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FUELING ORGANIZED CRIME: THE MEXICAN WAR ON DRUGS AND OIL THEFTS

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Fueling Organized Crime: The Mexican War on Drugs and Oil Thefts*

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Abstract

We show that the War on Drugs launched by the Mexican President Felipe Calderón in 2007 pushed drug cartels into large-scale oil thefts. Municipalities that the presidential candidate's party barely won at the local elections in 2007-2009 exhibit a larger increase in illegal oil taps over the following years, compared to municipalities in which the presidential candidate's party barely lost the elections. Challenger cartels in the drug market leapfrog incumbent drug cartels when entering the new illegal activity, analogous to what is typically observed in legal markets. Since challengers and incumbents specialize in different criminal sectors, the expansion of challengers does not increase violence in municipalities traversed by oil pipelines. At the same time, the municipalities traversed by a pipeline witness a decrease in schooling rates.

JEL Classification: K42, L20

Keywords: Organized crime, War on Drugs, Oil thefts, Leapfrogging

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1 Introduction

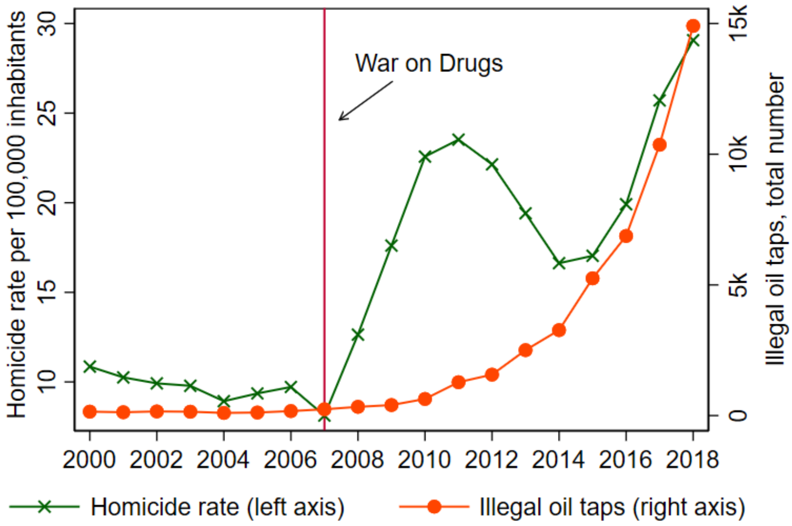
Criminal organizations are a major threat to security and human development in several regions, and Mexican drug cartels stand out in terms of violence and economic power (DEA, 2017). In 2007, the newly appointed President Felipe Calderón of the National Action Party (PAN) launched the Mexican War on Drugs, an extensive military campaign aimed at dismantling drug cartels. However, the crackdown led to an impressive escalation of violence, due to confrontations between the state and the cartels as well as between and within cartels (Calderón et al., 2015; Castillo and Kronick, 2020). Between 2007 and 2018, the homicide rate more than tripled – from 8 to 29 homicides per 100,000 inhabitants – making Mexico the 5^{th} deadliest country in the world. In addition, cartel activity spilled over from areas governed by PAN into new areas, spreading more violence (Dell, 2015).

In the same period there was spectacular growth in a new type of criminal undertaking: oil thefts. Large-scale oil theft is achieved by tapping the underground pipelines of Pemex, the state-owned petroleum company. Figure 1 shows that this new criminal business started to emerge shortly after the War on Drugs started, and grew exponentially over the following decade. The number of taps increased from a few hundred per year in the period before 2007 to around four thousand in 2014, and 15 thousand by 2018, with the value of stolen oil ranging between 1-2 US$ billion per year (Duhalt, 2017). This escalation was associated with numerous explosions of tapped pipelines as well as gasoline shortages across the country, making oil taps a major national problem.[1]

In this paper, we draw a causal relationship between the War on Drugs, which greatly reduced profit margins from drug-trafficking, and oil thefts. We characterize the types of cartels entering this new illegal business, and we estimate the socio-economic impacts of this reallocation from drug-trafficking to oil thefts in municipalities traversed by oil pipelines. Our empirical analysis leverages spatial, time-varying data on oil taps and cartel presence together with plausibly exogenous variation in the intensity of the War on Drugs across municipalities, as measured by the political alignment of the municipal government. Melissa Dell (2015) argues, indeed, that PAN candidates who succeeded in the first mayoral elections held after the start of the War on Drugs (2007-2009) favored the coordination of the crackdown on narcotics at the local level. Therefore, she estimates the effect of government crackdowns on drug-related violence and drug-trafficking routes by comparing municipalities in which PAN candidates won or lost by a narrow margin. Using the same Regression Discontinuity (RD) design within the sub-sample of municipalities traversed by oil pipelines, we show that municipalities in which the PAN candidate won a local election by a narrow margin in 2007-2009 had more taps over the following period, 2007-2014, compared to municipalities in which the PAN candidate lost by a narrow margin. This suggests that the drug crackdown pushed cartels already active within a municipality towards the new busi-

[1] See, for example, BBC News (2019a) and BBC News (2019b).

Figure 1: The Mexican War on Drugs, homicides, and illegal oil taps



Notes: This figure plots the homicide rate in Mexico (left scale) and the number of illegal oil taps (right scale) over the period 2000-2018.

ness of oil thefts. In our simplest specification (a local linear regression within an optimal bandwidth around the cutoff), the difference between municipalities where PAN candidates barely won or lost amounts to +6.6 taps per year, corresponding to more than a doubling over the baseline average number of taps during the same period in municipalities with pipelines (5.3 per year). The effect remains large and statistically significant across a variety of specifications – namely, employing different polynomial degrees, bandwidths, kernels within the bandwidth, and including state and year fixed effects.

We then study which cartels entered the new illegal business of oil thefts, exploiting variation across municipalities. Recent decades witnessed a growing fragmentation of criminal groups, leading to greater conflict and violence. Younger and smaller cartels, including the (in)famous "*Zetas*," challenged the drug market oligopoly of older and larger organizations, such as the "*Cartel del Golfo*." However, the challengers still have lower profit margins from drug-trafficking so they may have a comparative advantage in other criminal sectors, such as large-scale oil thefts. We provide evidence consistent with this theory using a difference-in-differences design together with time-varying data on cartel presence across municipalities, as found in Coscia and Rios (2012). In particular, we compare cartel presence in municipalities with pipelines and neighboring municipalities without pipelines, before and after the start of the War on Drugs. Coscia and Rios (2012) report the identity of all cartels present in each municipality, so we can study entry into pipeline municipalities separately by incumbents and challengers in drug-trafficking. We find that after 2007 cartel presence increased relatively more in areas with pipelines compared to neighboring municipalities without pipelines, and that the effect is entirely driven by challengers in the drug market entering new municipalities where they face no competition from other cartels. These patterns are consistent with evidence from industrial organization and international economics, whereby challengers in traditional, mature sectors may leapfrog incumbents when entering new, expanding sectors (see, e.g., Fudenberg et al., 1983; Brezis et al., 1993).

Finally, we estimate the effects of cartel expansion on different indicators of local socio-economic development, starting with the effect on homicide rates. In theory the effect is ambiguous: the entry of cartels into new activities and territories may have expanded the scope for violence, but the specialization of challengers into different criminal sectors may have attenuated competitive pressures in drug-trafficking and, consequently, reduced violent confrontations between cartels. Figure 1 shows a positive correlation between oil taps and murders over time, which may reflect, however, the effect of the War on Drugs on both variables. To isolate the causal effect of oil taps on murders, we compare homicide rates between municipalities with and without pipelines, before and after 2007. We find that a greater presence of cartels in pipeline municipalities after 2007 does *not* impact local homicide rates. This finding is consistent with additional evidence showing that challengers typically expand into pipeline municipalities where they face no competition from other cartels. At the same time, the entry of drug cartels brings a decline in schooling for children aged less than 15 years. In line with this finding, several Mexican reports have highlighted the widespread use of teenagers in this business, used as cheap labor.[2] This is an outcome that typically responds very quickly to changes in socio-economic conditions, including the presence of criminal groups (Sviatschi et al., 2019), and may have important consequences for long-term development.

We add to a burgeoning literature on the impact of the Mexican War on Drugs and other government crackdowns against criminal organizations in Latin America (see Lessing, 2017, for a survey). Much of this literature emphasizes the unintended consequences of crackdowns such as violence (Ríos, 2013; Dube and Naidu, 2015; Calderón et al., 2015; Lindo and Padilla-Romo, 2018; Daniele et al., 2020), refugee out-migration (Rios, 2014; Orozco-Aleman and Gonzalez-Lozano, 2017), and even increases in drug production (Prem, Vargas, and Mejía, Prem et al.). Importantly, the adverse effects of targeted enforcement policies may spill over to other regions within the same country, as they did in Mexico (Dell, 2015), and even to other countries, as occurred when cocaine seizures in Colombia increased conflict among Mexican drug cartels (Mejia and Restrepo, 2016; Castillo et al., 2020).

We contribute to this literature in two ways. First, we show that targeted government crackdowns may spill over not only to other geographical areas but also to other criminal sectors, and even initiate a new criminal business that did not exist previously (at least on an "industrialized" scale). Second, we show that the expansion of drug cartels into new geographical areas does not necessarily translate into higher violence.

[2] See for instance: "En los últimos 15 años, 4,145 menores han sido detenidos por huachicol, revela FGR"

In both respects, our paper is most closely related to Lopez Cruz and Torrens (2019), who compare changes in violence after the start of the War on Drugs between pipeline municipalities and all other municipalities in Mexico, finding an increase in homicides. Conversely, we find a null effect on homicides rates: the two papers differ upon several dimensions which can explain such different findings on violence.[3] Moreover, our main focus is on cartel presence and their strategic re-positioning across areas and sectors – notably, which cartels enter oil thefts – while Lopez Cruz and Torrens (2019) focus only on the effects on violence.

These results on the specialization of incumbent and challenger cartels in different criminal sectors contribute to existing evidence on the functioning and organization of illegal markets, and analogies with legal sectors (Reuter, 1985; Fiorentini and Peltzman, 1997; Fiorentini and Zamagni, 1999; Becker et al., 2006; Moore et al., 2009; Olken and Barron, 2009; Chimeli and Soares, 2017; Kronick, 2020). Specifically, we show that leapfrogging of incumbents by challengers when entering a new sector, which has been extensively documented in legal markets (see, e.g., Fudenberg et al., 1983, Brezis et al., 1993), is seen also in illegal markets.

We also add to the evidence on the effects of criminal organizations on local development. Although Pinotti (2015) and Acemoglu et al. (2020) document detrimental effects of Italian criminal organizations on economic activity and violence in Southern Italy, the evidence from Mexico remains mixed. Exploiting exogenous variation in opioid production due to Chinese immigration to Mexico at the beginning of the 20^{th} century, Murphy and Rossi (2020) estimate *positive* effects of drug cartels on several socio-economic outcomes. On the other hand, Gutiérrez-Romero and Oviedo (2017) reach an opposite conclusion with their difference-in-differences comparison of municipalities experiencing and not experiencing violence after the start of the War on Drugs. Our results complement these findings by showing that the possibility of reallocating activity to a different criminal business helps reduce both violent conflicts between cartels and their negative impacts on economic activity. On the other hand, we still detect negative effects on education, in line with Sviatschi et al. (2019).

Finally, our paper is related to the literature on natural resource wars (Dube and Vargas, 2013; Caselli et al., 2015; Berman et al., 2017; Gallea et al., 2020; Van der Ploeg and Rohner, 2012). In particular, Sobrino (2019) finds that growing demand for heroin after 2010 caused both an expansion in cartel presence and an increase in violence in territories suitable for opium production. In these territories, cartels were competing for the same criminal

[3] The main differences concern: i) the definition of the treated (and in turn control) units, as we consider only pipelines carrying refined oil, where taps take place; ii) their results are conditional to the inclusion of potentially endogenous controls (drug seizures and clashes between drug cartels and the army); iii) and the inclusion of population among control variables, which is also included in the denominator of the dependent variable (homicide rates); iv) their main analysis compares pipeline municipalities and all other municipalities in Mexico. Interestingly, in a further analysis they restrict the control group to neighboring municipalities finding a small and barely significant positive effect which more closely resembles our findings.

business, while in our case only challenger cartels expanded to pipeline municipalities after the crackdown on narcotics, due to their weaker position in this traditional sector. This important difference may explain the absence of any effect on violence in our case.

In the next Section we provide additional background information on Mexican drug cartels, the War on Drugs, and illegal oil tapping. Section 3 is a description of the data, and Section 4 contains the methodology and the results of our empirical analysis. The conclusion is in Section 5.

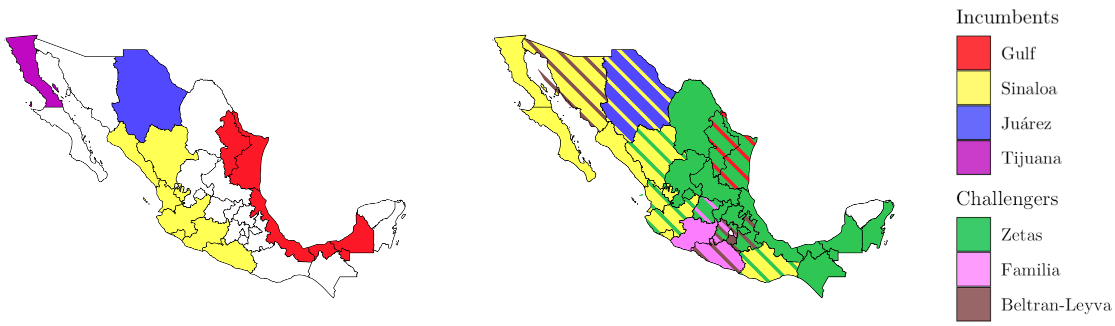
2 Institutional background

2.1 Mexican drug cartels and the Mexican War on Drugs

Traditionally the core business of Mexican criminal organizations is narcotics (particularly opium and marijuana), driven by high demand from the US (Boullosa and Wallace, 2015; Murphy and Rossi, 2020). The sector was very fragmented until the 1980s, when Felix Arellano Gallardo unified local producers and traffickers under the umbrella of the Guadalajara cartel in order to negotiate cocaine smuggling across the US border with the powerful Colombian cartels. However, the entry into the lucrative cocaine market attracted the attention of US authorities under Reagan, whose administration eventually dismantled the Guadalajara cartel in 1989. Before being arrested, Arellano Gallardo distributed the main trafficking routes among four groups: the Pacific route to the Sinaloa cartel; the Atlantic route to the Gulf cartel; and the two internal routes to the Tijuana and Juarez cartels. The map on the left in Figure 2 shows the areas of influence of each cartel in the 1990s (Trejo and Ley, 2020).

Figure 2: Areas of influence of Mexican cartels

(a) Dominant cartels in the 1990s (b) Dominant cartels in 2011



Notes: Panel (a) and (b) show the areas of influence Mexican drug cartels in the 1990s and in 2011, based on information from Trejo and Ley (2020) and Beittel (2011).

The four cartels coexisted without inter-cartel conflict through the 1990s, a period characterized by a generalized decline in violence (the homicide rate decreased from 19 to 10 homicides per 100,000 inhabitants). The equilibrium was sustained, among other things, by2 stable networks of collusion between drug cartels and the local branches of the *Partido Revolucionario Institucional* (PRI), which had been ruling Mexico continuously since 1929 (Dell, 2015; Trejo and Ley, 2018).

However, the political landscape changed dramatically at the turn of the century, when the *Partido Acciòn Nacional* (PAN) won the presidential elections in 2000 and then again in 2006. A few months after the 2006 elections, the new President Felipe Calderón launched a vast military campaign against drug cartels, increasing from 6,500 to 45,000 the number of federal troops deployed in the War on Drugs. This escalation resulted in a surge in violence, due especially to conflicts between and within the cartels over reduced profits from narcotics (Ríos, 2013; Medel and Thoumi, 2014; Calderón et al., 2015).

The increasing fragmentation and proliferation of cartels during the War on Drugs is evident in the two maps in Figure 2. The right map shows the areas of influence, in 2011, of the most important cartels emerging in the late 2000s – *Zetas*, *Familia Michoacana*, and *Beltran-Leyva* – alongside with older cartels already present in the 1990s – Gulf, Juarez, Sinaloa, and Tijuana. We refer to the former group of cartels as *challengers*, and to the latter as *incumbents*.

The two groups of cartels differed markedly in terms of specialization. As the early entrants in narcotics, incumbents always maintained a dominant position in the drug market, while challengers diversified their activities across a variety of different (criminal) sectors. This pattern is exemplified by the *Zetas*. Founded as the military arm of the Gulf cartel, they turned independent in 2010 and have become a multinational/transnational organization active in many illegal activities including narcotics, fuel theft, large-scale extortion, kidnapping, and human trafficking (Correa-Cabrera, 2017). This diversification is a strategic response by new cartels to reduced profits in drug-trafficking after the government crackdown on narcotics. The same strategy is less attractive for older cartels, which hold a dominant position (and higher profits) in the drug market. We will investigate this hypothesis for the specific case of oil theft, which emerged in the last 10-15 years as the main criminal business alongside drugs.

2.2 Oil theft

Mexico is a major oil producer, with hydrocarbons accounting for about a third of total government revenues (Segal, 2011). The main Mexican oil company, Pemex, was created in 1938 from the nationalization of the sector and is currently the 10^{th} largest oil producer in the world, and the second-largest in Latin America (Ali, 2020).

Pemex has lamented an exponential increase in large-scale oil thefts, as already shown in Figure 1. The oil is stolen by directly tapping refined oil from pipelines. Once perpetrated in a rudimentary fashion by small groups of *huachicoleros* (Spanish for "oil thieves"), oil taps have become a complex criminal business under the control of large criminal organizations. Drug cartels use their military power and considerable economic resources to acquire restricted information on the exact location of pipeline valves, through bribery and intimidation of Pemex employees. According to Farfan (2015), "*Pemex employees install tapping machines for third parties who pay up to $6,000 dollars for a single tap – a considerable amount given that households have an average yearly disposable income of approximately $13,000 dollars.*" Drug cartels also have access to the costly technologies and human capital required to tap pipelines on an industrial basis, store large amounts of refined oil, and sell it on the black market. When oil prices were at a peak, seven minutes of tapping could earn a cartel as much as $90,000 (Ralby, 2017).

3 Data

3.1 Oil taps and pipelines

Pemex has a division dedicated to monitoring illegal taps, capturing information about thefts that local law enforcement might miss. Its data on the annual number of illegal taps across municipalities was published in the newspaper *El Universal*.[4] These data are available for the period 2000-2014.[5]

We complement data on illegal taps with information on the location of pipelines. Although Pemex does not disclose this information for security reasons, the Mexican NGO "*CartoCritica*" determined the exact location of pipelines via multiple sources, including Freedom of Information Acts and data leaks. Based on these data, we identify municipalities that are traversed by pipelines, and those that are not.

Figure 3 shows the location of pipelines (Panel a) and taps (Panel b). We focus our main analysis on theft of refined oil, which is most profitable because it is easier to tap and resell. In Figure A.1 in the Appendix we show that refined oil taps account for virtually all fuel thefts. We will use gas pipelines as a placebo, as they share many characteristics with oil pipelines (e.g., their location should respond to the same constraints); at the same time, gas cannot be stolen and stored by criminals.

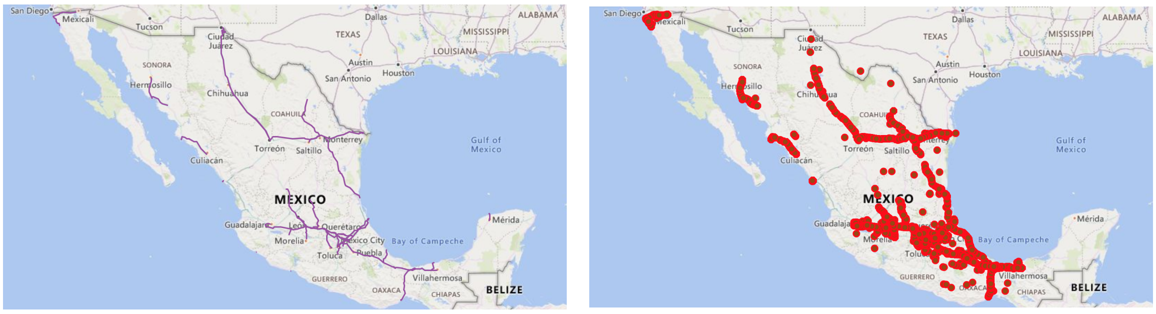
Refined oil pipelines cross 313 municipalities, 54 of which also host oil depots (*Terminales de Almacenamiento y Reparto*, TARs); see the first row of Appendix Table A.1. Table A.1 also shows that oil depots are typically located in large cities. The average population during the period 2000-2015 in municipalities with a pipeline and TARs was close to 440 thousand, ten times larger than in the average municipality and five times larger than in pipeline municipalities without TARs. Since part of our empirical analysis compares

[4] *El Universal*'s archive is available at https://archivo.eluniversal.com.mx.

[5] Figure 1 plots the number of taps through to year 2018, but only the total number of yearly taps (not their location) is available for the period after 2014.

Figure 3: Pipelines and illegal taps

(a) Pipelines (b) Illegal taps



Notes: Panel (a) shows the location of pipelines in Mexico. Panel (b) shows the location of illegal taps between 2008 and 2015. Source: *CartoCritica*.

(changes in) outcomes between pipeline municipalities and neighboring non-pipeline municipalities, we exclude municipalities with TARs in order to reduce differences in average population between the two groups.[6]

Panel A of Table 1 provides summary statistics on illegal taps over different periods of time. In line with the visual evidence in Figure 1, the average number of taps across municipalities with pipelines (columns 4-5) increased after the start of the War on Drugs – from 0.4 to 1 during the period 2007-2009, and then further to 5.3 during the period 2010-2014.

3.2 Cartel presence

Measures of organized crime based on judicial data are subject to severe under-reporting, especially in contexts where criminal organizations are very powerful (see, e.g., Pinotti, 2020). To overcome these difficulties, Coscia and Rios (2012) measure the presence of drug cartels across municipalities over the period 2000-2010 by systematically scraping and coding Google News entries about cartel activity. To minimize biases in reporting, they capture all news referring to either drug cartels or their members, and measure cartel presence by a dummy equal to 1 if (at least) one news item is recorded in a municipality-year. Most importantly for the purposes of our analysis, Coscia and Rios (2012) provide information on the cartel(s) involved in each event. In particular, they distinguish between each of the four incumbent cartels (Gulf, Juarez, Sinaloa, and Tijuana), each of the three challenger cartels (Beltran-Leyva, Familia Michoacana, and Zetas), and include a residual category of "other cartels."

Panel B of Table 1 confirms that drug cartels greatly expanded their presence across

[6] All results remain virtually identical when including municipalities with TARs. These results are available upon request.

Table 1: Descriptive statistics on taps and cartel presence

	(1)	(2)	(3)	(4)	(5)	(6)
	All municipalities			Pipelines municip. (no TARs)		
	2000-06	2007-09	post-2009	2000-06	2007-09	post-2009
Panel A: Illegal taps (2000-2014)						
Number of TAPs	0.061	0.16	0.786	0.416	1.035	5.32
	[0.489]	[0.991]	[6.065]	[1.162]	[2.343]	[14.696]
Any tap	0.03	0.054	0.06	0.217	0.353	0.418
	[0.17]	[0.225]	[0.237]	[0.413]	[0.478]	[0.493]
Panel B: Cartel presence (2000-2010)						
Any cartel	0.051	0.223	0.289	0.072	0.463	0.51
	[0.22]	[0.417]	[0.453]	[0.259]	[0.499]	[0.501]
Any incumbent	0.039	0.148	0.159	0.058	0.256	0.286
	[0.195]	[0.355]	[0.366]	[0.235]	[0.437]	[0.453]
Any challenger	0.024	0.175	0.255	0.031	0.315	0.475
	[0.153]	[0.38]	[0.436]	[0.175]	[0.465]	[0.5]

Notes: This table shows means and standard deviations (in squared brackets) for illegal taps and cartel presence (panels A and B), distinguishing between all municipalities and pipeline municipalities (columns 1-3 and 4-6), for different periods indicated on top of each column.

Mexican municipalities during the 2000s. In 2010 at least one cartel was active in close to 30% of municipalities, up from 5% before the War on Drugs. Interestingly, challengers expanded more aggressively, increasing their presence by ten times (from 2.4 to 25.5 percent of municipalities) compared to incumbents (up from 4 to 16 percent of municipalities), and both challengers and incumbents expanded more into municipalities with pipelines (columns 4-6 of Panel B). In our empirical analysis we investigate these changes in detail.

3.3 Other data

Following Dell (2015), we proxy for differences in the intensity of the War on Drugs at the local level by the political alignment of mayors appointed in the 2007-2009 round of municipal elections. In particular in the early years of the War on Drugs, mayors from the party of the President, PAN, should have collaborated more effectively with the government's anti-drug efforts. We took the electoral results of each Mexican state and computed the margin of victory (or loss) for PAN candidates in each municipality.

We also collect three measures of socio-economic development at the municipal level, for which we show the summary statistics in Appendix Table A.1. As is typical of many low and middle-income countries, the Mexican economy has a large informal sector so we proxy for economic activity with a measure of night-time light density for the period 2004-2013. In addition to capturing both official and unofficial activity, this measure has the additional advantage of being available at any level of geographical disaggregation and time-frequency (see, e.g. Donaldson and Storeygard, 2016; Alesina et al., 2016; Proville et al., 2017).[7] The Mexican National Statistical Institute (*Instituto Nacional de Estadistica y Geografia*, INEGI) provides the number of homicides during the period 2000-2016 and the number of children per 1,000 (aged between 6-14) not attending school in census years 2000, 2005, 2010, and 2015. Finally, INEGI provides several municipality geo-morphological characteristics, namely surface, altitude, temperature, slope, and distance to the US border; summary statistics for these variables are also presented in Appendix Table A.1.

4 Results

We present the empirical strategy and the results for three measures of cartel activity. First, we estimate the causal effect of the War on Drugs on oil thefts (Section 4.1). Second, we investigate which cartels entered this new criminal business (Section 4.2). Third, we estimate the impact of cartel expansion on local development across municipalities (Section 4.3).

[7]We follow the procedure developed by National Oceanic and Atmospheric Administration and del Valle et al. (2020), which filters out the transient light observed in the raw satellite imagery in order to obtain stable cloud-free night light images measuring human-made lights.

4.1 The impact of the Mexican War on Drugs on oil thefts

As already discussed, oil thefts became a major criminal business in Mexico only after the War on Drugs started (see Figure 1). To draw a causal relationship between these two phenomena, we exploit variation in the intensity of the War on Drugs across municipalities, as measured by the political alignment of the mayor.

4.1.1 Empirical strategy

As discussed by Dell (2015), political alignment between the central and local governments in the first years of the War on Drugs favored the coordination of the crackdown on narcotics at the local level. Dell (2015) compares violence between municipalities in which the PAN party (barely) won and lost local elections in the 2007-2009 electoral round. We employ the same RD design to estimate the effect on the number of taps.

We regress the average number of illegal $Taps$ per year between the election year and 2014 across municipalities with pipelines on a dummy for PAN candidates appointed in municipality i at the electoral round 2007-2009, a k-th order polynomial in the PAN's margin of victory (MV), and the interaction between the two:

$$Taps_i = \alpha + \beta PAN_i + \sum_k \delta_k MV^k + \sum_k \gamma_k (PAN_i \cdot MV^k) + FE_s + FE_e + \epsilon_i, \qquad (1)$$

where FE_s and FE_e are fixed effects for Mexican states and election years, and ϵ_i is a residual term summarizing other factors. To the extent that these factors are not systematically different between PAN and non-PAN municipalities (after controlling flexibly for the polynomial in MV and for state and election fixed effects), the coefficient β estimates the causal effect of crackdown efforts, as captured by the political alignment of the local government. To further reduce the impact of other omitted factors, we restrict the analysis to observations within a bandwidth of the cutoff $MV = 0$, chosen according to the criterion of Calonico et al. (2014).[8] Appendix Table A.2 confirms that predetermined municipality characteristics are balanced at the cutoff. Figure A.2, shows no discontinuity in the density of the running variable at the cutoff, as confirmed by the McCrary test (McCrary, 2008).

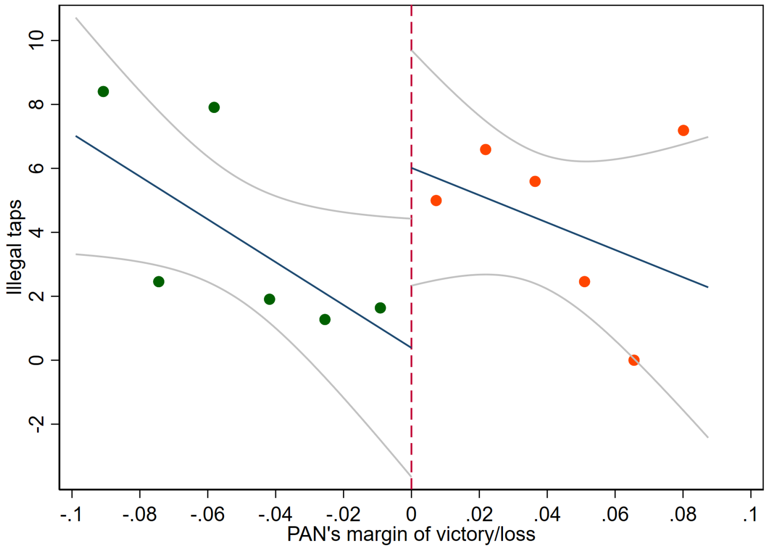
4.1.2 Estimates

Figure 4 shows the relationship between the PAN margin of victory at the 2007-2009 electoral round, MV, and the number of illegal taps per year over the following period. The average number of taps within equally-spaced intervals of MV is plotted in the graph, together with the fitted relationship and confidence intervals based on a linear regression (i.e., $k = 1$ in Equation 1). There is a clear discontinuity in the number of taps per year at the cutoff

[8] As recommended by Gelman and Imbens (2019), we only include first and second-order polynomials in the running variable (i.e., $k \leq 2$ in Equation 1), though our results are robust when including higher-order polynomials.

$MV = 0$. On average, there are more than 6 additional taps per year in municipalities in which the PAN barely won the elections compared to municipalities in which the PAN barely lost the elections, the difference being strongly statistically significant.

Figure 4: PAN's margin of victory and illegal taps



Notes: This figure shows the relationship between the PAN's margin of victory at the 2007-2009 electoral round (horizontal axis) and the number of illegal taps (vertical axis) across municipalities. The scatter plot represents averages over equally-spaced bins of the margin of victory. The predicted relationship and confidence intervals are based on a linear regression with heteroskedasticity-robust standard errors.

In Table 2, we quantify more precisely the effect in Figure 4 and assess its robustness to alternative specifications of Equation (1). In particular, the table reports bias-corrected RD coefficients when including linear or quadratic polynomials in the running variable MV, uniform or triangular kernel, and including or excluding state and year fixed effects. The optimal bandwidth and robust standard errors are computed according to Calonico et al. (2014); in Panel (b) of the table, we allow the bandwidth to be asymmetric around the cutoff.

According to the baseline linear specification (column 1), a marginal victory of PAN causes 6.6 additional taps per year, decreasing to 4 additional taps when controlling for state and year fixed effects (column 2). This is a large effect, corresponding to a 1.7 standard deviation increase in the number of taps over the period 2007-2009.[9] Point estimates are somewhat volatile between different specifications in Table 2, due to the small number of observations, but they remain statistically significant at conventional confidence levels and sizable in magnitude.

The estimated effect of PAN mayors captures the repositioning of drug cartels from

[9]The average and standard deviation of the number of taps per year are reported in Table 1.

drugs to oil thefts within (pipeline) municipalities in which they are already present – an "intensive" margin. Between municipalities, cartels should target mainly non-PAN municipalities, including municipalities with pipelines. Through this "extensive" margin, pipeline municipalities in the control group of the RDD should also experience an increase in oil thefts. Therefore, our estimates represent a lower bound to the increase in oil thefts were the crackdown implemented uniformly across areas – or, equivalently, in the absence of cartel mobility across areas.

Appendix Figure A.3 compares the actual RD estimate to a distribution of estimates obtained at placebo cutoffs. Results show that the estimated coefficient at the true electoral cutoff is abnormal compared to the distribution of placebo cutoffs. In particular, the estimate at the true cutoff is above the 90^{th} percentile of a placebo distribution when employing a symmetric bandwidth (left graph) and above the 95^{th} percentile when employing an asymmetric bandwidth (right graph).

Table 2: The Intensity of the War on Drugs and oil thefts: RD estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Polynomial:	Linear				Quadratic			
Kernel:	Uniform		Triangular		Uniform		Triangular	
State & year FEs:	No	Yes	No	Yes	No	Yes	No	Yes
(a): Symmetric bandwidth								
PAN's victory	6.580**	3.964*	6.158**	3.824*	6.193**	9.065**	5.145*	5.668*
	(2.615)	(2.048)	(2.516)	(2.018)	(2.969)	(4.063)	(2.949)	(3.006)
Observations	259	259	259	259	259	259	259	259
Bandwidth L/R	0.07/0.07	0.07/0.07	0.10/0.10	0.10/0.10	0.11/0.11	0.10/0.10	0.13/0.13	0.12/0.12
Obs. w/in band. L/R	38/28	38/28	52/31	52/32	60/34	52/31	71/41	62/35
(b): Asymmetric bandwidth								
PAN's victory	7.634***	4.410**	5.421**	3.398*	8.172**	10.091**	5.470*	7.986**
	(2.706)	(2.161)	(2.161)	(1.968)	(3.390)	(4.105)	(2.911)	(3.446)
Observations	259	259	259	259	259	259	259	259
Bandwidth L/R	0.06/0.08	0.07/0.09	0.09/0.15	0.10/0.11	0.13/0.10	0.13/0.09	0.13/0.14	0.17/0.11
Obs. w/in band. L/R	30/30	33/30	45/44	50/34	71/31	71/30	68/44	84/32

Notes: This table shows the coefficients of the RD regression, as estimated from Equation 1, on the yearly average number of illegal taps in each municipality during the period between local elections at the 2007-2009 electoral round and year 2014. The sample is restricted to municipalities with pipelines without a TAR deposit (259 in total) and to observations within a bandwidth of the cutoff, computed according to the criteria of Calonico et al. (2014, 2020); in particular, estimates for symmetric and asymmetric bandwidths are shown in Panel (a) and (b). Columns (1)-(4) include a linear RD specification, while columns (5)-(8) include a quadratic specification; even columns include fixed effects for Mexican states and years; and columns (3)-(4) and (7)-(8) weight observations by a triangular kernel in distance from the cutoff. Standard errors are robust to heteroskedasticity. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

The timing of the effect around elections is shown in Figure 5.[10] We find no differential pre-trend in the year before an election; see also Appendix Table A.3, which replicates all specifications in Table 2 for the placebo year 2006 (i.e., before the War on Drugs). The effect on oil taps appears, on average, the second year after the (marginal) victory of a PAN candidate, which would be consistent with criminal organizations taking some time to initiate a new criminal activity as the War on Drugs intensifies. Finally, the effect peaks four years after elections, i.e., beyond the duration of the municipal mandate (3 years). Enforcement activities that are the outcome of collaboration between the national and local government (e.g., the deployment of troops) and the response of criminal organizations may be characterized by a significant degree of persistence. In addition, a PAN victory at the 2007-2009 round of municipal elections greatly increases the probability of winning again in the same municipality at the next election; therefore, the persistence of the effect beyond the end of the first mandate may reflect, at least in part, PAN's retention of power at the local level.[11]

4.2 Oil thefts and cartel presence

In this section we identify the first-mover cartels and the impact on the relative power of different cartels.

4.2.1 Empirical strategy

Using the data from Coscia and Rios (2012), we compare cartel presence between municipalities with and without pipelines, before and after the start of the War on Drugs. We use the difference-in-differences specification:

$$Cartel_{i,t} = \alpha + \beta Pipeline_i \times Post2007_t + FE_i + FE_{s,t} + \varepsilon_{i,t}, \tag{2}$$

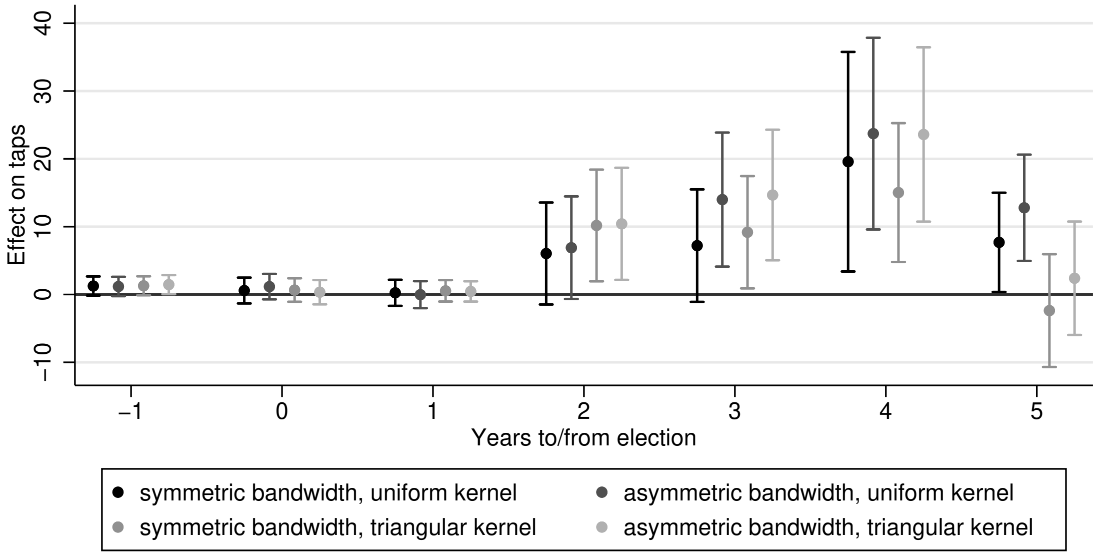
where $Cartel_{i,t}$ is a dummy for cartel presence in municipality i and year t, distinguishing between different types of cartels; $Pipeline_i$ and $Post2007_t$ are binary indicators for municipalities with pipelines and for the period starting in 2007; FE_i and $FE_{s,t}$ are fixed effects capturing municipality-specific effects and state-year shocks; finally, $\varepsilon_{i,t}$ is a residual term capturing the effect of other determinants of cartel presence.[12] Robust standard errors are clustered by municipality, all results are robust to using Conley-HAC spatial standard errors with arbitrary time and distance cutoffs (results available upon request).

[10] These estimates are based on the quadratic polynomial specification with state and year fixed effects, for different bandwidths and kernels.

[11] Using the same RD specifications as in Table 2, we estimate that a marginal victory of PAN at the 2007-2009 elections increases the probability of winning again in the following elections by more than 60 percentage points. These results, available upon request, are in line with evidence from other countries (see, e.g., Lee, 2008).

[12] We use 2007 as the first post-treatment year since Felipe Calderón's term as Mexican president officially started in December 2006.

Figure 5: PAN's margin of victory and illegal taps across time



Notes: This figure shows the RDD estimates of Equation (1) obtained using as dependent variable the yearly number of illegal taps (vertical axis) in different years before/after local elections in the electoral round 2007-2009 (horizontal axis), for different combinations of symmetric/asymmetric bandwidths and uniform/triangular kernels. All specifications include a quadratic polynomial in the running variable, in addition to state and year fixed effects. Standard errors are robust to heteroskedasticity, and 95%-confidence intervals are reported.

The coefficient β in Equation (2) captures the (differential) expansion of drug cartels into municipalities with pipelines after 2007, relative to municipalities without pipelines. Cartels' involvement in oil thefts should drive a positive coefficient, $\beta > 0$. Consistent estimation of β requires that, absent the War on Drugs (and controlling for the two sets of fixed effects, FE_i and $FE_{s,t}$), changes in cartel presence would be the same between pipeline and non-pipeline municipalities. This assumption is justified because the location of pipelines depends mostly on geo-morphological characteristics, and their construction predates the emergence of drug cartels (Zamora, 2016); in addition, municipality fixed effects absorb time-invariant characteristics affecting the presence of both oil thefts and drug cartels. At the same time, we cannot exclude that pipeline and non-pipeline municipalities differ along other dimensions correlated with changes in cartel presence over time. To reduce these concerns, we include in the sample only non-pipeline municipalities in the immediate neighborhood of pipeline municipalities, to preserve the similarity between the two groups. We will also provide placebo estimates for gas pipelines.

The final sample includes 259 municipalities with oil pipelines and 347 neighboring municipalities without oil pipelines. Appendix Figure A.4 shows the location of the municipalities with pipelines (green) and neighboring municipalities without pipelines. The map also reports the presence of incumbent and challenger cartels in 2007. Pipeline municipalities are scattered through the north-east and the south of the country. Both incumbent and challenger cartels are present in pipeline and neighboring municipalities in the north. Panel (a) of appendix Table A.4 shows a comparison of the two groups along several dimensions. Standardized differences with respect to all variables remain below 0.15 (column 3), indicating a high degree of similarity.[13] In panel (b) of the same table, we report means and standardized differences obtained when extending the control group to all Mexican municipalities without pipelines. In this case, all but one of the standardized differences are above the 0.15 threshold; our approach of restricting to pipeline municipalities and their neighbors greatly improves comparability between the two groups.

We assess the plausibility of the "parallel trends" assumption with the event-study equation:

$$Cartel_{i,t} = \alpha + \sum_{t=2000}^{2010} \beta_t Pipeline_i \times Year_t + FE_i + FE_{s,t} + \varepsilon_{i,t}, \tag{3}$$

where $Year_t$ is a set of dummy variables for each year, and the β_ts are the coefficients of their interaction with $Pipeline_i$. The coefficients for the period 2007-2010 estimate the dynamic treatment effects of the War on Drugs, while the (placebo) coefficients for previous years capture any differential trend between pipeline and non-pipeline municipalities before the War on Drugs. Therefore, evidence that $\beta_{2000} = ... = \beta_{2006} = 0$ would be consistent with the assumption of parallel trends between the two groups of municipalities. In a different type of placebo exercise, we re-estimate Equation (2) and Equation (3) after replacing refined oil pipelines with gas pipelines.

4.2.2 Estimates

Table 3 presents estimates of Equation (2) for different configurations of cartel presence. Column (1) shows that the probability of observing (at least) one cartel after 2007 increases by 6.5 percentage points (or 33% over the baseline) in pipeline municipalities compared to municipalities without pipelines. Importantly, the increase is entirely driven by challenger cartels, whereas incumbents in the drug market do not increase their presence in pipeline municipalities (columns 2-3). The remaining columns of Table 3 show that, on average, challengers enter pipeline municipalities in which no other cartel is present, so they should face little competition; at the end of this section, we will examine the implications for levels of violence.[14]

[13] As already discussed in Section 3.1, pipeline and non-pipeline municipalities become very imbalanced in terms of population when we include in the former group municipalities with TARs; see column (6) of Appendix Table A.4. For this reason, we exclude these municipalities in the main sample, though all results are robust to their inclusion.

[14] Appendix Table A.5 shows the estimates obtained without controlling for State-Year fixed effects, and they almost identical to those showed in Table 3.

Table 3: Oil thefts and the presence of drug cartels, difference-in-differences estimates

	(1) At least 1 cartel	(2) At least 1 inc.	(3) At least 1 chall.	(4) 1 inc.	(5) 2+ inc.	(6) 1 chall.	(7) 2+ chall.	(8) 1 inc. & 1. chall.	(9) Other mult.
Pipeline * Post 2006	0.065**	0.013	0.069***	0.002	-0.006	0.052***	0.000	0.011	0.006
	(0.026)	(0.022)	(0.025)	(0.012)	(0.007)	(0.016)	(0.009)	(0.016)	(0.014)
	[0.028]**	[0.951]	[0.022]**	[0.981]	[0.951]	[0.022]**	[0.981]	[0.951]	[0.951]
Observations	6,666	6,666	6,666	6,666	6,666	6,666	6,666	6,666	6,666
R-squared	0.629	0.604	0.536	0.250	0.273	0.241	0.312	0.331	0.403
Within R-squared	0.004	0.0002	0.005	0.000	0.000	0.005	0.000	0.000	.0001
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	0.2	0.16	0.1	0.07	0.02	0.03	0.01	0.05	0.01

Notes: This table shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with pipelines and neighboring municipalities without pipelines, during the period 2000-2010, as estimated from Equation (2). The equation is estimated for different outcomes, listed on top of each column. All specifications include municipality and state-year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the municipal level. P-values corrected for multiple hypothesis testing, based on Westfall et al. (1993), are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

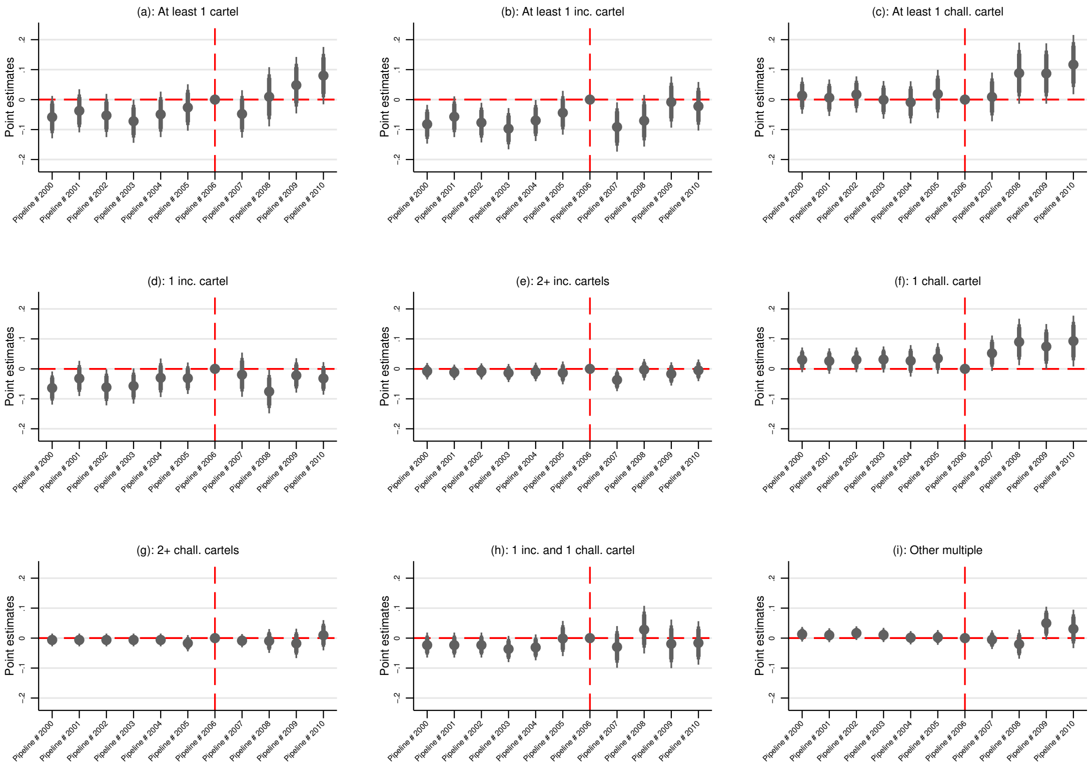
Table 3 also reports p-values adjusted for multiple hypothesis testing (in square brackets), as computed according to the step-down procedure in Westfall et al. (1993); all conclusions are unaffected. Graphs in Figure 6 confirm that the increase in the presence of (challenger) cartels in pipeline municipalities occurs after 2007, as there are no differential trends with respect to other municipalities in previous years. Overall, the evidence presented in Table 3 is consistent with challengers in the traditional business (i.e., narcotics) leapfrogging incumbents to enter the new criminal activity of oil theft.

4.2.3 Robustness tests

To check that differential trends between pipeline and non-pipeline municipalities after 2007 are truly driven by the presence of oil pipelines, as opposed to other differences, we replicate the analysis replacing oil pipelines with gas pipelines. Gas cannot be easily extracted and stored by criminals, so gas thefts never became a major criminal business (see Figure A.1). Table A.6 shows (placebo) estimates for the impact of gas pipelines on cartel presence. When accounting for multiple hypothesis testing, no coefficient is robustly significant at conventional confidence levels.

We test whether the War on Drugs induced a reallocation of drug cartels towards areas suitable for cultivation of other valuable export-oriented agricultural commodities, such as

Figure 6: Oil Thefts and the presence of drug cartels, event-study estimates



Notes: This figure shows the effect of the War on Drugs on the presence of drug cartels in municipalities with pipelines relative to neighboring municipalities without pipelines during the period 2000-2010, as estimated by the interaction coefficients in Equation (3). In particular, the plots refer to the probability of observing at least one cartel (Panel a), at least one incumbent cartel (Panel b), at least one challenger cartel (Panel c), only one incumbent cartel (Panel d), two or more incumbent cartels (Panel e), only one challenger cartel (Panel f), two or more challenger cartels (Panel g), one incumbent and one challenger cartel (Panel h), and other combinations of multiple cartel presence (Panel i). All specifications include municipality and state-year fixed effects. The vertical gray lines represent confidence intervals at 99% confidence level, on standard errors clustered at the municipality-level. The vertical red-dashed line represents the year before the beginning of the War on Drugs (i.e., 2006).

citrus, cocoa, and coffee.[15] Appendix Table A.7 shows no displacement of drug cartels towards municipalities more suitable for these crops after the start of the War on Drugs. Therefore, the effect seems specific to oil thefts. This is likely due to the higher value of this market and to the larger demand for stolen oil compared to agricultural crops.[16]

The period of our analysis also corresponds to a dramatic surge in the international oil

[15]Suitability indicators from the *Food and Agriculture Organization Global Agro-Ecological Zones* project are defined over a grid of 1' resolution, and they range from 1 (no suitable) to 9 (very suitable).

[16]As explained in the Introduction, the value of stolen oil ranges between 1-2US$ billion per year Duhalt (2017). Conversely, the export value of those crops in 2019 was \$307 million for coffee, \$649 million for lemons, and \$696 million for cocoa beans (Source: OEC.world).

price, which could be a confounding factor behind the increase in oil thefts. To address this concern, we re-estimate Equation 3, controlling for $Pipeline * LogOilPrice$, where $Pipeline$ is the dummy for pipeline presence and $LogOilPrice$ is the logarithm of the international price for crude oil, collected from the *International Financial Statistics*; results are unaffected, as shown in Figure A.5.

To further validate the idea of a switch from drugs to oil, in Table A.8, we restrict the control group to only neighbouring municipalities suitable for drug production. Not only previous findings are confirmed: the estimated effects are slightly higher than in Table 3, in line with a relocation from drug producing to oil carrying municipalities.

In addition, Appendix Figure A.6 shows that all results are robust to replacing the control group of neighboring non-pipeline municipalities with all non-pipeline municipalities located within 25, 50, and 100 kilometers. These results are also robust to computing Conley-HAC spatial standard errors (Conley, 1999) with arbitrary spatial and time cutoffs.

4.2.4 Displacement and entry

The War on Drugs induced a higher presence of drug cartels in municipalities with oil pipelines. This finding might be driven by cartels' entry into new municipalities after the start of the War on Drugs, or by cartels avoiding exit from areas with pipelines in the same period. In Table A.9, we replicate the estimation of Table 3 by restricting the sample to municipalities which never experienced any cartel presence before 2007 (top panel). Results are similar to the estimation on the whole sample, suggesting that our results reflect differential entry of cartels into new municipalities with pipelines. Again, effects are concentrated among challenger drug cartels. In the bottom panel, we consider instead municipalities in which cartels were present (at least in one year) before 2007. These municipalities also experience an increase in cartel presence after 2006 (column 1) but the effect is driven, in this case, by incumbent cartels (column 4). Therefore, it seems that where drug cartels were already active, substitution from drugs to oil took place within the same municipality and favored the survival of incumbent cartels.[17]

4.3 The War on Drugs, pipelines, and socio-economic development

In Table 4 we compare changes in three local outcomes after 2007 between municipalities with and without pipelines using the difference-in-differences specification in Equation (2).[18] The first column of the table shows that the homicide rate does not change, in spite of the increase in cartel presence documented in Table 3. This finding is consistent with the

[17]We could run a similar analysis looking at taps with the RDD of Table 5, by differentiating between pipelines municipalities with/without drug cartels and with/without PAN before/after 2007. Unfortunately, the very limited number of observations does not allow us to run this further analysis.

[18]The sample size varies across columns because different variables are available for different periods; see Section 3.3 for additional details.

evidence, also shown in Table 3, that (challenger) cartels enter pipeline municipalities in which they face no competition from other cartels.

Table 4: The War on Drugs, pipelines, and local development, difference-in-differences estimates

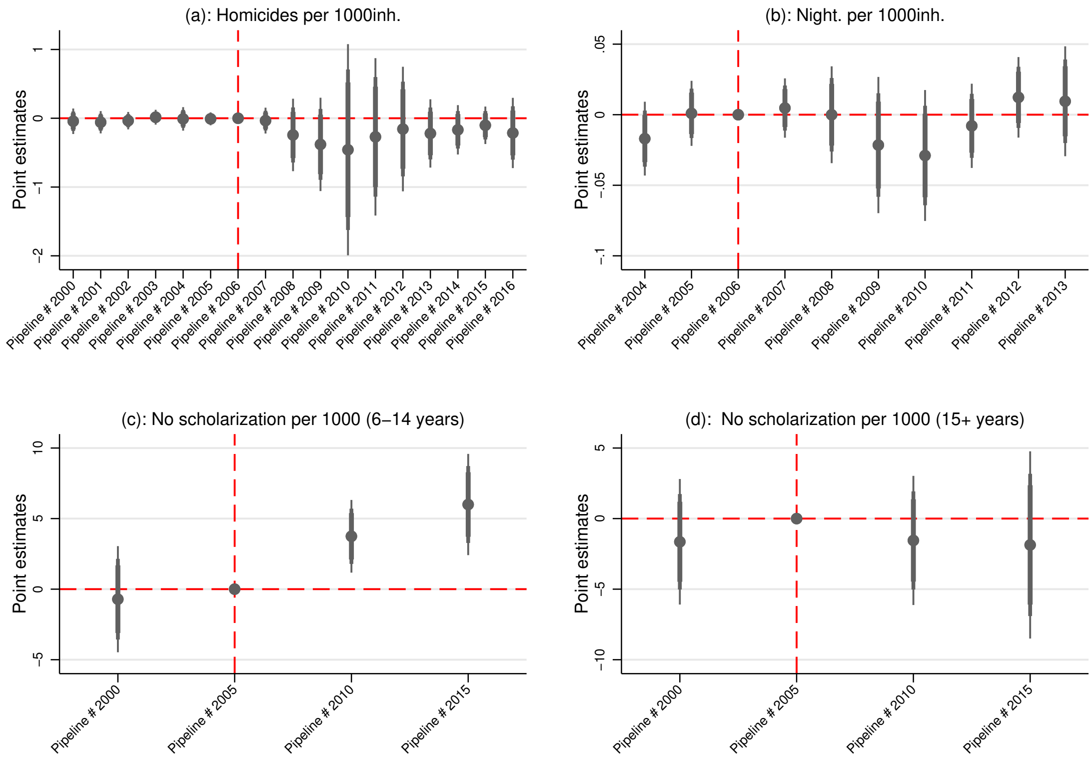
	(1) Homicides per 1000inh.	(2) Nighttime light density	(3) No school (6-14 years)	(4) No school (15+ years)
Pipeline * Post2006	-0.205	0.001	5.520***	-0.886
	(0.250)	(0.012)	(1.368)	(2.345)
Observations	10,302	6,060	2,418	2,418
R-squared	0.590	0.992	0.901	0.988
Within R-squared	0.0004	0.000	0.0147	0.0002
Mun. FE	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES
Base value - Ref. year	0.321	0.595	53	453

Notes: This table shows the effect of the War on Drugs on variables measuring local economic development in municipalities with pipelines and in neighboring municipalities, during the period 2000-2010. The estimating equation is the same as in Equation (2), but using local development variables as outcomes, reported on top of the relative column. All specifications include municipality and state-year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the municipal level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Columns 2-4 show the effects on socio-economic outcomes. There is no discernible effect on local economic activity as measured by night-time light density (column 2). Column (3) reports the impact on the rate of children under 15 not in formal education. This is an important outcome, as schooling choices may respond very quickly to the presence of drug cartels (Sviatschi et al., 2019), and also bear important consequences for long-term development. The number of children out of formal schooling increases by 5 per 1,000 (or 10 percent over the baseline rate) in pipeline municipalities after the start of the War on Drugs. As a placebo, we also estimate the effect on schooling levels of individuals older than 15; as expected, there is no significant effect (column 4). To summarize, pipeline municipalities do not experience any significant change in the level of economic activity after the entry of drug cartels into illegal oil tapping, but school attendance decreases. Figure 7 confirms that the latter effect emerges only after the start of the War on Drugs, while trends in homicide rates and night-time light density are the same between pipeline and non-pipeline municipalities, before and after 2007.

Finally, results are robust to controlling for possible trends related to oil price (i.e., Appendix Figure A.8); replacing the group of neighboring non-pipeline municipalities separately with all those within 25, 50, and 100 kilometers from a pipeline municipality (i.e., Appendix Figure A.7); and computing Conley-HAC spatial standard errors with arbitrary spatial and time cutoffs.

Figure 7: Oil Thefts and Local Development: Event Study Estimates



Notes: This figure shows the effect of the War on Drugs on local development in pipeline municipalities, relative to neighboring municipalities, during the period 2000-2010, as estimated by the interaction coefficients in Equation (3). The four graphs refer to different socio-economic outcomes, indicated on top of each graph. All specifications include municipality and state-year fixed effects. The vertical gray lines represent confidence intervals at 99% confidence level, based on standard errors clustered at the municipality-level. The vertical red-dashed line represents the year before the beginning of the War on Drugs (i.e., 2006).

5 Conclusions

We show that the War on Drugs launched by the Mexican government in 2007 pushed drug cartels into a new illegal activity, large-scale oil thefts. In line with evidence about specialization observed for incumbents and challengers in the formal economy, we find that challenger cartels holding residual shares in drug-trafficking leapfrog dominant drug cartels in the new illegal activity.

From a policy perspective, these findings suggest that government crackdowns on a specific criminal activity may trigger illegal activity in another area. This depends, in this case, on the organizational flexibility of Mexican drug cartels and their ability to innovate, so spillover effects could be weaker in other contexts. Many criminal groups, such as mafia-type organizations in Italy and Eastern Europe, are probably similar to drug cartels in these respects. Our results suggest that Becker's parallel between the drivers of individual behavior in legal and illegal activities carry through to the activities of larger enterprises in formal and informal markets.

Finally, our results suggest that the entry of drug cartels into oil tapping was not associated with increases in violence because the relocation of some criminal groups to the new sector actually lowered competition with incumbents in drug-trafficking. An important caveat is that part of our analysis – notably, on the entry of drug cartels into the new sector – is limited to the period up to 2010, as we lack information on cartel presence in the following years. On the other hand, even within this relatively short period of time, we detect significant decreases in educational attainment.

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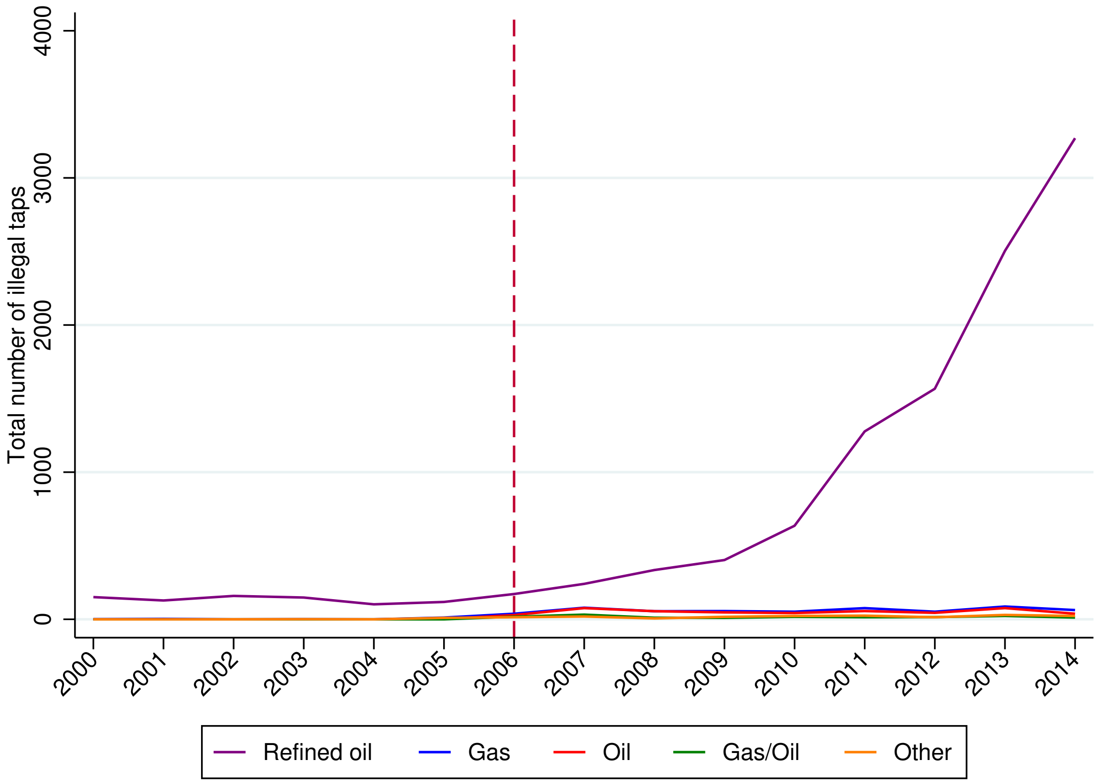
Appendices

Figure A.1: Illegal taps over time



Source: *El Universal*.

Table A.1: Descriptive statistics on taps and cartel presence

	(1)	(2)	(3)	(4)
	All municipalities	Municipalities with pipelines		
		All	Only TARs	No TARs
Number of municipalities	2454	313	54	259
Population, 2000-2015	44.117	144.997	438.241	83.857
	[129.756]	[274.306]	[365.137]	[203.871]
Homicides per 1000 inh., 2000-2016	0.546	0.443	0.134	0.477
	[3.108]	[3.904]	[0.742]	[4.106]
Nighttime light density/pop, 2004-2013	0.811	0.479	0.084	0.523
	[1.772]	[1.032]	[0.099]	[1.079]
No scholariz. per 1,000 inh. (6-14 years), 2000-2015	64.369	52.404	41.849	54.609
	[44.090]	[29.891]	[19.987]	[31.128]
No scholariz. per 1,000 inh. (15+ years), 2000-2015	375.958	474.655	628.594	457.491
	[12.968]	[150.372]	[99.028]	[145.278]
Surface (km^2)	800.543	1284.786	2970.949	933.231
	[1.273]	[3746.217]	[7680.822]	[1988.668]
Altitude (km)	1.273	1.273	0.937	1.343
	[0.823]	[0.937]	[0.916]	[0.926]
Temperature (Celsius degree)	19.701	18.8	19.747	18.602
	[3.877]	[4.303]	[4.379]	[4.261]
Slope (degree)	0.315	0.206	0.257	0.195
	[0.315]	[0.233]	[0.235]	[0.232]
US border distance (km)	732.252	593.574	545.791	603.536
	[260.95]	[256.146]	[272.554]	[251.482]
Drug suitability (km2)	51.78	44.862	66.48	40.355
	[153.405]	[146.32]	[209.467]	[128.904]

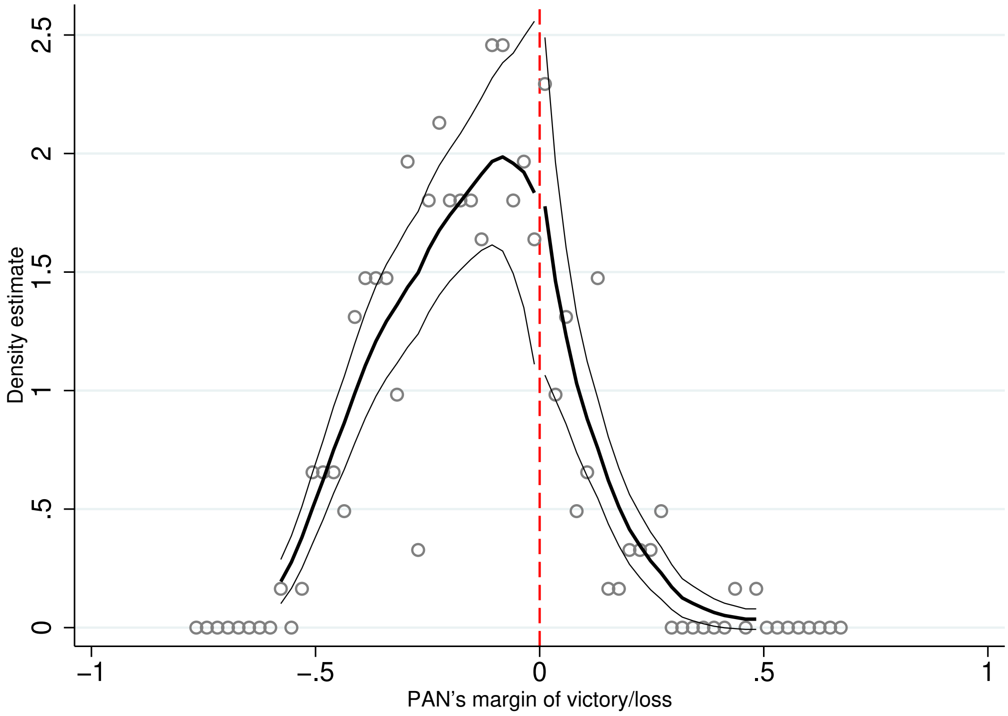
Notes: This table shows means and standard deviations (in squared brackets) for different municipality characteristics, distinguishing between different groups of municipalities indicated on top of each column.

Table A.2: Differences in observable characteristics at the RD cutoff

	Symmetric bandwidth		Asymmetric bandwidth	
	RD Effect	Robust p-val	RD Effect	Robust p-val
(a): Geographic characteristics				
Surface (km^2)	-99.872	0.894	-226.643	0.751
Altitude (m)	-199.845	0.501	56.430	0.818
Temperature (C)	2.354	0.183	0.677	0.636
Slope (degrees)	-0.100	0.426	0.136	0.286
Distance from US border (Km)	44.380	0.219	28.296	0.39
(b): Socio-economic characteristics				
Population in 1000s (2005)	-17.142	0.881	-39.376	0.716
PAN incumbent (%, 2006)	0.279	0.448	0.34	0.312
Cartel presence (%, 2006)	0.077	0.612	-0.027	0.887
Homicides per 1000inh. (2006)	0.022	0.948	0.042	0.9
Nighttime light density per 1,000 inh. (2005)	0.175	0.624	0.334	0.359
No scholar. per 1000 inh. (6-14 years) (2005)	4.085	0.722	14.932	0.242
No scholar. per 1000 inh. (15+ years) (2005)	-27.872	0.692	20.575	0.742

Notes: This table shows the coefficients and associated p-values of RD regressions testing for (absence of) significant differences between municipalities in which the PAN won or lost the local elections at the electoral round 2007-2009. The optimal symmetric and asymmetric bandwidths are based on the criteria of Calonico et al. (2014, 2020). The regressions use a quadratic functional specification of the RD polynomial, and they also include Mexican state and year of election fixed effects. Standard errors are robust to heteroskedasticity. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Figure A.2: Discontinuity density test for manipulation of the cutoff to win the elections



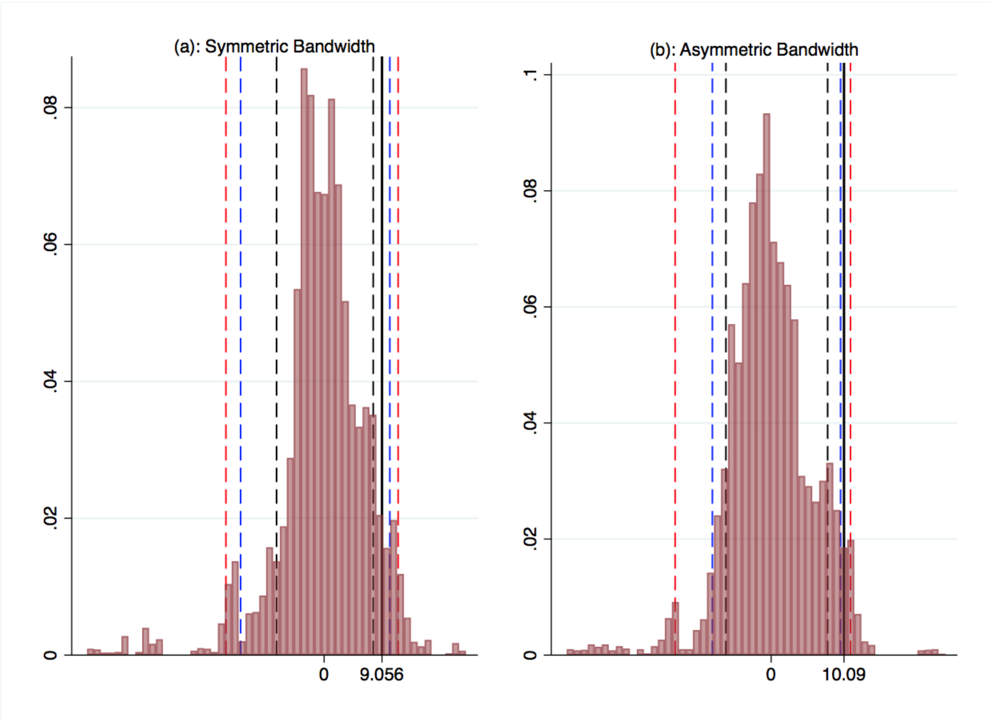
Notes: The figure shows the fitted density and associated confidence intervals of PAN's margin of victory.

Table A.3: The intensity of the War on Drugs and oil thefts, placebo estimates for the year before the start of the War on Drugs (2006)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Polynomial:	Linear				Quadratic			
Kernel:	Uniform		Triangular		Uniform		Triangular	
State & year FEs:	No	Yes	No	Yes	No	Yes	No	Yes
	Taps	Taps	Taps	Taps	Taps	Taps	Taps	Taps
(a): Symmetric bandwidth								
PAN's victory	-0.229	-0.175	-0.204	-0.260	-0.345	-0.368	-0.364	-0.306
	(0.750)	(0.388)	(0.686)	(0.281)	(0.823)	(0.370)	(0.820)	(0.381)
Observations	259	259	259	259	259	259	259	259
Bandwidth L/R	.08/.08	.06/.06	.1/.1	.1/.1	.13/.13	.11/.11	.15/.15	.12/.12
Obs. w/in band. L/R	38/28	32/25	49/31	50/31	68/40	60/34	79/44	66/37
(b): Asymmetric bandwidth								
PAN's victory	-0.186	-0.189	-0.123	-0.294	-0.078	-0.176	-0.257	-0.352
	(0.710)	(0.332)	(0.639)	(0.281)	(0.688)	(0.434)	(0.805)	(0.441)
Observations	259	259	259	259	259	259	259	259
Bandwidth L/R	.12/.07	.08/.07	.15/.09	.13/.1	.14/.17	.13/.1	.18/.15	.14/.11
Obs. w/in band. L/R	60/28	38/28	74/31	68/31	72/45	67/31	94/44	73/33

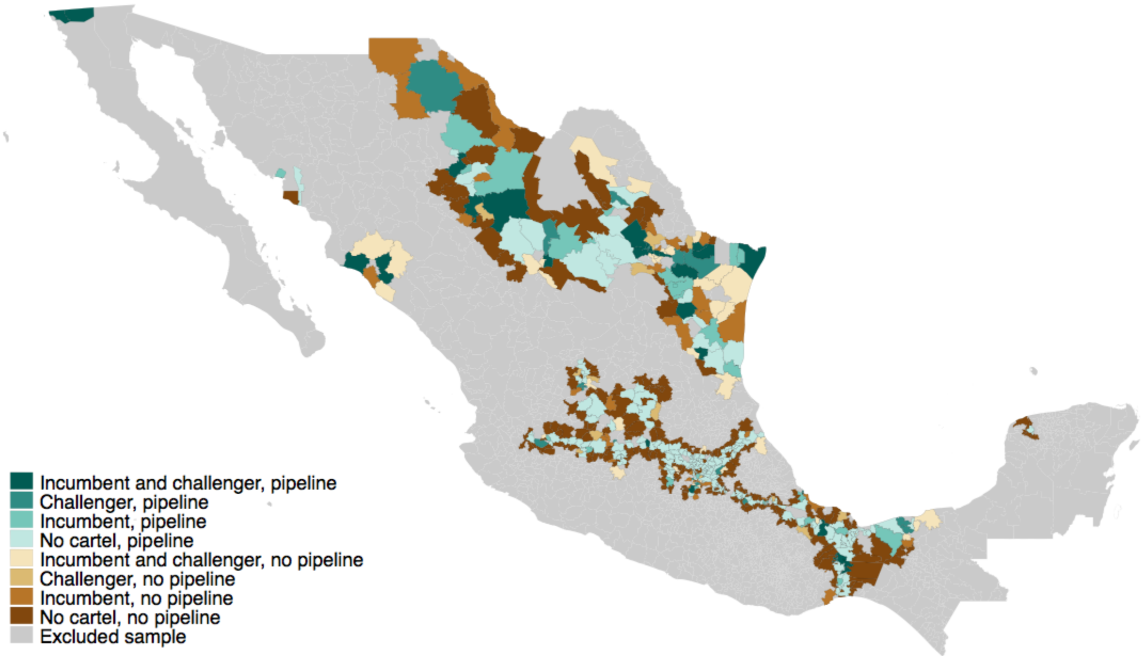
Notes: This table shows the coefficients of the RD regression, as estimated from Equation 1, on the yearly average number of illegal taps in each municipality in the year before the start of the War on Drugs (i.e., 2006). The sample is restricted to municipalities with pipelines (259 in total) and to observations within a bandwidth of the cutoff, computed according to the criteria of Calonico et al. (2014, 2020); in particular, estimates for symmetric and asymmetric bandwidths are shown in Panel (a) and (b). Columns (1)-(4) include a linear RD specification, while columns (5)-(8) include a quadratic specification; even columns include fixed effects for Mexican states and years; and columns (3)-(4) and (7)-(8) weight observations by a triangular kernel in distance from the cutoff. Standard errors are robust to heteroskedasticity. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Figure A.3: The intensity of the War on Drugs and oil theft, permutation tests



Notes: Distribution of RD estimates for the effect of PAN's electoral victory on oil thefts at 10,000 equally-spaced placebo cutoffs between the 10^{th} and 90^{th} percentiles of PAN's margin of victory. All estimates are based on a quadratic specification for the margin of with year and state fixed effects. Estimates in the left-hand panel are based on a symmetric bandwidth; estimates in the right-hand panel are based on an asymmetric bandwidth. Black, blue, and red dashed lines report 90^{th}, 95^{th}, and 97.5^{th} percentiles of distribution of estimates. Solid black line reports RDD estimate for actual cut-off (0).

Figure A.4: Cartel presence and pipelines, 2007



Notes: The figure shows the location of pipeline municipalities (green) and neighboring municipalities without pipelines (brown) in 2007, shaded in different colors depending on the presence of cartels.

Table A.4: Differences between municipalities with and without pipelines

(a): municipalities with or close to pipelines

	All municipalities (excl. TAR)			All municipalities		
	Mean Treated	Mean Control	Std. Diff.	Mean Treated	Mean Control	Std. Diff.
Surface (Km^2)	933.231	873.897	0.032	1284.786	879.092	0.140
Altitude (Km)	1.343	1.381	-0.042	1.273	1.379	-0.115
Temperature (Km)	18.602	18.583	0.005	18.800	18.592	0.049
Slope	0.195	0.223	-0.120	0.206	0.223	-0.073
US border distance (Km)	603.536	622.219	-0.074	593.574	620.503	-0.106
Population in 1000s (2000)	73.809	62.802	0.062	127.754	63.055	0.309

(b): all Mexican municipalities

	All municipalities (excl. TAR)			All municipalities		
	Mean Treated	Mean Control	Std. Diff.	Mean Treated	Mean Control	Std. Diff.
Surface (Km^2)	933.231	712.105	0.119	1284.786	729.388	0.190
Altitude (Km)	1.343	1.279	0.074	1.273	1.273	-0.001
Temperature (Km)	18.602	19.816	-0.301	18.800	19.833	-0.255
Slope	0.195	0.331	-0.484	0.206	0.331	-0.444
US border distance (Km)	603.536	753.986	-0.594	593.574	752.775	-0.622
Population in 1000s (2000)	73.809	24.528	0.340	127.754	26.994	0.547

Notes: Panel (a) of this table shows the average characteristics of pipeline municipalities and neighboring municipalities, and the standardized difference between the two groups. Panel (b) shows the average characteristics of pipeline municipalities and all other municipalities, and the standardized difference between the two groups.

Table A.5: Oil thefts and the presence of drug cartels, difference-in-differences estimates without state-year fixed effects

	(1) At least 1 cartel	(2) At least 1 inc.	(3) At least 1 chall.	(4) 1 inc.	(5) 2+ inc.	(6) 1 chall.	(7) 2+ chall.	(8) 1 inc. & 1. chall.	(9) Other mult.
Pipeline * Post2006	0.080***	0.025	0.084***	0.005	-0.009	0.052***	0.003	0.018	0.011
	(0.029)	(0.025)	(0.028)	(0.012)	(0.007)	(0.016)	(0.010)	(0.018)	(0.015)
Observations	6,666	6,666	6,666	6,666	6,666	6,666	6,666	6,666	6,666
R-squared	0.541	0.507	0.433	0.195	0.187	0.196	0.173	0.239	0.314
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	0.2	0.16	0.1	0.07	0.02	0.03	0.01	0.05	0.01

Notes: This table shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with pipelines and neighboring municipalities without pipelines, during the period 2000-2010, as estimated from Equation (2). The equation is estimated for different outcomes, listed on top of each column. All specifications include municipality and year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the municipal level. P-values corrected for multiple hypothesis testing, based on Westfall et al. (1993), are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A.6: Gas pipelines, War on Drugs, and the presence of drug cartels

	(1) At least 1 cartel	(2) At least 1 inc.	(3) At least 1 chall.	(4) 1 inc.	(5) 2+ inc.	(6) 1 chall.	(7) 2+ chall.	(8) 1 inc. & 1. chall.	(9) Other mult.
Gas Pipeline * Post 2006	0.020	0.021	0.028	-0.011	0.002	-0.016	0.016	0.002	0.027**
	(0.026)	(0.020)	(0.025)	(0.012)	(0.008)	(0.017)	(0.010)	(0.013)	(0.012)
	[0.834]	[0.808]	[0.639]	[0.834]	[0.922]	[0.834]	[0.483]	[0.922]	[0.117]
Observations	6,061	6,061	6,061	6,061	6,061	6,061	6,061	6,061	6,061
R-squared	0.611	0.517	0.531	0.273	0.271	0.274	0.293	0.282	0.334
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	0.2	0.15	0.11	0.08	0.01	0.05	0.01	0.04	0.01

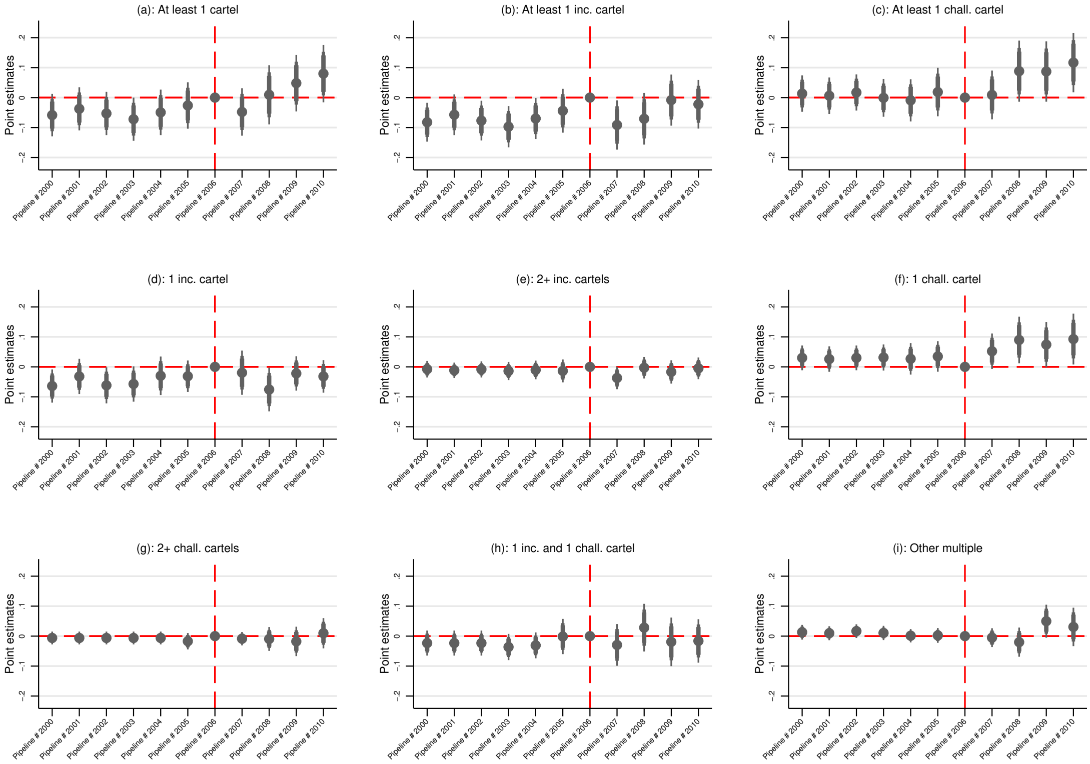
Notes: This table shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with gas pipelines and in neighboring municipalities, during the period 2000-2010, as estimated from Equation (2). The different outcomes we test for are listed at the top of each column. All specifications include municipality and state-year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the municipal level. P-values corrected for multiple hypothesis testing, based on Westfall et al. (1993), are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A.7: Agricultural production and the presence of drug cartels

	(1)	(2)	(3)	(4)	(5)	(6)
	1 inc.	2+ inc.	1 chall.	2+ chall.	1 inc. & 1 chall.	Other multiple
Citrus * Post2006	-0.012	0.003	-0.024	-0.008	0.008	0.006
	(0.014)	(0.004)	(0.017)	(0.009)	(0.016)	(0.015)
Observations	3,651	3,651	3,651	3,651	3,651	3,651
R-squared	0.273	0.195	0.257	0.326	0.258	0.321
Mun. FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES
Cocoa * Post2006	0.009	0.011	-0.063**	0.000	-0.118***	-0.006
	(0.019)	(0.009)	(0.027)	(0.000)	(0.041)	(0.006)
Observations	2,574	2,574	2,574	2,574	2,574	2,574
R-squared	0.234	0.228	0.252	0.407	0.363	0.307
Mun. FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES
Coffee * Post2006	-0.004	-0.002	-0.043*	-0.008*	-0.025	-0.008
	(0.005)	(0.003)	(0.026)	(0.004)	(0.017)	(0.006)
Observations	3,740	3,740	3,740	3,740	3,740	3,740
R-squared	0.270	0.162	0.265	0.389	0.306	0.308
Mun. FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES

Notes: This table shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with higher suitability to the cultivation of citrus (top-panel), cocoa (mid-panel), and coffee (bottom-panel), during the period 2000-2010, as estimated from Equation (2). The different outcomes we test for are listed at the top of each column. All specifications include municipality and state-year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the municipal level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Figure A.5: Oil thefts and the presence of drug cartels, controlling for international oil price



Notes: This figure shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with pipelines and in neighboring municipalities, during the period 2000-2010. as estimated from Equation 3, controlling for $Pipeline * LogOilPrice$, where $Pipeline$ is the dummy for pipeline presence and $LogOilPrice$ is the logarithm of the international price for crude oil. In particular, the plots refer to the probability of observing at least one cartel (Panel a), at least one incumbent cartel (Panel b), at least one challenger cartel (Panel c), only one incumbent cartel (Panel d), two or more incumbent cartels (Panel e), only one challenger cartel (Panel f), two or more challenger cartels (Panel g), one incumbent and one challenger cartel (Panel h), and other combinations of multiple cartel presence (Panel i). All specifications include municipality and state-year fixed effects. The vertical gray lines represent confidence intervals at 99% confidence level, on standard errors clustered at the municipality-level. The vertical red-dashed line represents the year before the beginning of the War on Drugs (i.e., 2006).

Table A.8: Oil thefts and the presence of drug cartels, difference-in-differences estimates, with only neighbouring municipalities suitable for drug production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	At least 1 cartel	At least 1 inc.	At least 1 chall.	1 inc.	2+ inc.	1 chall.	2+ chall.	1 inc. & 1. chall.	Other mult.
Pipeline * Post2006	0.111**	0.051	0.096**	0.012	0.003	0.047*	0.013	0.001	0.035
	(0.044)	(0.039)	(0.040)	(0.024)	(0.005)	(0.027)	(0.013)	(0.029)	(0.023)
Observations	4,004	4,004	4,004	4,004	4,004	4,004	4,004	4,004	4,004
R-squared	0.640	0.622	0.562	0.299	0.272	0.275	0.315	0.352	0.426
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Drug-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	0.2	0.07	0.02	0.07	0.02	0.03	0.01	0.05	0.01

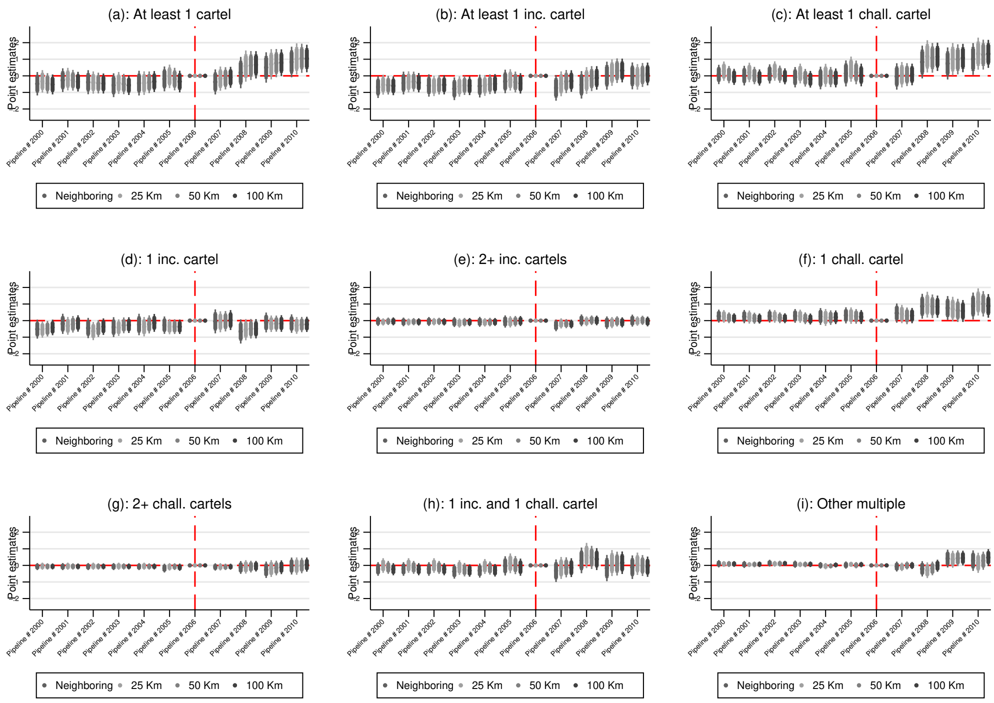
Notes: This table shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with pipelines and neighboring municipalities without pipelines but suitable for drug production, during the period 2000-2010, as estimated from Equation (2). The equation is estimated for different outcomes, listed on top of each column. All specifications include municipality, state-year and drug suitability-year fixed effects. Drug suitability represent the municipal amount of Km^2 potentially suitable for production of either opium or cannabis, as constructed by Daniele et al. (2020). We consider a municipality as potentially suitable for drug production if there is a positive number of Km^2 suitable for drug production. Standard errors are robust to heteroskedasticity and clustered at the municipal level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table A.9: Oil thefts and the presence of drug cartels, difference-in-differences estimates, by cartels presence before 2007

No cartel before 2007	(1) At least 1 cartel	(2) At least 1 inc.	(3) At least 1 chall.	(4) 1 inc.	(5) 2+ inc.	(6) 1 chall.	(7) 2+ chall.	(8) 1 inc. & 1. chall.	(9) Other mult.
Pipeline * Post2006	0.069**	0.022	0.066**	0.001	0.002	0.046**	0.001	0.001	0.018**
	(0.032)	(0.023)	(0.028)	(0.009)	(0.005)	(0.022)	(0.011)	(0.016)	(0.008)
Observations	5,071	5,071	5,071	5,071	5,071	5,071	5,071	5,071	5,071
R-squared	0.528	0.463	0.494	0.230	0.359	0.296	0.281	0.351	0.343
Cartels before 2007	NO	NO	NO	NO	NO	NO	NO	NO	NO
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Drug-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	0	0	0	0	0	0	0	0	0
At least 1 cartel before 2007									
Pipeline * Post2006	0.112**	0.050	0.069	0.081*	-0.037	0.041	0.021	-0.016	0.023
	(0.050)	(0.060)	(0.052)	(0.046)	(0.031)	(0.034)	(0.033)	(0.062)	(0.062)
Observations	1,507	1,507	1,507	1,507	1,507	1,507	1,507	1,507	1,507
R-squared	0.635	0.597	0.604	0.239	0.306	0.270	0.365	0.367	0.472
Cartels before 2007	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mun. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Drug-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Base value 2006	0.78	0.29	0.09	0.29	0.09	0.11	0.05	0.22	0.03

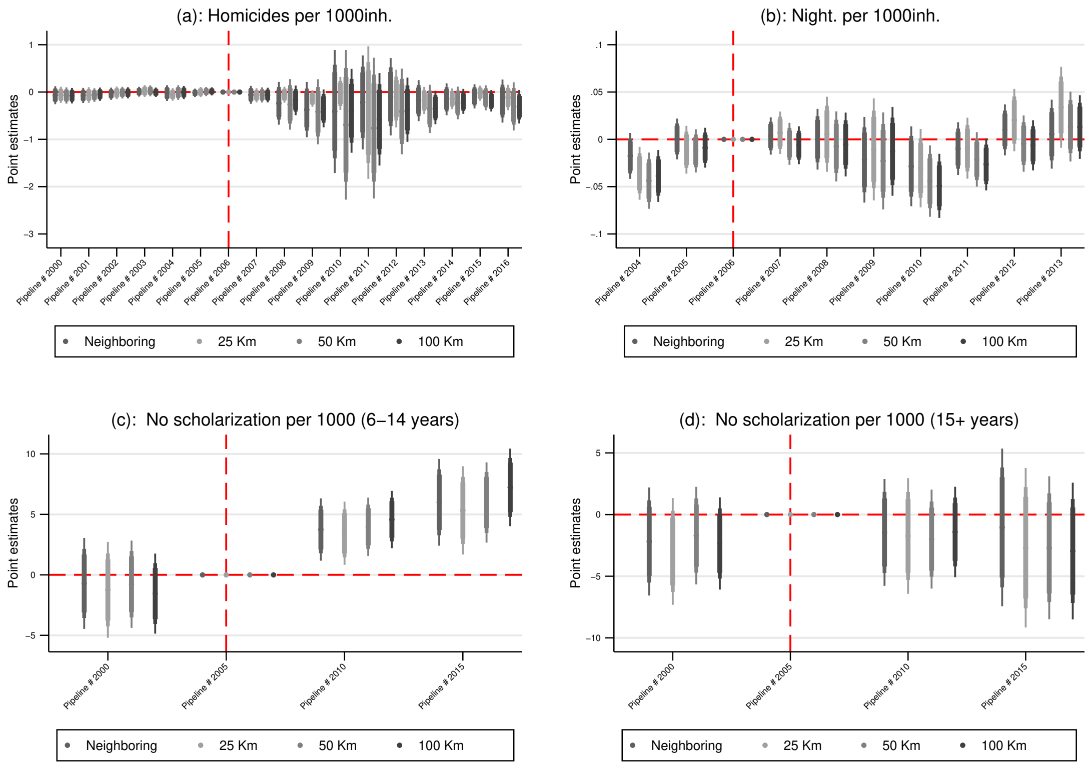
Notes: This table shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with pipelines and neighboring municipalities without pipelines, during the period 2000-2010, as estimated from Equation (2). Panel A, include in the regression sample only municipalities that never experienced the presence of a cartel before 2007, while Panel B only those experiencing such a presence. The equation is estimated for different outcomes, listed on top of each column. All specifications include municipality and state-year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the municipal level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Figure A.6: Oil thefts and the presence of drug cartels, different distances from treated municipalities



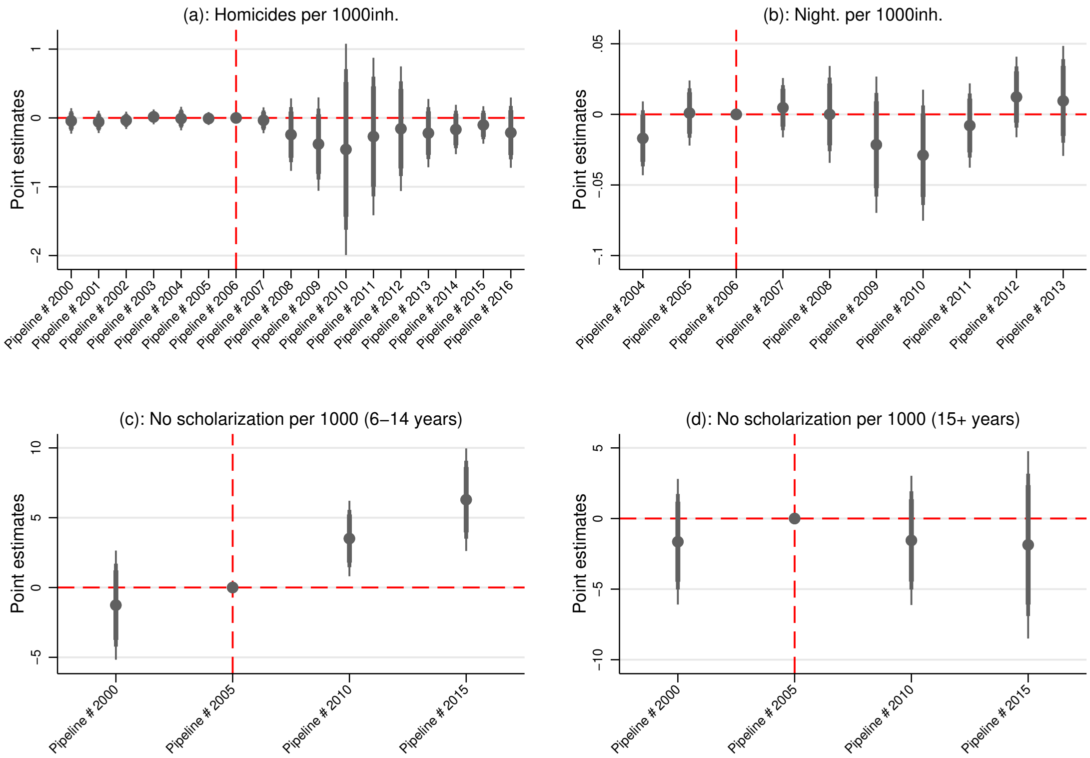
Notes: This figure shows the effect of the War on Drugs on the relative presence of drug cartels in municipalities with pipelines and in neighboring municipalities or municipalities at 25km or 50Km without a gasoline pipeline, during the period 2000-2010, as estimated by the interaction coefficients in Equation (3). In particular, the plots refer to the probability of observing at least one cartel (Panel a), at least one incumbent cartel (Panel b), at least one challenger cartel (Panel c), only one incumbent cartel (Panel d), two or more incumbent cartels (Panel e), only one challenger cartel (Panel f), two or more challenger cartels (Panel g), one incumbent and one challenger cartel (Panel h), and other combinations of multiple cartel presence (Panel i).The coefficients are obtained by the estimation of Equation 3 where the variable $Pipeline\#Year$ denotes interaction terms of *Pipeline* a dummy equal to 1 if the municipality has a gasoline pipeline and 0 for neighboring municipalities or municipalities at 25Km, 50Km, 100Km from the latter, or all Mexican municipalities without a gasoline pipeline – with indicator variables for each year. All specifications include municipality and state-year fixed effects. The vertical gray lines represent confidence intervals at 99% confidence level, on standard errors clustered at the municipality-level. The vertical red-dashed line represents the year before the beginning of the War on Drugs (i.e., 2006).

Figure A.7: Oil Thefts and Local Development: Different Distances from Treated Municipalities



Notes: This figure shows the evolution over time of the differential effect of the War on Drugs on homicides per 1,000 inhabitants (Panel a), nightlights brightness per 1,000 inhabitants (Panel b), infants' deaths per 1,000 inhabitants (Panel c), and children under 15 who are not in school per 1,000 inhabitants (Panel d) in municipalities with a pipeline transporting refined gasoline with respect to those at different distances from the latter. All dependent variables are transformed through the inverse hyperbolic sine transformation. The coefficients are obtained by the estimation of Equation 3 where the variable $Pipeline \# Year$ denotes interaction terms of $Pipeline$ a dummy equal to 1 if the municipality has a gasoline pipeline and 0 for neighboring municipalities or municipalities at 25Km, 50Km, 100Km from the latter, or all Mexican municipalities without a gasoline pipeline – with indicator variables for each year. All specifications include municipality fixed effects, and macro-region-year fixed effects. The vertical gray lines represent confidence intervals at 90% (i.e., least-wide spikes), 95% (i.e., medium-wide spikes), and 99% (i.e., widest spikes). Confidence intervals are based on standard errors clustered at the municipal level. The red-dashed lines represent the year before the beginning of the War on Drugs.

Figure A.8: Oil Thefts and Local Development: Controlling for International Oil Price



Notes: This figure shows the evolution over time of the differential effect of the War on Drugs on homicides per 1,000 inhabitants (Panel a), nightlights brightness per 1,000 inhabitants (Panel b), children under 15 who are not in school out of 1,000 (Panel c), and inhabitants with 15 years or more who have not completed basic schooling out of 1,000 (Panel d) in municipalities with a pipeline transporting refined gasoline with respect to their neighboring municipalities. All dependent variables are transformed through the inverse hyperbolic sine transformation. The variable $Pipeline\#Year$ denotes interaction terms of $Pipeline$ – a dummy equal to 1 for municipalities with a gasoline pipeline and 0 for their neighboring municipalities – with indicator variables for each year. The coefficients are obtained by the estimation of Equation 3. All specifications include the interaction between $Pipeline$ and the international oil price (in log scale), as well as municipality and state-year fixed effects. The vertical gray lines represent confidence intervals at 90% (i.e., least-wide spikes), 95% (i.e., medium-wide spikes), and 99% (i.e., widest spikes). Confidence intervals are based on standard errors clustered at the municipal level. The red-dashed line represents the reference year, which is the last one available before the beginning of the War on Drugs.