geopraphy of Drugs, Oil and Violence

Figure C.1 shows a map with municipalities valuable for drug trafficking, municipalities crossed by the OPN and the location of hydrocarbon plants.

Panel A. Drug valuable municipalities



Panel B. The Mexican Oil Pipeline Network

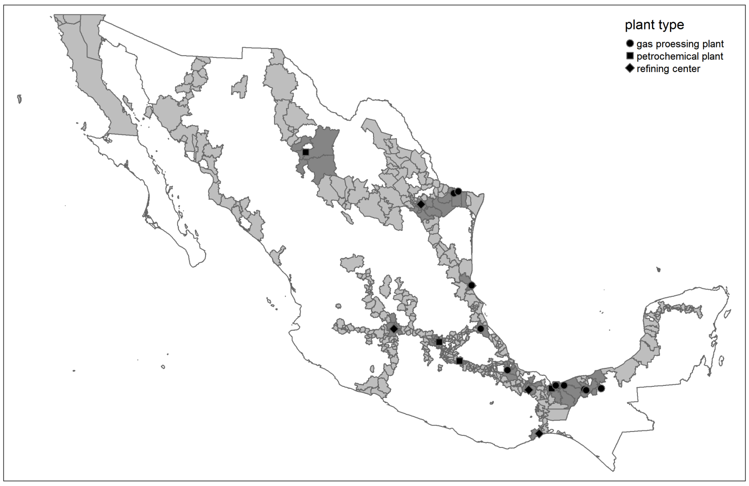
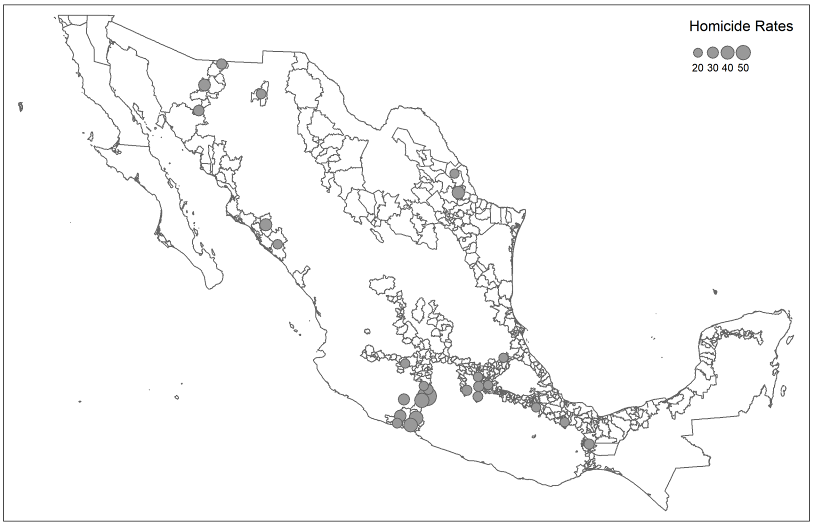


Fig. C.1: Drug valuable municipalities, the OPN and hydrocarbon plants. *Notes*: *Panel A*. The darker areas represent the set of municipalities valuable for drug trafficking activities. *Panel B.* This map shows the group of municipalities that contains portions of the OPN. The municipalities in dark grey, share borders with municipalities hosting an hydrocarbon processing plant. The light grey municipalities are OPN members farther away from hydrocarbon processing plants. *Panel C*: This map shows the group of municipalities that encompass portions of the OPN. The municipalities in dark grey, are in the interior of a 80 kilometers-radius buffers sorrounding all the hydrocarbon processing plants. The light grey municipalities are OPN members outside the buffers. *Sources*: Insight Crime (2010), Osorio (2015), INEGI (2015), El Universal (2015), and Carto Critica (2017).

Figure C.2 shows a map with the spatial distribution of homicide rates before and after the MWD.

Panel A. Average homicide rates before 2007



Panel B. Average homicide rates after 2007

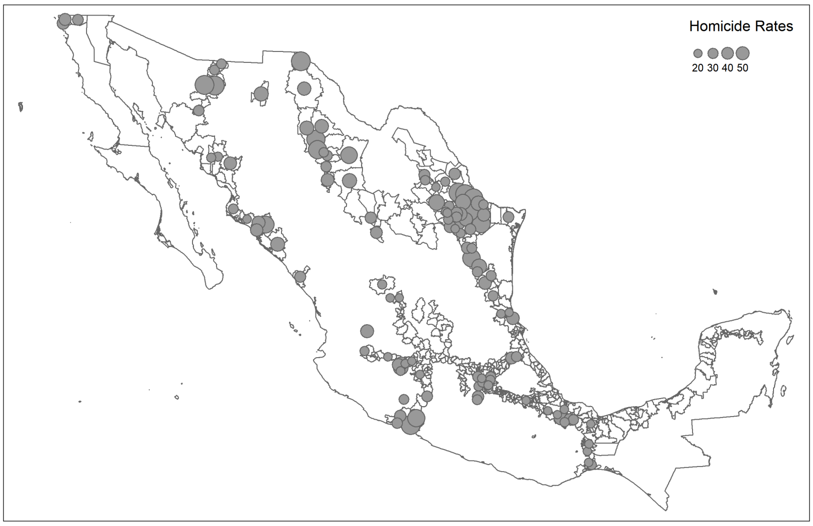


Fig. C.2: Spatial distribution of violence across the OPN. *Notes*: *Panel A.* The bubbles in the map reflect average homicide rates between 2001 and 2006. *Panel B.* The bubbles in the map reflect average homicide rates between 2007 and 2015. *Sources*: Insight Crime (2010), INEGI (2015, 2016), and El Universal (2015).

C.2 Spatial Definitions

C.2.1 Oil Region

Tables C.1 and C2 shows the estimations in Tables 3 and 4 when we reclassify the municipalities close to hydrocarbon plants as those intersecting an 80 kilometers buffer around hydrocarbon plants.

Table C.1: Effect of the structure of the OPN on homicide rates (DID model).

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	9.50***	9.80***	9.70***	8.97***	8.57***	8.72***
	(1.56)	(1.53)	(1.52)	(2.69)	(2.56)	(2.56)
oil_c.MWD	2.96**	3.87***	3.97***	1.13	2.42	2.47
	(1.38)	(1.42)	(1.43)	(1.64)	(1.66)	(1.66)
oil_c.drug.MWD	−3.82	−3.44	−3.13	−3.29	−2.18	−2.20
	(2.90)	(2.80)	(2.81)	(3.63)	(3.57)	(3.55)
oil_f.MWD	11.98**	11.79**	11.76**	10.16*	9.72*	9.68*
	(6.06)	(5.98)	(5.96)	(6.12)	(5.84)	(5.82)
oil_f.drug.MWD	−8.75	−7.77	−7.56	−8.22	−6.17	−6.27
	(6.62)	(6.51)	(6.48)	(6.97)	(6.63)	(6.63)
gov_violence			5.86***			4.44***
			(1.40)			(1.70)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	39.95***	33.41***	34.64***	25.11***	21.20***	21.22***

Notes: This table reports the results of estimating model (11), after incorporating indicators for municipalities close or far away from hydrocarbon plants. The dependent variable is homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities enclosed in (outside) a 80 kilometers buffer around hydrocarbon plants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.2: Effect of the structure of the OPN on homicide rates (SARAR model)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.73	0.01	100.05	0.00
rho	-0.59	0.01	-39.84	0.00
drug.MWD	3.97	0.69	5.79	0.00
oil_c.MWD	2.18	0.92	2.38	0.02
oil_c.drug.MWD	-2.15	1.69	-1.28	0.20
oil_f.MWD	6.44	1.60	4.02	0.00
oil_f.drug.MWD	-5.60	2.34	-2.40	0.02
gov_violence	3.75	0.54	6.98	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	4.62	0.00	10.36	0.00	14.98	0.00
oil_c.MWD	2.54	0.01	5.69	0.01	8.23	0.01
oil_c.drug.MWD	-2.50	0.23	-5.62	0.23	-8.12	0.23
oil_f.MWD	7.48	0.00	16.80	0.00	24.28	0.00
oil_f.drug.MWD	-6.51	0.02	-14.61	0.02	-21.12	0.02
gov_violence	4.36	0.00	9.79	0.00	14.15	0.00

Notes: This table reports maximum likelihood estimations of model (12), after incorporating indicators for municipalities close or far away from hydrocarbon plants. The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities enclosed in (outside) a 80 kilometers buffer around hydrocarbon plants. The upper panel shows the coefficients resulting from the maximum likelihood estimation of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

Tables C.3 and C.4 show the estimations in Tables 1 and 2 (columns 1-3) when OPN members are labelled as non-oil municipalities and vice versa.

Table C.3: Effect of oil on homicide rates (DID model, falsification test)

	Dependent variable:		
	Homicide rate		
	(1)	(2)	(3)
drug.MWD	8.78***	9.65***	9.57***
	(1.36)	(1.38)	(1.37)
oil.MWD	1.20	1.24	1.29
	(1.19)	(1.20)	(1.20)
oil.drug.MWD	0.19	−1.07	−0.79
	(3.01)	(2.94)	(2.93)
gov_violence			5.85***
			(1.39)
Covariates	N	Y	Y
Neighbors	N	N	N
Observations	36,825	36,825	36,825
F Statistic	42.67***	34.61***	35.87***

Notes: This table reports the results of estimating model (11) when OPN members are labelled as non-oil municipalities and vice versa. The dependent variable is homicide rate per 100,000 inhabitants. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4: Effect of oil on homicide rates (SARAR model, falsification test)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.74	0.01	108.41	0.00
rho	-0.59	0.01	-41.87	0.00
drug.MWD	3.92	0.69	5.70	0.00
oil.MWD	0.15	0.80	0.19	0.85
oil.drug.MWD	-0.64	1.52	-0.42	0.67
gov_violence	3.73	0.54	6.94	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	4.56	0.00	10.26	0.00	14.82	0.00
oil.MWD	0.18	0.88	0.40	0.88	0.57	0.88
oil.drug.MWD	-0.75	0.60	-1.69	0.60	-2.43	0.60
gov_violence	4.33	0.00	9.76	0.00	14.09	0.00

Notes: This table reports maximum likelihood estimations of model (12) when OPN members are labelled as non-oil municipalities and vice versa. The model includes a spatial lag of the outcome variable and a spatial autoregressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The upper panel shows the coefficients resulting from maximum likelihood estimations of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

C.2.2 Drug Region

Tables C.5-C.7 show the estimations in Tables 1, 3 and 4 when the drug-valuable region is defined using only the geographic criterion.

Table C.5: Effect of oil on homicide rates (DID model, drug region defined by geographic criteria)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	8.27**	9.55***	9.11***	11.14	11.55*	11.39*
	(3.36)	(3.32)	(3.30)	(7.23)	(6.91)	(6.89)
oil.MWD	5.32***	6.32***	6.45***	3.10*	4.56***	4.56***
	(1.42)	(1.49)	(1.49)	(1.66)	(1.72)	(1.71)
oil.drug.MWD	−3.41	−5.25	−4.92	−6.28	−7.39	−7.32
	(5.19)	(5.05)	(5.06)	(8.24)	(7.95)	(7.95)
gov_violence			5.81***			4.31**
			(1.42)			(1.70)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	39.61***	32.76***	34.05***	26.42***	21.93***	21.88***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined using a geographic criteria (national borders and coastal lines). The dependent variable is homicide rate per 100,000 inhabitants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.6: Effect of the structure of the OPN on homicide rates (DID model, drug region defined by geographic criteria)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	8.27**	9.55***	9.11***	11.14	11.55*	11.39*
	(3.36)	(3.32)	(3.30)	(7.23)	(6.91)	(6.89)
oil_c.MWD	6.50***	7.71***	7.63***	4.27**	5.87***	5.70***
	(2.01)	(1.95)	(1.95)	(2.18)	(2.09)	(2.08)
oil_c.drug.MWD	−13.68***	−15.41***	−16.01***	−16.55**	−17.19**	−17.79**
	(4.06)	(4.16)	(4.19)	(7.58)	(7.36)	(7.37)
oil_f.MWD	5.09***	6.04***	6.22***	2.87	4.30**	4.34**
	(1.63)	(1.69)	(1.69)	(1.83)	(1.90)	(1.89)
oil_f.drug.MWD	−0.77	−2.65	−2.04	−3.64	−4.87	−4.60
	(5.93)	(5.74)	(5.76)	(8.72)	(8.43)	(8.44)
gov_violence			5.85***			4.37**
			(1.43)			(1.72)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	35.65***	30.48***	31.79***	23.82***	20.42***	20.44***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined using a geographic criteria (national borders and coastal lines). The dependent variable is homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.7: Effect of oil on homicide rates (SARAR model, drug region defined by geographic criteria)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.74	0.01	100.04	0.00
rho	-0.59	0.01	-40.18	0.00
drug.MWD	3.90	1.08	3.63	0.00
oil_c.MWD	3.33	1.42	2.34	0.02
oil_c.drug.MWD	-13.04	4.28	-3.05	0.00
oil_f.MWD	3.22	0.69	4.64	0.00
oil_f.drug.MWD	-2.89	2.29	-1.26	0.21
gov_violence	3.77	0.54	7.01	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	4.55	0.00	10.37	0.00	14.92	0.00
oil_c.MWD	3.88	0.02	8.85	0.02	12.73	0.02
oil_c.drug.MWD	-15.19	0.00	-34.66	0.00	-49.86	0.00
oil_f.MWD	3.75	0.00	8.55	0.00	12.30	0.00
oil_f.drug.MWD	-3.37	0.22	-7.69	0.21	-11.07	0.22
gov_violence	4.39	0.00	10.01	0.00	14.39	0.00

Notes: This table reports maximum likelihood estimations of model (12) when the municipalities valuable for drug trafficking are defined using a geographic criteria (national borders and coastal lines). The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. The upper panel shows the coefficients resulting from maximum likelihood estimations of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

Tables C8-C10 show the estimations in Tables 1, 3 and 4 when only drug seizures are employed to determine if a municipality is valuable for drug trafficking.

Table C.8: Effect of oil on homicide rates (DID model, drug region defined through drug seizures)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	10.05***	10.27***	10.28***	10.08***	9.49***	9.67***
	(1.63)	(1.60)	(1.59)	(2.86)	(2.71)	(2.71)
oil.MWD	5.06***	5.62***	5.72***	3.52*	4.27**	4.29**
	(1.87)	(1.90)	(1.90)	(2.05)	(2.10)	(2.09)
oil.drug.MWD	−4.43	−3.70	−3.55	−4.46	−2.81	−2.89
	(2.92)	(2.86)	(2.84)	(3.75)	(3.61)	(3.59)
gov_violence			5.99***			4.49***
			(1.42)			(1.70)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	43.93***	35.69***	37.04***	27.71***	22.82***	22.80***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined as those exhibiting high levels of drug seizures. The dependent variable is homicide rate per 100,000 inhabitants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.9: Effect of the structure of the OPN on homicide rates (DID model, drug region defined through drug seizures)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	10.05***	10.27***	10.28***	10.08***	9.50***	9.67***
	(1.63)	(1.60)	(1.59)	(2.86)	(2.71)	(2.71)
oil_c.MWD	2.69*	3.71***	3.76***	1.15	2.40	2.37
	(1.38)	(1.40)	(1.42)	(1.61)	(1.64)	(1.65)
oil_c.drug.MWD	−0.98	−0.79	−1.32	−1.01	−0.08	−0.65
	(3.62)	(3.56)	(3.59)	(4.31)	(4.19)	(4.22)
oil_f.MWD	5.47**	5.95***	6.05***	3.93*	4.58**	4.62**
	(2.16)	(2.18)	(2.18)	(2.31)	(2.34)	(2.34)
oil_f.drug.MWD	−5.11	−4.27	−3.96	−5.13	−3.35	−3.31
	(3.25)	(3.18)	(3.17)	(4.01)	(3.87)	(3.85)
gov_violence			5.99***			4.49***
			(1.43)			(1.72)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	39.35***	33.07***	34.42***	24.83***	21.15***	21.19***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined as those exhibiting high levels of drug seizures. The dependent variable is homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.10: Effect of oil on homicide rates (SARAR model, drug region defined through drug seizures)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.73	0.01	103.60	0.00
rho	-0.59	0.01	-41.12	0.00
drug.MWD	4.24	0.73	5.79	0.00
oil_c.MWD	1.43	1.99	0.72	0.47
oil_c.drug.MWD	-1.66	3.16	-0.53	0.60
oil_f.MWD	3.13	0.86	3.62	0.00
oil_f.drug.MWD	-2.46	1.63	-1.51	0.13
gov_violence	3.84	0.54	7.14	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	4.92	0.00	11.04	0.00	15.96	0.00
oil_c.MWD	1.66	0.44	3.72	0.44	5.38	0.44
oil_c.drug.MWD	-1.93	0.52	-4.32	0.52	-6.25	0.52
oil_f.MWD	3.63	0.00	8.14	0.00	11.78	0.00
oil_f.drug.MWD	-2.86	0.16	-6.40	0.16	-9.26	0.16
gov_violence	4.47	0.00	10.01	0.00	14.48	0.00

Notes: This table reports maximum likelihood estimations of model (12) when the municipalities valuable for drug trafficking are defined as those exhibiting high levels of drug seizures. The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. The upper panel shows the coefficients resulting from maximum likelihood estimations of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

Tables C11-C13 show the estimations in Tables 1, 3 and 4 when the drug region is defined through a drug producion index built by the National Defense Secretariat (SEDENA).

Table C.11: Effect of oil on homicide rates (DID model, drug region defined through a drug producion index)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	4.52***	4.04***	3.84***	7.69**	5.88*	5.77*
	(1.27)	(1.25)	(1.25)	(3.38)	(3.28)	(3.28)
oil.MWD	6.13***	6.86***	6.93***	4.06**	5.07***	5.04***
	(1.54)	(1.59)	(1.59)	(1.71)	(1.75)	(1.74)
oil.drug.MWD	−0.91	−1.14	−0.81	−4.08	−3.25	−3.04
	(3.09)	(3.07)	(3.05)	(4.40)	(4.28)	(4.26)
gov_violence			5.87***			4.34**
			(1.43)			(1.71)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	39.56***	32.18***	33.55***	26.53***	21.71***	21.67***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined as those suitable for drug production (SEDENA index different from 0). The dependent variable is homicide rate per 100,000 inhabitants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.12: Effect of the structure of the OPN on homicide rates (DID model, drug region defined through a drug producion index)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	4.52***	4.04***	3.84***	7.69**	5.88*	5.77*
	(1.27)	(1.25)	(1.25)	(3.38)	(3.28)	(3.28)
oil_c.MWD	5.10***	6.05***	5.71***	3.03*	4.15**	3.79**
	(1.68)	(1.64)	(1.64)	(1.83)	(1.76)	(1.75)
oil_c.drug.MWD	5.42	4.88	5.63	2.25	3.25	3.77
	(6.49)	(6.26)	(6.28)	(7.21)	(7.06)	(7.09)
oil_f.MWD	6.35***	7.04***	7.19***	4.28**	5.28***	5.31***
	(1.80)	(1.85)	(1.85)	(1.94)	(1.99)	(1.98)
oil_f.drug.MWD	−1.95	−2.12	−1.87	−5.12	−4.31	−4.17
	(3.37)	(3.37)	(3.34)	(4.61)	(4.48)	(4.46)
gov_violence			5.88***			4.35**
			(1.44)			(1.72)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	35.47***	29.85***	31.21***	23.80***	20.14***	20.17***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined as those suitable for drug production (SEDENA index different from 0). The dependent variable is homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.13: Effect of oil on homicide rates (SARAR model, drug region defined through a drug producion index)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.74	0.01	101.96	0.00
rho	-0.59	0.01	-40.41	0.00
drug.MWD	1.48	0.63	2.36	0.02
oil_c.MWD	1.27	1.43	0.89	0.37
oil_c.drug.MWD	5.58	4.43	1.26	0.21
oil_f.MWD	3.61	0.77	4.71	0.00
oil_f.drug.MWD	-1.57	1.83	-0.86	0.39
gov_violence	3.76	0.54	7.00	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	1.72	0.02	3.93	0.02	5.65	0.02
oil_c.MWD	1.48	0.36	3.38	0.37	4.86	0.37
oil_c.drug.MWD	6.50	0.30	14.80	0.30	21.30	0.30
oil_f.MWD	4.21	0.00	9.59	0.00	13.79	0.00
oil_f.drug.MWD	-1.83	0.39	-4.17	0.40	-6.00	0.40
gov_violence	4.38	0.00	9.99	0.00	14.37	0.00

Notes: This table reports maximum likelihood estimations of model (12) when the municipalities valuable for drug trafficking are defined as those suitable for drug production (SEDENA index different from 0). The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. The upper panel shows the coefficients resulting from maximum likelihood estimations of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

Tables C.14-C16 show the estimations in Tables 1, 3 and 4 when we define the drug-valuable region employing the measure of connectivity used by Calderon et al. (2016).

Table C.14: Effect of oil on homicide rates (DID model, drug region defined through a connectivity measure)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	7.89***	10.15***	9.47***	3.58	5.62*	5.59*
	(2.17)	(2.16)	(2.06)	(3.16)	(3.11)	(3.08)
oil.MWD	5.17***	6.04***	6.13***	2.40	3.79**	3.79**
	(1.50)	(1.53)	(1.53)	(1.82)	(1.82)	(1.81)
oil.drug.MWD	−3.73	−4.95	−4.10	0.57	−0.03	0.11
	(3.99)	(3.80)	(3.79)	(4.60)	(4.38)	(4.36)
gov_violence			7.13***			5.73**
			(1.64)			(2.33)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,540	36,540	36,540	15,870	15,870	15,870
F Statistic	39.10***	32.64***	34.42***	25.69***	21.57***	21.71***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined employing the measure of connectivity used by Calderon et al. (2016). The dependent variable is homicide rate per 100,000 inhabitants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.15: Effect of the structure of the OPN on homicide rates (DID model, drug region defined through a connectivity measure)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	7.89***	10.15***	9.46***	3.58	5.62*	5.58*
	(2.17)	(2.15)	(2.06)	(3.16)	(3.11)	(3.08)
oil_c.MWD	5.16***	6.10***	6.02***	2.39	3.75*	3.61*
	(1.88)	(1.80)	(1.81)	(2.15)	(2.02)	(2.02)
oil_c.drug.MWD	−6.02	−6.63	−6.80	−1.71	−1.54	−2.20
	(5.22)	(5.23)	(5.29)	(5.70)	(5.79)	(5.83)
oil_f.MWD	5.17***	6.03***	6.15***	2.41	3.79*	3.82*
	(1.72)	(1.75)	(1.75)	(2.01)	(2.01)	(2.00)
oil_f.drug.MWD	−3.17	−4.54	−3.42	1.14	0.34	0.70
	(4.53)	(4.29)	(4.29)	(5.08)	(4.78)	(4.78)
gov_violence			7.15***			5.76**
			(1.64)			(2.34)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,540	36,540	36,540	15,870	15,870	15,870
F Statistic	35.00***	30.23***	31.97***	22.99***	19.97***	20.17***

Notes: This table reports the results of estimating model (11) when the municipalities valuable for drug trafficking are defined employing the measure of connectivity used by Calderon et al. (2016). The dependent variable is homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.16: Effect of oil on homicide rates (SARAR model, drug region defined through a connectivity measure)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.73	0.01	106.58	0.00
rho	-0.59	0.01	-41.25	0.00
drug.MWD	4.01	0.69	5.78	0.00
oil_c.MWD	1.57	2.03	0.77	0.44
oil_c.drug.MWD	-1.80	3.16	-0.57	0.57
oil_f.MWD	3.43	0.90	3.83	0.00
oil_f.drug.MWD	-2.78	1.60	-1.74	0.08
gov_violence	4.74	0.62	7.65	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	4.66	0.00	10.40	0.00	15.06	0.00
oil_c.MWD	1.82	0.41	4.06	0.41	5.87	0.41
oil_c.drug.MWD	-2.09	0.50	-4.66	0.50	-6.75	0.50
oil_f.MWD	3.99	0.00	8.90	0.00	12.88	0.00
oil_f.drug.MWD	-3.23	0.11	-7.20	0.11	-10.43	0.11
gov_violence	5.51	0.00	12.29	0.00	17.80	0.00

Notes: This table reports maximum likelihood estimations of model (12) when the municipalities valuable for drug trafficking are defined employing the measure of connectivity used by Calderon et al. (2016). The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The dependent variable is the homicide rate per 100,000 inhabitants. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. The upper panel shows the coefficients resulting from maximum likelihood estimations of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

C.3 Sources of Violence

Tables C.17-C19 show the estimations in Tables 1, 3 and 4 when the outcome variable is $Imports_{m,t}/Homicides_{m,t}$, where $Imports_{m,t}$ is the number of homicides in the municipality m in the year t when the victim is a legal resident of a municipality different from m and $Homicides_{m,t}$ is the total number of homicides in the municipality m in the year t.

Table C.17: Effect of oil on $Imports_{m,t}/Homicides_{m,t}$ (DID model)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	2.77***	2.83***	2.80***	0.99	1.17	1.24
	(0.84)	(0.83)	(0.83)	(1.59)	(1.56)	(1.56)
oil.MWD	7.78***	7.39***	7.41***	4.58***	4.57***	4.58***
	(1.06)	(1.07)	(1.07)	(1.30)	(1.31)	(1.31)
oil.drug.MWD	−6.78***	−6.13***	−6.05***	−4.99**	−4.54**	−4.57**
	(1.72)	(1.70)	(1.70)	(2.19)	(2.15)	(2.14)
gov_violence			1.96***			1.98***
			(0.67)			(0.44)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	61.84***	45.25***	44.03***	43.52***	31.45***	30.57***

Notes: This table reports the results of estimating model (11) when the dependent variable is $Imports_{m,t}/Homicides_{m,t}$. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.18: Effect of the structure of the OPN on $Imports_{m,t}/Homicides_{m,t}$ (DID model)

	Dependent variable:					
	Homicide rate					
	(1)	(2)	(3)	(4)	(5)	(6)
drug.MWD	2.77***	2.83***	2.80***	0.99	1.18	1.25
	(0.84)	(0.83)	(0.83)	(1.59)	(1.56)	(1.56)
oil_c.MWD	5.68**	5.61*	5.62*	2.47	2.67	2.66
	(2.88)	(2.90)	(2.90)	(2.98)	(2.98)	(2.98)
oil_c.drug.MWD	−0.03	0.28	0.16	1.75	1.96	1.74
	(3.86)	(3.81)	(3.82)	(4.09)	(4.02)	(4.03)
oil_f.MWD	8.16***	7.70***	7.72***	4.95***	4.91***	4.92***
	(1.12)	(1.12)	(1.12)	(1.35)	(1.35)	(1.35)
oil_f.drug.MWD	−8.25***	−7.55***	−7.41***	−6.47***	−5.98***	−5.96***
	(1.84)	(1.82)	(1.81)	(2.29)	(2.24)	(2.23)
gov_violence			1.92***			1.93***
			(0.67)			(0.44)
Covariates	N	Y	Y	N	Y	Y
Neighbors	N	N	N	Y	Y	Y
Observations	36,825	36,825	36,825	16,095	16,095	16,095
F Statistic	55.71***	42.15***	41.11***	39.27***	29.35***	28.59***

Notes: This table reports the results of estimating model (11) when the dependent variable is $Imports_{m,t}/Homicides_{m,t}$. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. Columns 4-6 restrict the sample to OPN members and their non-oil neighbors. All regressions include individual fixed effects and year fixed effects. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was employed. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.19: Effect of oil on $Imports_{m,t}/Homicides_{m,t}$ (SARAR model)

	Estimate	Std. Error	t-value	Pr(>|t|)
lambda	0.41	0.02	20.54	0.00
rho	-0.40	0.03	-14.73	0.00
drug.MWD	1.03	0.56	1.85	0.06
oil_c.MWD	3.89	1.30	3.00	0.00
oil_c.drug.MWD	4.56	3.84	1.19	0.23
oil_f.MWD	4.60	0.69	6.68	0.00
oil_f.drug.MWD	-4.30	1.60	-2.68	0.01
gov_violence	1.83	0.47	3.89	0.00

Impact Analysis:

	Direct	p.Direct	Indirect	p.Indirect	Total	p.Total
drug.MWD	1.07	0.07	0.69	0.08	1.77	0.07
oil_c.MWD	4.03	0.00	2.62	0.00	6.65	0.00
oil_c.drug.MWD	4.72	0.33	3.06	0.34	7.78	0.33
oil_f.MWD	4.76	0.00	3.09	0.00	7.85	0.00
oil_f.drug.MWD	-4.45	0.00	-2.89	0.00	-7.34	0.00
gov_violence	1.89	0.00	1.23	0.00	3.12	0.00

Notes: This table reports maximum likelihood estimations of model (12) when the dependent variable is $Imports_{m,t}/Homicides_{m,t}$. The model includes a spatial lag of the outcome variable and a spatial auto-regressive component in the error term. The variable Oil_c_m (Oil_f_m) is an indicator for municipalities neighboring (far away from) municipalities hosting hydrocarbon processing plants. The upper panel shows the coefficients resulting from maximum likelihood estimations of (12). The lower panel shows the corresponding impact effect analysis with p values obtained through Monte Carlo simulations. Standard errors clustered at the municipality level in parenthesis. In all cases, the robust variance matrix estimator suggested by Arellano (1987) was used.

C.4 Spatial Model Specification

To determine the most accurate specification to deal with spatial dependency, we resorted to locally robust Lagrange Multiplier tests based on Anselin et al. (1996) and adapted to panel data structures by Debarsy and Ertur (2010). Such procedures test the absence of spatial correlation in the outcome variable (captured by the parameter λ) and a spatial auto-regressive component in the error term (captured by the parameter ρ without having to estimate the unconstrained model. Following Bouayad, Le Gallo and Vedrine (2018), we refer to the test for the absence spatial correlation in the outcome variable as the SAR test and the test for the absence a spatial auto-regressive component in the error term as the SEM test. These two tests are often accompanied by procedures that test for the absence of either of the parameters, say λ, while the other parameter, say ρ, is present in the model. The test that leaves ρ in the model is called the RLMlag test, while the test that leaves λ in the model is called the RLMerr test. Due to computational power constraints, we had to run these tests on groups of subsamples, each of them comprising different subsets of years between 2001 and 2015. Each column in Tables C.20 and C.21 refers to the results of these tests applied to four different subsamples. The corresponding small p-values lead us to reject the absence of either spatial parameter, which justifies using the SARAR model.

Table C.20: Specification tests for spatial models (outcome variable: homicide rate per 100,000 inhabitants)

	1	2	3	4	5	6	7	8
SAR	1681.65	1587.19	134.68	40.21	0.00	0.00	0.00	0.00
SEM	1040.48	995.26	71.40	26.18	0.00	0.00	0.00	0.00
RLMlag	1761.47	1627.33	218.13	83.99	0.00	0.00	0.00	0.00
RLMerr	409.88	365.68	114.14	69.95	0.00	0.00	0.00	0.00

Notes: The underlying model is (12). SAR (SEM) tests for the absence of a spatial auto-regressive process in the outcome variable (error term). RLMlag (RLMerr) tests for the absence of a spatial auto-regressive process in the outcome variable (error term) when the model comprises a spatial auto-regressive term in the error term (outcome variable). Columns 1-4 employ groups of years given by $\{01, 05, 09, 11\}$, $\{03, 07, 11, 15\}$, $\{02, 04, 08, 10\}$, and $\{04, 06, 12, 15\}$, respectively. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.21: Specification tests for spatial models (outcome variable: $Imports_{m,t}/Homicides_{m,t}$)

	1	2	3	4	5	6	7	8
SAR	1682.60	1589.15	131.88	38.43	0.00	0.00	0.00	0.00
SEM	1040.58	995.42	71.27	26.11	0.00	0.00	0.00	0.00
RLMlag	1761.18	1627.23	217.18	83.23	0.00	0.00	0.00	0.00
RLMerr	409.40	365.28	113.10	68.99	0.00	0.00	0.00	0.00

Notes: The underlying model is (12). SAR (SEM) tests for the absence of a spatial auto-regressive process in the outcome variable (error term). RLMlag (RLMerr) tests for the absence of a spatial auto-regressive process in the outcome variable (error term) when the model comprises a spatial auto-regressive term in the error term (outcome variable). Columns 1-4 employ groups of years given by $\{01, 05, 09, 11\}$, $\{03, 07, 11, 15\}$, $\{02, 04, 08, 10\}$, and $\{04, 06, 12, 15\}$, respectively. Significance values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.