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**HEROIN AND DEFORESTATION:
UNEXPECTED IMPACT OF THE
OXYCONTIN REFORMULATION
ON MEXICAN FORESTS**

Berk OKTEM

UMR TREE 6031

Avenue du Doyen Poplawski
64016 PAU Cedex

Mail : tree-wp@univ-pau.fr

Internet : <http://tree.univ-pau.fr/>



Heroin and deforestation: Unexpected impact of the OxyContin reformulation on Mexican forests

Berk Öktem*

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Abstract

By and large, agricultural expansion is the main cause of deforestation, and crop prices are found to be an important driver. Yet, we know very little about how illicit crop prices affect cultivation decisions and deforestation. By examining a heroin demand shock from the United States, I investigate the association between the rising demand for opium poppy, higher prices, and their impact on land use and, particularly, on deforestation in Mexico. I employ an empirical strategy borrowed from [Daniele et al. \(2023\)](#), based on exploiting geographic variation in the agro-ecological opium poppy suitability index and the additional shock of the OxyContin reformulation in 2010. The latter led to a substitution between OxyContin, a widely used semi-synthetic opioid, and street heroin in the United States, increasing opium poppy demand and prices in Mexico—the main supplier of heroin to the United States. My primary findings suggest that a positive shock to farm-gate poppy prices reduced deforestation and agricultural and livestock activities. The reduction in deforestation continued even when poppy prices fell back to pre-2010 levels, which can be explained by an income boost channeled into off-farm work or out-migration. Overall, this paper studies a rather rare case where a price boom for a crop reduces deforestation and attempts to explain the possible mechanisms behind this relationship.

Keywords : Deforestation; crop price; illicit crops; poppy; Mexico; heroin; OxyContin reformulation

JEL classification : Q15; Q23; Q34; Q56; O13

*Universite de Pau et des Pays de l'Adour, E2S UPPA, CNRS, TREE, Bayonne, France
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1 Introduction

The global agricultural landscape is constantly evolving. It continuously expands at the expense of the world’s forests, leading to biodiversity loss and increased greenhouse gas emissions (Ceballos et al., 2015; Betts et al., 2017; Curtis et al., 2018; Balboni et al., 2023). Global crop price fluctuations play an important role in shaping farmers’ decisions regarding land use. Existing literature often suggests a positive relationship between deforestation and increasing prices (Assunção et al., 2015; Berman et al., 2023; Jouf and Lawson, 2022; Lim et al., 2023).

In this article, I study the impact of a price boom for opium poppy—the raw ingredient of heroin—on deforestation in Mexico. The latter is both the principal heroin supplier to the United States since 2013 and the third-largest producer of opium poppy after Afghanistan and Myanmar (UNODC, 2023). Additionally, Mexico, which hosts 50% of pine and 40% of oak species worldwide in its temperate forests (Galicia and Zarco-Arista, 2014) and is part of the Mesoamerican Forest Corridor, a global biodiversity hotspot, is losing its tree cover at an alarming rate, mainly due to the pressure of agricultural expansion (Figuroa et al., 2021).¹

To establish this link, I borrow the empirical strategy of Daniele et al. (2023), which exploits the timing of the OxyContin reformulation in the United States and the variation of the agro-ecological opium poppy suitability index between Mexican municipalities using a continuous difference-in-differences setup. The authors also create a cannabis suitability index to restrict the sample to poppy and/or cannabis suitable municipalities (i.e., municipalities that potentially have illicit crop cultivation). Daniele et al. (2023) show that the poppy suitability index is not associated with initial municipality characteristics when the sample is restricted to only poppy and/or cannabis suitable municipalities and when controlling for changes related to the cannabis market by introducing an interaction term between the cannabis suitability index and the post-2010 dummy. By interacting poppy suitability with a post-2010 dummy, this setup captures the change in deforestation rates in more poppy-suitable municipalities compared to less suitable ones before and after the OxyContin reformulation in Mexico, once controlled for the cannabis demand.

OxyContin is a highly addictive, semi-synthetic opioid that has been extensively used for recreational purposes (Powell and Pacula, 2021).² When used as expected, its extended-release properties ensure the distribution of the active ingredient over time. However, prior to 2010, individuals were able to experience its full impact in one dose by simply crushing the pill (Evans et al., 2019). OxyContin was reformulated with the purpose of decreasing its recreational usage; however, an unexpected consequence of this policy was an increased demand for street heroin, a widely available substitute in the United States (Evans et al., 2019). This policy also had long-term effects on the U.S. drug market by reducing access to a legally prescribable opioid, thus increasing the demand for illicit drugs (Powell and Pacula, 2021).

Even though heroin demand increased immediately after the OxyContin reformulation, opium poppy production did not follow. Prior to 2014, Mexico was exporting black tar heroin, which had a lower purity level than Colombia’s white powder. Around 2014, cartels adopted improved refinement techniques for

¹ An estimated 8.8% of tree cover loss occurred between 2001 and 2022, according to Global Forest Watch: <https://www.globalforestwatch.org/dashboards/country/MEX/>

² OxyContin’s active ingredient, oxycodone, and heroin are both semi-synthetic opioids, which can be “synthesized from natural opioid alkaloids and are structurally similar to morphine” (Salle et al., 2019).

heroin production, achieving even higher purity levels than Colombian white powder while also reducing their costs (Washington Post, 2015; Esquire, 2016). Cartels benefited from the increasing heroin demand to capture the market with their low-cost heroin (NDTA, 2017). Their aggressive strategy is reflected in the plummeting retail and wholesale heroin prices in the United States (see Figure A1). A New York Times article explains how cartels pressured retail-level dealers to increase their market and reduce heroin prices in St. Louis (New York Times, 2016). Consequently, by 2015, heroin from Mexico accounted for more than 90% of the market share, replacing Colombia due to its low price and increased quality (DEA, 2020).³

However, the farm-gate prices of opium poppy followed a different trend, according to several field studies and interviews (Le Cour Grandmaison et al., 2019; Tamariz et al., 2023; Buxton, 2015; Ospina et al., 2018). Between 2010 and 2017, poppy plant demand increased, as did poppy prices. During this period, cartels were increasing the heroin supply, producing more and more heroin, thus they needed more raw material. Heroin seizure trends corroborate this idea, showing a permanent increase in heroin seizures since 2010 in the United States, with a slight downward trend since 2019 (see Figure A4). After reaching its highest level in 2017, the price of opium poppy unexpectedly fell to its pre-shock level just one year later, in 2018 and stayed low (Le Cour Grandmaison et al., 2019; Tamariz et al., 2023).

The reason behind this collapse was the introduction of fentanyl to the U.S. drug market around 2014 (De Haro-Lopez, 2023). Fentanyl is a synthetic drug that can be consumed separately or laced with heroin or cocaine to raise potency, which increase profit margins and reduce demand for pure heroin (De Haro-Lopez, 2023). Moreover, Powell and Pacula (2021) argue that increasing demand for illicit opioids may explain fentanyl’s entrance to the United States, expanding demand in the illicit market. To distinguish between the high poppy price period (2010–2017) and the low price period (2018–2021), I slightly modified the main specification of Daniele et al. (2023) by interacting the poppy suitability index with two period dummies and also conducted an event study analysis. While it might be preferable to use annual farm-gate poppy prices, due to the lack of data, I formed these periods based on price reports from field studies (Le Cour Grandmaison et al., 2019; Ospina et al., 2018).

I calculate deforestation at the municipality-year level using the satellite-based Global Forest Change dataset (Hansen et al., 2013). For legal crops and livestock, I rely on agricultural statistics from the Mexican Ministry of Agriculture (SAGARPA). To complement data on legal crops, I use poppy eradication statistics from the Mexican military (SEDENA), often used as a proxy for poppy cultivation (Dube et al., 2016). Economic activity is measured using nighttime lights data, and cartel activity comes from the “Organized Criminal Violence Event Data” (OCVED), which provides municipality-year level information on violent events committed by cartels, including the name of the cartel (Osorio and Reyes, 2017).

The baseline results show a reduction in deforestation after 2010 in municipalities that are more suitable for poppy cultivation. A municipality with 100 km^2 more poppy-suitable area is associated with an estimated 0.012% less deforestation annually, which is equivalent to a 24% decrease from the pre-shock median deforestation rate. Replacing the continuous poppy suitability index with a binary variable that indicates municipalities with suitability higher than the median increases this reduction to an estimated 0.041 hectares. I also find that this reduction persisted and even increased during the period from 2018 to 2021, when the demand for heroin and poppy was lower.

³ This did not happen in a single year. Mexican cartels were already increasing their market share each year, but prior to 2014, they had access to low-purity black tar heroin.

Area allocated to annual crops (except maize) and livestock volume are also negatively associated with poppy suitability after 2010 and have not recovered since the fall in poppy demand. On the other hand, poppy eradication, used as a proxy for its cultivation, is significantly affected only during 2010–2017 before returning to its pre-shock level. I interpret this as a long-term reduction of agricultural activities in more poppy-suitable municipalities during both high and low poppy demand periods. I argue that farmers allocate more labor to poppy cultivation during the high price period and do not return to agricultural activities afterward, investing their newly earned capital in out-migration or off-farm work as a plausible mechanism. These results are in line with [Tamariz et al. \(2023\)](#), which explains that in regions with alternative livelihoods, poppy farmers do not return to agricultural activities, and resonate with [Daniele et al. \(2023\)](#), which shows an increasing out-migration from more poppy-suitable municipalities after the OxyContin reformulation.

This study relates to the broader economic discourse concerning the relationship between agricultural output prices and deforestation, as existing literature tends to converge towards a positive association ([Busch and Ferretti-Gallon, 2023](#)). For instance, [Berman et al. \(2023\)](#) consider the impact of international crop price variations on deforestation in tropical regions. By interacting the agronomic suitability index of a crop with its international price, the authors estimate that a 10% increase in the crop price index corresponds to a 12.4% rise in deforestation during the 2001–2018 period ([Berman et al., 2023](#)). Similarly, [Assunção et al. \(2015\)](#) demonstrate a strong positive effect of crop prices on deforestation in the Brazilian Amazon. Addressing the same question in a European context, [Jouf and Lawson \(2022\)](#) obtain similar results, implying that agricultural expansion and deforestation are challenges not limited to tropical regions. Investigating palm oil expansion and deforestation in Indonesia, [Lim et al. \(2023\)](#) test the Borlaug hypothesis (i.e., an expected negative relation between agricultural yield and deforestation) and demonstrate that improvements in yield spare forests only when the demand for the crop is highly inelastic and prices are very low.

My contribution to this literature is that I analyze for the first time the relation between a demand shock on an illicit crop and deforestation. Poppy plant differs from legal crops for several reasons: Firstly, opium poppy farmers have to disguise their cultivation to reduce the risk of eradication. Among other techniques, they scatter poppy cultivation in small patches among forests and mountains ([Le Cour Grandmaison et al., 2019](#)) or cover opium poppy with taller maize plants ([Martinez, 2021](#)). This situation limits agricultural land expansion. Second, opium poppy is relatively simple to grow in terms of input but highly labor-intensive and time-consuming during the harvest period, thus necessitating labor allocation from other economic activities ([Buxton, 2015](#); [Lind et al., 2014](#)). Third, it has a substantial land-to-profit ratio, with up to three harvest cycles per year ([De Haro-Lopez, 2023](#)).

Hence, expanding poppy cultivation does not necessarily result in deforestation, as is the case in the model of [Assunção et al. \(2015\)](#) that applies to traditional crops. A price boom in opium poppy may incentivize farmers to spend less time and dedicate less area to other crops, which would in turn decrease agricultural expansion and slow down deforestation. Furthermore, the nature of poppy cultivation requires farmers to disguise their activities to avoid detection and eradication by the Mexican military. This need for concealment means that poppy cultivation often takes place in isolated, mountainous regions. Large forest clearances would attract attention and increase the risk of eradication, so farmers tend to plant poppy in small, scattered plots within the forest or among other crops. Consequently, this limits the demand for land conversion from forest to farmland.

Clearly, there is a story about the substitution effect between illicit and legal crop cultivation. A

theoretical framework on farmers’ decisions between planting opium poppy or legal crops has been developed by [Lind et al. \(2014\)](#). In a simple model with two crop choices (wheat and poppy), the authors show that farmers’ decisions depend on the opportunity cost of illegal activity ([Lind et al., 2014](#)). In Afghanistan, the authors argue that having a strong warlord increases perceived lawlessness, which favors poppy cultivation. The deterioration of irrigation and road infrastructure due to clashes between warlords and the army decreases the profitability of wheat, which benefits more from irrigation, and again favors the expansion of poppy cultivation. They add that farm-gate poppy prices go down simultaneously with expansion as drug dealers benefit from lawlessness and their price-setting status by suppressing the price up to a point to maximize their profit without disincentivizing poppy farmers ([Lind et al., 2014](#)).

Their model is based on several assumptions that are well-suited to Afghanistan, but not all of them are applicable to Mexico. First, the similarities: Poppy farmers are price-takers. They have a labor constraint to allocate between poppy and legal crops, and they face the risk of eradication by the state. Farmers in both Afghanistan and Mexico make their cultivation choices independently of cartels or warlords. However, there are many dissimilarities. Cartels do not operate in the same manner as warlords. After producing the heroin or buying it from middlemen, cartels smuggle it to the United States and sell it to retail-level dealers. They can influence heroin prices in the United States, which is not the case in the model of [Lind et al. \(2014\)](#), where heroin prices are exogenous. Additionally, Mexican cartels compete with Colombian heroin and develop strategies accordingly. I do not test the model of [Lind et al. \(2014\)](#) directly, but I use it as a guide to interpret and understand farmers’ decision between illicit and legal crops.

The remainder of this paper is organized as follows. In section 2, I explain the background of poppy cultivation in Mexico, the recent evolutions in heroin trade on both sides of the border, the OxyContin reformulation, and review some closely related studies. Section 3 provides a description of data, variables, and empirical strategy. In section 4, I present the main results of the article, thoroughly discuss mechanisms, and conduct a heterogeneity analysis related to cartel presence. Section 5 concludes this study.

2 Opium poppy cultivation and heroin trade

A. Opium poppy cultivation in Mexico

Historically, opium production was introduced in Mexico during the great Chinese migration around the 1910s ([Murphy and Rossi, 2020](#); [Velázquez and Smith, 2022](#)). Chinese immigrants with access to land began cultivating opium poppy and producing smoking opium on a small scale ([Velázquez and Smith, 2022](#)). Separated by the U.S.-Mexico border, they became important actors in smuggling activities ([Murphy and Rossi, 2020](#)). Following the Harrison Narcotics Tax Act of 1914, opium prices on the northern side of the border increased, raising the incentives for drug trafficking ([Murphy and Rossi, 2020](#)).⁴ Over time, the scale of poppy cultivation grew, and control over the drug market shifted to drug trafficking organizations known today as cartels. The importation of opium-related know-how and the establishment of smuggling networks had a long-term impact on Mexican organized crime and

⁴ A law that regulates opium and coca leaf trade and production in the United States ([Murphy and Rossi, 2020](#)).

contributed to socioeconomic development at the local level, as noted by [Murphy and Rossi \(2020\)](#).

Geographically, opium poppy cultivation in Mexico coincides with two mountain ranges. The Sierra Madre Occidental, located in northwest Mexico, has been home to poppy cultivation since the 1910s. This region, also called the “Golden Triangle,” includes Sonora, Sinaloa, Chihuahua, and Nayarit states ([UNODC, 2022](#)). Around the 1980s, poppy cultivation expanded towards the Southern Sierra Madre mountains, also known as the red mountains—first because of its communist political leaning and then due to the color of the opium poppy flower ([Gaussens, 2018](#)). Opium gum production became an important source of income for farmers in the states of Guerrero and Oaxaca. Today, Guerrero is the main poppy cultivator and faces high levels of eradication activities ([Gaussens, 2018](#)). Additionally, poppy-growing regions overlap with temperate forests in the Sierra Madre mountain range, providing essential ecosystem services to millions of people. These services include drinking water, wood, carbon sequestration, cultural and spiritual services, and eco-tourism, among others ([Galicía and Zarco-Arista, 2014](#)).

The Mexican military has been conducting operations to dismantle and destroy poppy fields since the 1970s ([Felbab-Brown, 2020](#)). The military searches areas with illicit crop cultivation with a view to subsequently eradicating them ([Dube et al., 2016](#)). The most commonly used method is manual eradication, which involves harvesting and destroying, primarily by burning, poppy plants. The second method is aerial spraying with helicopters, using an herbicide called Paraquat, but only a very small part of eradication is done this way.⁵ In 2017, more than an estimated 40,000 hectares of land were allocated to opium poppy cultivation in Mexico ([UNODC, 2022](#)), while around 24,000 hectares of poppy fields were reported to be eradicated during the same period (see [Figure 1](#)). The military may conduct operations in the same area several times a year because poppy can have up to three harvest seasons annually ([Le Cour Grandmaison et al., 2019](#)). [Figure B1](#) shows the distribution of total opium poppy areas eradicated by the Mexican military at the municipality level for 2005–2018.

Despite the fact that the annual amount of poppy eradication reaches an estimated 75% of annual poppy cultivation ([Dube et al., 2016](#)), there have been doubts about its efficiency and its true goal. Firstly, the amount of eradication does not reduce the heroin supply in the United States ([Felbab-Brown, 2020](#)), raising questions about its effectiveness. Secondly, the poppy eradication campaign has been criticized for being used as a pretext for military presence, particularly in southern Mexico ([Alvarez et al., 2022](#); [Martínez, 2021](#)). Even though the motivations behind eradication activities are not always clear, this is the only data available to track annual and geographical trends in poppy cultivation.⁶

Once harvested, opium poppy flowers are converted into opium paste before being sold to a middleman, called *acaparador*, who transforms it into heroin and delivers it to cartels for distribution ([Le Cour Grandmaison et al., 2019](#); [De Haro-Lopez, 2023](#)). A back-of-the-envelope calculation suggests that cultivating one hectare of poppy flowers is significantly more profitable than, for instance, growing avocados—a known cash crop. In 2013, it was possible to earn 165,000 pesos per hectare from poppy cultivation in Mexico ([De Haro-Lopez, 2023](#)), while the amount was approximately 45,301 pesos for high-quality avocados produced in Michoacán.⁷ In 2017, the estimated potential pure heroin production in Mexico

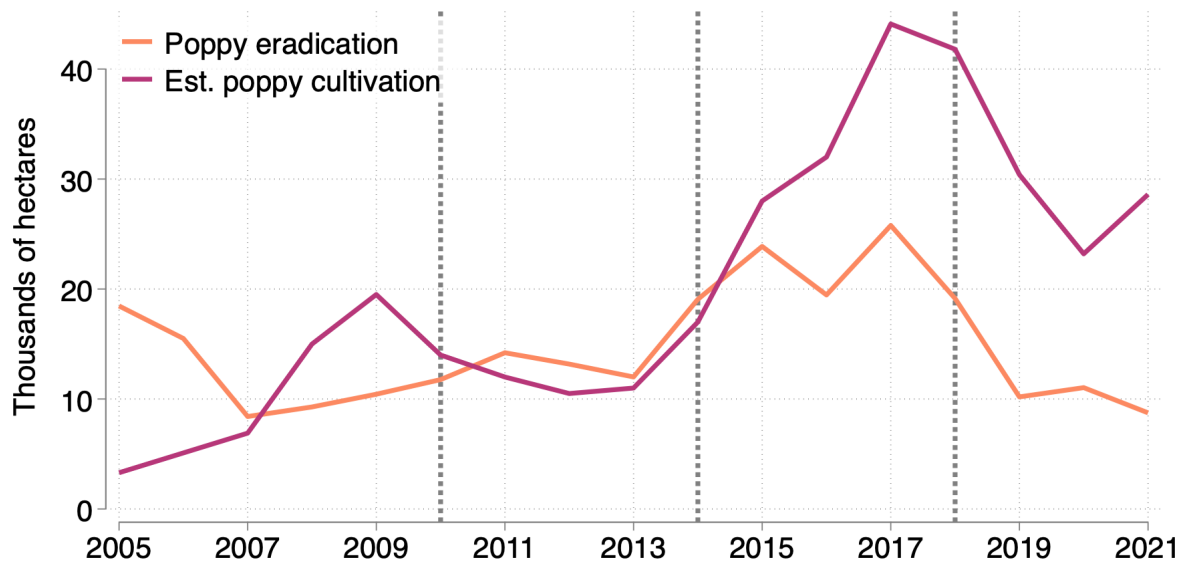
⁵ More information on eradication methods can be found here: <https://noria-research.com/es-violenta-la-ampola-en-mexico/>

⁶ The UNODC and the Mexican government have collaborated on a poppy atlas since 2014, but this data is not publicly available.

⁷ From two hectares of poppy flower cultivation, it is possible to produce 22 kg of opium paste, which could be sold for 15,000 pesos per kg in 2013 ([De Haro-Lopez, 2023](#)). The avocado value per hectare for 2013 is calculated using agricultural

reached 111 tons before decreasing due to the introduction of fentanyl to the drug market (White House, 2022).

Figure 1: Evolution of estimated poppy cultivation and eradication in Mexico



Note: Poppy eradication data is provided by the Mexican military (SEDENA) and includes both manual and aerial eradication. The estimated area of poppy cultivation comes from the White House Office of National Drug Control Policy (ONDCP). Three dashed lines in 2010, 2014, and 2018 indicate the OxyContin reformulation, the increase in Mexican heroin purity, and the fall in poppy prices, respectively.

B. Heroin market

In the early 2000s, Colombian heroin dominated the U.S. market, while Mexico-sourced heroin, due to its lower quality, served smaller markets on the West Coast (Felbab-Brown, 2020). However, the landscape underwent a profound shift around 2014 when Mexican cartels refined their heroin production methods, resulting in a product with higher purity. This change allowed cartels to rapidly expand their influence, and capture a substantial share of the U.S. heroin market with enhanced purity levels, low heroin prices and well-established distribution rings (DEA, 2020). Notably, the share of Mexico-sourced heroin surged from 47% in 2013 to an overwhelming 82% in 2014 and then stabilized, as illustrated in Figure 2.⁸ Moreover, the estimated poppy area and eradicated area also increased substantially but not immediately after the OxyContin reformulation. This shift, evidenced by the substantial increase in the area eradicated in 2014 by the Mexican military (see Figure 1), is also supported by anecdotal evidence and field studies (Ospina et al., 2018; Le Cour Grandmaison et al., 2019; Felbab-Brown, 2020).

data from SIAP by multiplying the average yield with the average price in Michoacán.

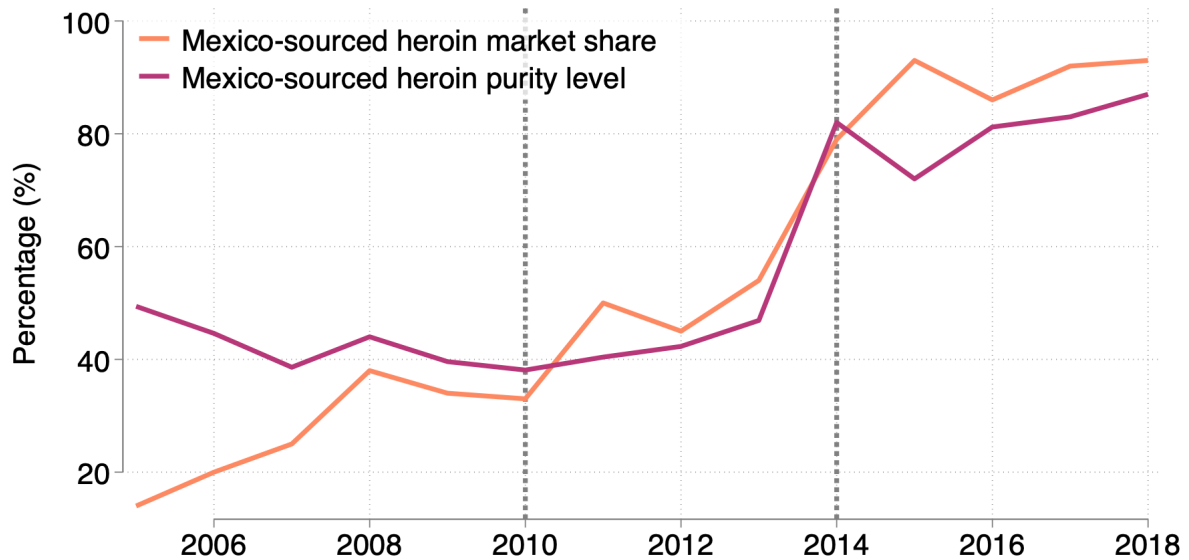
⁸ The United States Drug Enforcement Administration (DEA) tracks the origin country of heroin through two distinct programs: the Heroin Signature Program (HSP) and the Heroin Domestic Monitor Program (HDMP). The HSP conducts analyses on a subset of samples from heroin seizures made at borders (Finklea, 2019). It serves as an indicator of the geographic origins of heroin and allows for the detection of trends, although its sample size is not representative and it does not provide information at the retail level (Finklea, 2019). On the other hand, the HDMP aims to monitor heroin at the retail level. DEA agents purchase heroin from retail sellers in 27 cities across the United States. Both programs provide information on purity levels and geographical origin. According to HSP data, four distinct periods can be defined by the primary supplier region (DEA, 2020): (1) Mexico from 1920 to the 1970s, (2) Asia (including Turkey) from 1979 to 1993, (3) South America (mostly Colombia) from 1994 to 2013, and (4) Mexico. Since 2003, the market share of Mexican heroin has steadily increased. The Mexican cartels have supplied more than 90% of the heroin in the U.S. since 2015, according to the HSP (DEA, 2020).

Since 2014, the U.S. drug market has experienced the gradual introduction of fentanyl, a synthetic opioid. Initially, fentanyl was produced in China and shipped to the U.S. through conventional postal services. This practice continued until 2018, when the U.S. and China reached an agreement to reduce fentanyl shipments (Le Cour Grandmaison et al., 2019). In recent years, however, there have been reports of low-quality fentanyl production by Mexican cartels (Pardo and Reuter, 2020). Additionally, fentanyl seizure events at the U.S.-Mexico border increased from 270 kg in 2016 to 6,668 kg in 2022, while heroin seizures decreased, indicating a shift in cartel interests towards fentanyl (de la Fuente, 2023). Fentanyl production is less costly than heroin, and Mexican cartels possess the infrastructure and expertise from methamphetamine production. Moreover, its potency in smaller quantities makes fentanyl easier to smuggle, even through postal services (InSight Crime, 2021). Fentanyl can also be pressed into counterfeit pills resembling OxyContin, Xanax, and other medications (InSight Crime, 2021). All these factors make fentanyl a highly profitable and attractive option for cartels compared to heroin.

Fentanyl has impacted the drug market not only as an alternative to heroin but also by increasing heroin's potency when laced with it. Pure heroin is often adulterated with substances like caffeine and sugar, or more dangerous additives such as xylazine and fentanyl (Alexander et al., 2022). The purpose of lacing is to increase retail-level margins by reducing the cost of heroin and enhancing its potency (De Haro-Lopez, 2023). This practice has significantly elevated the risk of overdoses, particularly in the United States. Overdoses related to synthetic-laced heroin, which often includes fentanyl, surpassed those from non-synthetic-laced heroin in 2017 (see Figure A2). According to the Centers for Disease Control and Prevention (CDC), 80,997 opioid-related overdoses were reported in 2021, with more than 85% of these deaths linked to synthetic opioids such as fentanyl.⁹ In 2018, as fentanyl usage increased, the demand for heroin declined, leading to a sharp drop in farm-gate poppy prices (De Haro-Lopez, 2023). The price of a kilo of opium gum fell from approximately 1050 USD in 2016 to 157 USD in 2018 (Tamariz et al., 2023).

⁹ Link to data source: <https://www.cdc.gov/nchs/nvss/vsrr/drug-overdose-data.htm>

Figure 2: Evolution of Mexico-sourced heroin market share and its purity level



Note: Data comes from the United States Drug Enforcement Administration (DEA) Heroin Signature Program (HSP). The period is limited to 2018 because the latest available HSP report dates from 2018. The dashed lines in 2010 and 2014 signify the OxyContin reformulation and the increase in Mexican heroin purity, respectively.

C. Heroin demand shock: the OxyContin reformulation in U.S.

OxyContin, an opioid-based painkiller derived from oxycodone a semi-synthetic opioid, was released to the market in 1996 by Purdue Pharma as a “non-addictive” painkiller. It was highly successful for its producer due to an aggressive advertising campaign promoting its supposedly less addictive characteristics, which were later found to be untrue (Evans et al., 2019). Prescription rates for oxycodone, including OxyContin, increased by 70% between 2000 and 2010 (Kenan et al., 2012). A distinctive feature of OxyContin was its extended-release property. When used as intended, OxyContin releases oxycodone slowly over a period of 12 hours. However, individuals could easily crush these pills to obtain the full impact with a single snort or injection before August 2010 (Evans et al., 2019). With the reformulation, OxyContin became harder to abuse and use for recreational purposes.

The unintended consequence of this policy, for those who were addicted, was a shift from OxyContin to street heroin. The OxyContin reformulation reduced opioid deaths but concurrently led to a parallel increase in heroin-related deaths due to overdoses in states where heroin was highly available (Evans et al., 2019). In the Appendix, Figure A2, shows the increasing heroin overdoses since 2010. On the other hand, fentanyl-laced heroin overdoses began to rise gradually in 2014, reducing demand for pure heroin (De Haro-Lopez, 2023).¹⁰ I interpret the rise in overdoses as indicative of a growing demand. Overall, the demand for heroin increased during the period 2010–2017, which translated to increased opium poppy demand and prices, particularly in the 2014–2017 period, on the other side of the border (Sobrinho, 2020; Daniele et al., 2023; Le Cour Grandmaison et al., 2019). Since 2018, fentanyl-laced heroin overdoses have surpassed those related to pure heroin, and the demand for the latter has decreased, along

¹⁰ When fentanyl is laced with heroin, it increases the potency of the heroin. This allows dealers to use less heroin while still maintaining the same level of potency, thereby achieving the same amount of profit with a reduced quantity of heroin (De Haro-Lopez, 2023).

with farm-gate opium poppy demand and prices.

This positive demand shock was unexpected for cartels and poppy farmers in Mexico. They did not have foreknowledge of the reformulation of OxyContin, and they couldn't have influenced it. However, the poppy eradication data, presented in Figure 1, do not show an immediate increase in poppy cultivation or eradication. While heroin overdoses steadily increased between 2010 and 2018, suggesting an increase in heroin consumption in the U.S., poppy cultivation and eradication did not rise until 2014, the year when cartels adopted the novel heroin production method and significantly expanded their market share in the United States. Moreover, farm-gate poppy prices reached their peak in 2017, showing that the introduction of fentanyl did not reduce them immediately (Le Cour Grandmaison et al., 2019). Altogether, these pieces of evidence imply two distinct periods after the OxyContin reformulation. A similar periodical pattern appears also in Sobrino (2020) and Daniele et al. (2023), where both studies find a change of trend in regard to their outcome variables, homicide rate, and out-migration starting in 2014. A significant contribution of this study is the extension of the analysis period up to 2021, which includes the low poppy price period, unlike previous studies that have a limited time frame and do not analyze the fentanyl period when poppy prices are high.¹¹

3 Empirical strategy and data

3.1 Empirical strategy

The identification strategy employed in this study is borrowed from Daniele et al. (2023). The authors exploit the timing of heroin demand shock, as well as the spatial distribution of the opium poppy suitability index. I use the same setup and investigate the relationship between increasing poppy prices and deforestation.

The baseline specification is as follows:

$$Y_{it} = \beta_1 \text{PoppySuit}_i * \text{Post2010}_t + X'_{it}\gamma + \delta_i + \phi_t + \psi_{mt} + \epsilon_{it} \quad (1)$$

Y_{it} represents the outcomes in municipality i and year t . The continuous treatment variable is the poppy suitability index (in hundreds of km^2) - PoppySuit_i - interacted with a post-2010 dummy, which equals one since 2010. I prefer using the treatment variable in its raw form instead of the inverse hyperbolic sine (IHS) transformation, as used by (Daniele et al., 2023). In the IHS case, the magnitude and significance of the estimated coefficients depend on the pre-transformed unit of the variable (Chen and Roth, 2023).¹² In Appendix F, I re-run Equation 1 by converting the treatment variable with IHS for four different pre-transformed units of poppy suitability.¹³ The results are highly volatile both in terms of magnitude and

¹¹ With the exception of De Haro-Lopez (2023), where the author investigates the impact of decreasing demand for heroin, due to the introduction of fentanyl on avocado producing municipalities and the author finds an increasing violence from cartels toward civilians to capture the avocado rent.

¹² The same is valid for the $\log(x + 1)$ transformation (Chen and Roth, 2023).

¹³ These units are hundreds of km^2 , km^2 , hectares, and m^2 .

coefficient significance. Therefore, I do not use the IHS-transformed treatment variable in this study.

X'_{it} includes an interaction term between the cannabis suitability index (in hundred km^2) and post-2010 dummy for changes in the cannabis market. δ_i represents municipality fixed effects, controlling for time-invariant characteristics of municipalities. ϕ_t denotes year fixed effects, capturing time shocks common to all municipalities. ψ_{mt} includes macro region-year fixed effects.¹⁴ ϵ_{it} is the error term, and the standard errors are clustered at the Mexican state-year level to account for potential correlations of errors within each Mexican state over different years (Daniele et al., 2023). Clustering at the state level is appropriate for this study as state-level policies may influence deforestation. In robustness section, Table E4 presents baseline results when clustered at the municipality level, and the results are robust.

I expand the study period to 2005-2021, and I keep only municipalities suitable for cannabis and/or opium poppy cultivation and those with at least 5% or more tree cover in 2000. My main sample consists of 832 municipalities. I conduct several sensitivity checks in Appendix E.1 related to these choices.

The main outcome of this study, deforestation, has a long right-tailed distribution with 20% of the observations having zero values (see descriptive statistics at Table C1 in Appendix C), which may introduce noise to estimation (Chen and Roth, 2023). It is common to use a log-like transformation when the outcome has strictly positive values, and $\log(1+x)$ or $\text{arcsinh}(x)$ transformation when it also includes zero values. These methods also facilitates interpretation in terms of percentage changes. However, the latter two methods are found to introduce bias as the estimated coefficient depends on the choice of the unit of measurement of dependent variable (Chen and Roth, 2023). In the case of zero-valued variables, there is no solution that simultaneously provides point-identified estimates, remains independent of the units of pre-transformed variables, and estimates the average treatment effect (Chen and Roth, 2023).

Among other options, the authors propose to divide the outcome with a pre-determined value to make a scale-invariant transformation which allows also an interpretation in percentage change and gives point-identified estimates (Chen and Roth, 2023). Following the authors suggestion, I create the deforestation rate variable which is the part of deforestation out of the forest area in 2000 in percentage.

As an alternative transformation, I normalize the raw deforestation variable by subtracting the mean and dividing by the standard deviation for the period 2005-2021 (see Equation 2). The advantages of this transformation are that it is scale-invariant, smooths the distribution of outcome values, and captures the relative change in deforestation between municipalities, thus reducing the effect of outliers (Assunção et al., 2023). However, the interpretation of the estimated coefficients is less straightforward compared to the deforestation rate. I follow the normalization process described in Assunção et al. (2023) and apply it to the raw deforestation, agricultural area, and livestock outcomes (Y_{it} in Equation 1).¹⁵

$$\text{NormalizedVar}_{it} = (\text{Var}_{it} - \text{VarMean}_{i,(2005-2021)}) / \text{VarSD}_{i,(2005-2021)} \quad (2)$$

¹⁴ Macro regions, created by the Mexican National Institute of Statistics, share similar environmental characteristics and divide the country into 8 regions (Daniele et al., 2023).

¹⁵ (Chen and Roth, 2023) also propose the Poisson pseudo-maximum likelihood regression (PPML) estimator. I conduct a robustness analysis with the PPML estimator using raw deforestation as the dependent variable. The results, presented in Table F1, are similar to the baseline results.

3.1.1 Threats to identification

The described strategy differs from the canonical difference-in-differences setup, which typically involves exactly two time periods and binary treatment. In the canonical case, two assumptions lead to causal identification: parallel trends of outcomes prior to the treatment start between the treatment and control group, and no anticipation of treatment. In the continuous treatment variable case, difference-in-differences combines an estimation of two effects: the level effect, which is the difference between being treated and its counterfactual, and the slope effect, which is the difference between different doses of treatment (Callaway et al., 2024). While the level effect is similar to the binary treatment case in the canonical difference-in-differences setup and necessitates the same basic assumptions for causal identification (the (weak) parallel trends and no anticipation of treatment), the slope effect implies a stronger parallel trend assumption. This stronger parallel trend assumption consists of treatment effect homogeneity in all dose groups (Callaway et al., 2024). Unfortunately, it is not possible to test this assumption with classical tools in the case of continuous treatment.

To reduce concerns related to the continuous treatment variable, I construct a binary variable. I calculate the median poppy suitability among poppy-suitable municipalities and generate a binary variable that equals one if a municipality has median or above suitability for poppy cultivation. In this specification, I replace the continuous $PoppySuit_{it}$ variable in Equation 1 with the binary variable. I also drop from the sample the municipalities with lower than median poppy suitability to compare high poppy suitable municipalities with non-poppy suitable units. The results from this specification are similar to the baseline.

The unexpected nature of this shock satisfies the other critical assumption of difference-in-differences: no anticipation of treatment. The increasing heroin demand is a result of U.S. policies independent of the poppy cultivators in Mexico—the main actors of this analysis. In the end, the farm-gate poppy prices are determined by cartels and middlemen, not by poppy cultivators (Sobrinho, 2020), and the transformation from opium paste to heroin is not done by farmers. Moreover, to ensure the exogeneity of the heroin demand shock and poppy suitability index, I conduct the following tests. First, in a cross-sectional setup, I investigate the relationship between pre-treatment municipality characteristics and the poppy suitability index, similar to Daniele et al. (2023). Reassuringly, deforestation-related municipality-level pre-characteristics do not have a statistically significant relationship with poppy suitability (Table D3 in Appendix D), which implies that the treatment is not influenced by the initial forest cover.

The only municipality characteristic that is associated with poppy suitability is the distance to U.S. border entry points. I conduct two robustness checks: first, by interacting the distance variable with year linear trends, and second, by interacting it with the post-2010 dummy in Table E1 and E2. The results remain unchanged. Moreover, the inclusion of unit fixed effects in Equation 1 controls for time-invariant characteristics of municipalities.

Tables D1 and D2 in Appendix D present the tests for linear differential trends prior to the OxyContin reformulation (i.e., 2010), following Daniele et al. (2023), but complement them with outcomes related to land use. I use the baseline specification (Equation 1) and restrict the sample to the years 2005-2009, the pre-treatment period. I estimate the coefficients of interaction between the poppy suitability index and the linear year variable on various municipality-level outcomes. All estimated coefficients are statistically insignificant.

Finally, I employ the classical event study approach to visualize the (weak) parallel trend test and to investigate dynamic treatment patterns. Event study graphs are presented in Section D. First, in Figures D1 and D2, I estimate event study coefficients for the continuous treatment variable. Except for one slightly positive coefficient for normalized deforestation five years prior to treatment, all coefficients are not significantly different from zero in the pre-shock period. I conduct the same exercise with the median treatment variable, where the (weak) parallel trend holds in all specifications (see Figures D3 and D4).

Another limitation of this strategy is the inability to capture the annual variation of farm-gate poppy prices. Ideally, it would be preferable to use annual prices instead of a post-2010 dummy, but besides field studies, there is no data on annual poppy prices received by farmers. One might argue that heroin prices in the U.S. might reflect poppy prices. Figure A1 presents the evolution of wholesale and retail heroin prices. Wholesale prices have a decreasing trend since 2005 and retail prices decreased between 2010-2014 and started to increase afterwards reaching its highest level in 2021, which does not correspond with the variation of farm-gate poppy prices. Heroin prices in the United States are not exogenous to Mexican cartels. While the decreasing retail level prices until 2014 reflects cartels aggressive strategy, the increase afterward is about the reducing importance of heroin and Mexican cartels pushing for fentanyl production and smuggling which is more lucrative than heroin trade (InSight Crime, 2021).

The dummy variable indicating the post-2010 period captures the increasing poppy cultivation fairly well. At least it is highly associated with poppy eradication and does not bear the limitations related to heroin price data. To disentangle high and low price periods, I add a second dummy variable to Equation 1 for the period 2018-2021, when opium prices are at their lowest level since 2010 (see Table 2).

3.2 Data

1. *Deforestation.* The Global Forest Change (GFC) data provides satellite-based information on tree cover loss across the globe at the pixel level with a spatial resolution of 30×30 meters (at the equator) (Hansen et al., 2013). It is collected using multispectral satellite imagery and corrected with supervised machine learning algorithms (Hansen et al., 2013). A pixel is defined as forest if it is covered with vegetation higher than five meters. Tree cover variable shows the pixel area covered with forest in 2000. Tree cover loss variable is a dummy indicating the year on which any deforested pixel was lost (i.e., complete canopy removal).¹⁶ The GFC data does not provide information on the amount of deforestation in a given pixel; therefore, it is not possible to detect thinning or selective logging. I keep only pixels with tree cover higher than 30% in 2000 because low tree-covered pixels may falsely be defined as forest instead of agricultural land such as avocado plantations. I calculate annual deforestation in each municipality by multiplying the number of deforested pixels with the pixel size within municipal borders and create deforestation rate and normalized deforestation outcomes as explained in Section 3.1.¹⁷

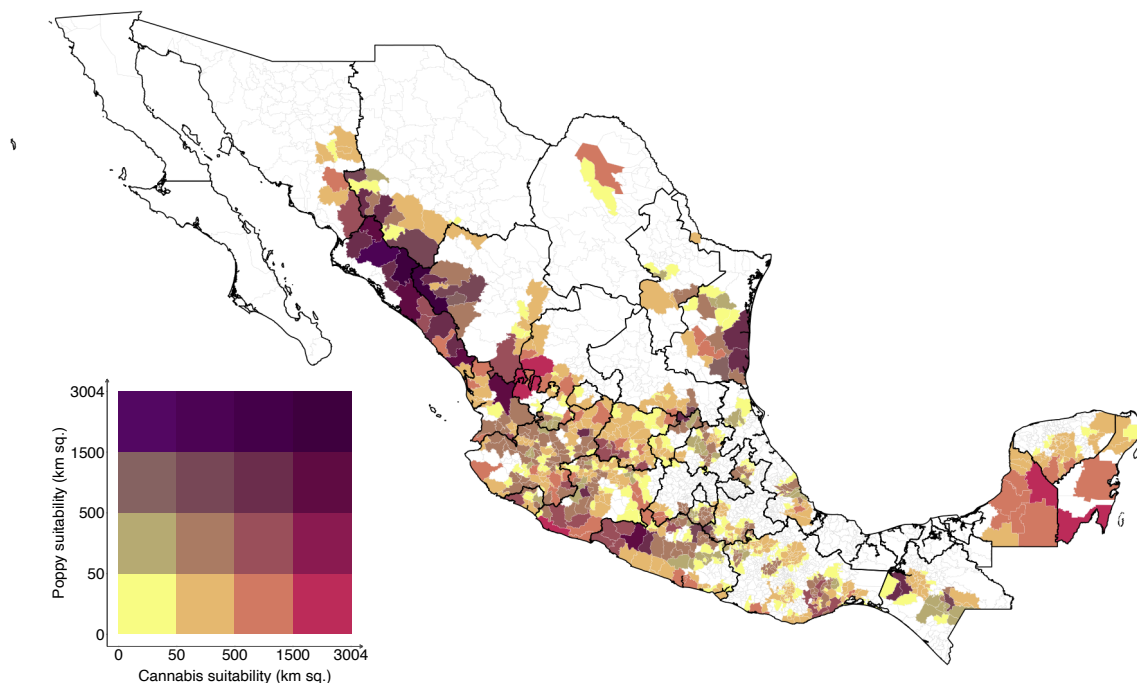
2. *Poppy and cannabis suitability indices.* The widely used FAO/GAEZ database, which provides spatial data on crop suitability and potential yield for various legal crops, does not include information on illicit

¹⁶ For more information: <https://data.globalforestwatch.org/maps/gfw::tree-cover-loss-1/about>

¹⁷ Recent literature on measurement errors introduced by satellite-derived measures indicates that, if uncorrected, these errors can significantly bias estimation results (Alix-Garcia and Millimet, 2023; Proctor et al., 2023). Proctor et al. (2023) proposes a multiple imputation technique that significantly reduces these errors but requires ground-truth data. I plan to use Mexican land use maps provided by INEGI as ground-truth data for calibration and apply the multiple imputation method proposed by Proctor et al. (2023). Therefore, the estimates provided in this article contain some measurement errors and should be interpreted with caution.

crops. Literature on poppy and cannabis cultivation relies on author-made suitability indices (Daniele et al., 2023; De Haro-Lopez, 2023; Sobrino, 2020). I employ the poppy index elaborated by Daniele et al. (2023) because it comes with a cannabis index allowing control for changes in the cannabis market. Both poppy and cannabis indices are based on the Mexican land use map, which divides Mexico into territories with similar agro-ecological characteristics (Daniele et al., 2023). The authors create a dummy variable that equals one if a territory has the necessary temperature, rainfall, and soil pH characteristics adapted for poppy or cannabis cultivation.¹⁸ Then, by matching these territories with municipality borders, they calculate poppy and cannabis suitable land area (in km^2) for each municipality (Daniele et al., 2023). Figure 3 shows the distribution of the poppy and cannabis indices. The white areas in Figure 3 are not suitable for poppy and cannabis cultivation, and they are excluded from the main sample.

Figure 3: Distribution of opium poppy and cannabis suitability indices



Note: Suitability indices are from Daniele et al. (2023). The indices show the area suitable for opium poppy and/or cannabis cultivation in a municipality (in km^2). White municipalities are not suitable for opium poppy or cannabis cultivation. These municipalities are excluded from the sample of analysis. The map was prepared using the “bimap” package in Stata by Asjad Naqvi.

3. *Agriculture.* The statistical services of the Mexican Ministry of Agriculture (SIAP/SAGARPA) provide annual data on production, area, yields, and prices for more than 400 crops at the municipality level for the period 2003–2021. This dataset is the only annual panel data available to track agricultural indicators in Mexico. The data were collected by local representatives of SIAP/SAGARPA and are based on self-reports from farmers. Although this process may lead to misreporting errors, I expect these errors to be randomly distributed and thus believe they do not significantly influence my estimation. I calculate

¹⁸ Information on environmental requirements of poppy and cannabis comes from the FAO EcoCrop database.

the total agricultural area as the sum of the cultivated areas for each crop. Additionally, I calculate the annual area allocated to the most cultivated crop types.¹⁹

Livestock data comes from the same source but it is only available since 2006. It provides number of animal by livestock type at municipality level. However, from 2006 to 2011, 189 municipalities are missing.

4. *Poppy and cannabis eradication.* The data come from the Mexican military (SEDENA) and cover the period from 1990 to 2021. I calculate total eradicated area, the sum of manual and aerial eradication, at the municipality level by crop type (poppy or cannabis). I use these variables to roughly approximate poppy and cannabis sown areas like [Dube et al. \(2016\)](#). However, the recent literature indicates that military activities are not motivated solely by poppy or cannabis eradication. Some studies suggest that the military uses eradication as a pretext to establish a presence in certain municipalities ([Alvarez et al., 2022](#)). This situation may result in a non-random distribution of measurement error, and therefore, findings related to these variables should be interpreted with caution.

5. *Homicide rate.* Homicide data are derived from the mortality database maintained by the Mexican National Institute of Statistics (INEGI). I extract the number of homicides of males aged 25-40 at the municipality level over 2005-2021. I chose to focus on this specific demographic group because they are more likely to be murdered due to activities related to drug trafficking ([Herrera and Martinez-Alvarez, 2022](#)). The number of homicides is divided by the interpolated annual population. The latter is obtained by interpolating annual municipality-level population derived from census data, reported at five-year intervals and retrieved from the National Municipality Information System (Sistema Nacional de Información Municipal).²⁰

6. *Cartels.* There is no openly accessible official data on cartel presence at the municipality-year level in Mexico. Studies related to organized drug trafficking employ datasets based on news reports ([Coscia and Rios, 2012](#); [Osorio and Beltrán, 2020](#); [Sobrino, 2020](#); [Daniele et al., 2023](#); [Alcocer, 2022](#)). In this study, I use the open-access “Organized Criminal Violence Event Data (OCVED),” which covers the period from 2000 to 2018 for all of Mexico ([Osorio and Beltrán, 2020](#)).

OCVED provides information on the existence of violent events and the names of the involved cartels ([Osorio and Beltrán, 2020](#)). OCVED collects information (news reports) from 36 federal and local government agencies and 69 national/local news outlets for the period 2000-2018 (authors use the EMIS database as a news aggregator).²¹ First, OCVED selects reports from the EMIS data using queries with specific keywords and criteria.²² Selected documents then undergo a two-step classification process. In the manual process, research assistants manually assess whether a report is relevant using predefined inclusion and exclusion criteria. In the second step, authors train machine learning algorithms, select the one with the highest precision, and apply it to the pool of reports. As a result, 43,681 news articles are classified as relevant to organized criminal violence. Authors then employ Eventus ID software ([Osorio and Reyes, 2017](#)), which creates an event study dataset by conditioning on coding rules based on actors and locations in Spanish.²³ Finally, OCVED presents the date and municipality of a violent

¹⁹ Link to data source: <http://infosiap.siap.gob.mx/gobmx/datosAbiertos.php>

²⁰ Link to data source: <http://www.snim.rami.gob.mx>

²¹ EMIS is “a large collection of newspapers containing indexed news articles” ([Osorio and Beltrán, 2020](#)).

²² Some keywords include: “crimen organizado,” “narco,” “amapola,” “marihuana,” etc. Additional criteria include not being a sports article (similar terms used such as “attack”), not being related to conflicts in Iraq or natural disasters, etc.

²³ For detailed information, please see the website: https://github.com/javierosorio/OCVED_2.0

event induced by a cartel and the cartel’s name. I compare OCVED with widely-used [Coscia and Rios \(2012\)](#) data for the 2000-2010 period in Appendix G. Overall, the two datasets show similar trends.

I use OCVED as it is the only data available online which covers the study period, and I create two cartel indicators. The first one is a dummy variable equal to one if a violent event related to cartels happened in municipality i in year t . The second variable indicates the number of different cartels implicated in these events in municipality i in year t and serves as a proxy for competition between cartels.

7. Nighttime lights. Nighttime lights (NTL) are widely used as a proxy for economic activity at different spatial scales. They capture the nocturnal luminosity collected by satellites at high spatial resolution. NTL products are derived from two data sources: DMSP (1992–2013) and VIIRS (2012–2022). This gives rise to a problem of compatibility between these two data when one seeks to use an extended NTL time series. They have different spatial resolutions and satellite overpass times ([Wu and Wang, 2019](#)). DMSP is not calibrated, meaning that it should be calibrated to have a consistent time series, but VIIRS data are annually comparable ([Wu and Wang, 2019](#)). The unit indicating luminosity is an integer between 0 and 63 in DMSP and an absolute radiation value in VIIRS, but, most importantly, VIIRS provides higher-quality detection ([Wu and Wang, 2019](#)). Several techniques have been proposed to overcome these issues and generate consistent nighttime light time series ([Li et al., 2020](#); [Chen et al., 2021](#)). I calculate municipality level annual NTL derived from the method proposed by [Chen et al. \(2021\)](#). Authors generate a VIIRS-like extended nighttime light data with very high-level consistency at a spatial resolution of 30 arcsec.²⁴

4 Results, heterogeneity, and mechanisms

4.1 Main results

The coefficients estimated by the baseline specification (Equation 1) are presented in Table 1. The first two columns present coefficients with a continuous treatment variable, while the last two columns use a binary treatment variable, as explained in Section 3.1. All four specifications include an interaction term between cannabis suitability and the post-2010 dummy as a control variable. Additionally, all regressions account for macro region-year fixed effects, which allow for comparisons between municipalities within similar ecological regions.

The coefficients of interest are significant across all specifications with at least 95% confidence, indicating reduced deforestation in more poppy-suitable municipalities after 2010 (Table 1). Municipalities that are 100 km^2 more suitable for poppy cultivation have a yearly reduction in deforestation of 0.012 percentage points compared to less poppy-suitable municipalities post-OxyContin reformulation (column 1). While the magnitude is not large, it is quite significant. The pre-2010 median deforestation rate in the sample is 0.05% (with a mean of 0.22%), which means that a 0.012 percentage point reduction represents a 24% decrease from the median deforestation rate. The same coefficient translates to a 0.041 standard deviation decrease when the raw deforestation variable is normalized by the unit’s mean and standard deviation (column 2), which shows that the treatment effect is not due to a right-skewed distribution of

²⁴ When compared to 2012 DMSP values, extended NTL series have city-level consistency at R^2 of 0.95 ([Chen et al., 2021](#)).

the dependent variable.

In columns 3-4, the treatment variable is the interaction term between the binary poppy variable and the post-2010 dummy. The binary poppy variable equals one if the poppy suitability index is above the median value of poppy-suitable municipalities. Municipalities below the median poppy suitability are dropped from the sample. Thus, in this specification, I compare above-median poppy-suitable municipalities with cannabis-suitable but not poppy-suitable municipalities. Being an above-median poppy-suitable municipality is associated with a 0.04% or 0.24 standard deviation reduction in deforestation compared to cannabis-suitable units (columns 1 and 2, respectively).

Table 1: Impact of OxyContin reformulation on deforestation in Mexico

	Continuous treatment		Median treatment	
	(1) Def. rate	(2) Normalized	(3) Def. rate	(4) Normalized
Poppy suit. X Post2010	-0.012*** (0.003)	-0.041*** (0.012)		
Median dummy X Post2010			-0.041** (0.017)	-0.240*** (0.061)
Cannabis suit. X Post2010	0.011*** (0.003)	0.039*** (0.007)	0.010*** (0.004)	0.036*** (0.007)
Observations	14,144	14,144	10,625	10,625
Mean Y	0.219	-0.000	0.230	-0.000
R ²	0.003	0.004	0.003	0.005
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The sample consists of poppy and/or cannabis suitable municipalities in columns 1-2. In columns 3-4, municipalities with lower than median poppy suitability are dropped. The period of analysis is 2005-2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are dropped in all specifications (Correia, 2015).

The negative coefficient can be interpreted in two ways: either deforestation in municipalities more suitable for cannabis production increased after 2010 while it remained the same in municipalities more suitable for poppy production, implying that the deforestation rate did not decrease but rather did not increase; or deforestation in municipalities more suitable for poppy production decreased compared to less suitable ones. To better understand this dynamic, I present Figure A3, which compares the raw deforestation amounts in above-median poppy-suitable municipalities with those suitable only for cannabis production. The overall picture implies that average deforestation in above-median poppy-suitable municipalities has not decreased since 2010 but remained stable over time, while in municipalities suitable only for cannabis production, it increased after 2014. Hence, the difference between the two groups has increased after the adaptation of new heroin-producing techniques by Mexican cartels. This is also the year when poppy eradication and the estimated area allocated to poppy cultivation saw a significant increase.

On the other hand, the cannabis suitability index, when interacted with the post-2010 dummy variable, shows the opposite effect. This interaction term is used to account for changes in the cannabis market resulting from the decriminalization and legalization of cannabis use in the United States (Daniele et al., 2023). The positive effect observed corroborates the descriptive evidence presented in Figure A3 and suggests increased deforestation in municipalities more suitable for cannabis cultivation after 2010. InSightCrime reports that cannabis seizures in the southern United States decreased from 450 tons in 2012 to approximately 5 tons in 2021 (Norris, 2022). Anecdotal evidence from interviews indicates that cannabis growers are shifting to other legal crops or economic activities, such as off-farm work (Los

[Angeles Times, 2015](#)). Increasing economic activity or expanding agricultural areas may explain the increase in deforestation in municipalities more suitable for cannabis cultivation.

The high poppy prices during 2010–2017 may have reduced farmers’ incentives to expand their agricultural lands for the cultivation of legal crops in more poppy suitable municipalities. Poppy cultivation, by being a labor intensive activity, reduces available labor. Farmers might allocate more time to poppy-related activities instead of cultivating other crops or producing livestock which may explain reducing deforestation. As an income source, poppy cultivation surpassed all other agricultural activities until 2018 ([De Haro-Lopez, 2023](#)). However, with the introduction of fentanyl to the United States, farm-gate poppy prices reached their lowest level in 2018. In Table 2, I investigate this hard change in prices by introducing two binary treatments, one covering the high and the second covering the low price periods.

Table 2: Disentangling high and low poppy price periods

	Continuous treatment		Median treatment	
	(1) Def. rate	(2) Normalized	(3) Def. rate	(4) Normalized
Poppy suit. X P.(2010-2017)	-0.010*** (0.003)	-0.030** (0.014)		
Poppy suit. X P.(2018-2021)	-0.015*** (0.004)	-0.061*** (0.014)		
Median dummy X P.(2010-2017)			-0.031** (0.015)	-0.122* (0.064)
Median dummy X P.(2018-2021)			-0.069*** (0.025)	-0.318*** (0.085)
Cannabis suit. X Post2010	0.011*** (0.003)	0.039*** (0.007)	0.009*** (0.003)	0.034*** (0.007)
Observations	14,144	14,144	10,625	10,625
Mean Y	0.219	-0.000	0.235	-0.000
R ²	0.003	0.004	0.003	0.006
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The sample consists of poppy and/or cannabis suitable municipalities in columns 1-2. In columns 3-4, municipalities with lower than median poppy suitability are dropped. The period of analysis is 2005-2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are dropped in all specifications ([Correia, 2015](#)).

The reduction in deforestation not only continues but even doubles after 2018 compared to the pre-2010 period, as shown in all columns in Table 2. This suggests that those who cultivated poppy during the 2014-2017 period did not return to the agricultural sector, or if they did, they did not yet expand their agricultural lands. Additionally, [Daniele et al. \(2023\)](#) identify an increasing out-migration starting from 2014, which may also contribute to the reduced pressure on forests.

A recent study conducted interviews with small-scale farmers incarcerated in Oaxaca and analyzed satellite images from three municipalities where poppies are grown ([Tamariz et al., 2023](#)). The study aims to understand how farmers are coping with the drop in poppy prices. Across all three areas, there was an immediate decrease in farmland, but over time, different patterns emerged. In two cases, there was either a complete recovery or a lasting decrease in farmland after 2018. The lasting decrease occurred in a municipality where farmers traditionally practiced “milpa” (shifting cultivation) and had other income sources, such as producing “mezcal,” a type of alcohol made from agave plants that is becoming increasingly popular in Oaxaca ([Tamariz et al., 2023](#)). The rebound happened in an area with a long history of growing poppies, extreme poverty, and limited access to other markets ([Tamariz et al., 2023](#)). Neither scenario implies more deforestation, which corroborates the results shown in Table 1 and 2.

Overall, the main findings suggest that deforestation decreased during periods of both high and low poppy prices. This is likely because farmers shifted from other crops to poppy during the price boom and subsequently developed adaptation strategies tailored to their regional characteristics (Tamariz et al., 2023). Some of these strategies include not returning to agriculture, which explains the lack of recovery in deforested areas.

These results withstand several sensitivity analyses and robustness checks presented in Appendix E. In Table E1 and Table E2, from columns 1-3, I reduce the sample size by increasing the lower limit of the initial tree cover condition. In column (4), I introduce distance-year linear trends, and in column (5), I control for distance-related changes by interacting it with the post-2010 dummy.²⁵ In Table E4, I modify the cluster structure by clustering at the municipality level instead of the state-year level. Coefficients remain significant and similar to the baseline results.

Finally, similar to a placebo test, I reshuffle the poppy and cannabis suitability indices and re-run the baseline regression. I randomly distribute the suitability indices among the municipalities and reapply the exercise three times. The results are presented in Table E3 and show no to very weak association between poppy suitability and deforestation when suitability indices are randomly attached to municipalities.²⁶ Overall, the findings presented here appear robust to changes and remain stable across various specifications.

4.2 Mechanisms and heterogeneity

4.2.1 Rising poppy cultivation and decline in agricultural and livestock activities

First, I test whether poppy and/or cannabis eradication (used as an approximation for poppy cultivation) has been affected after 2010. The eradication data consist of both aerial and manual eradication for poppy and cannabis, separately. Aerial eradication is used to a much lesser extent compared to manual eradication. The results are presented in Table 3. For the period 2010-2017, both manual and aerial eradication of poppy are positively associated with the poppy suitability index, while the latter has no effect on cannabis eradication (columns 1-2). During the period of low poppy prices, however, the coefficients for poppy eradication are not significant. Overall, this indicates an increase in poppy cultivation during periods of high poppy prices. On the other hand, cannabis suitability has a negative and highly significant relationship with cannabis eradication after 2010, indicating that cannabis production is declining.

²⁵ The distance variable represents the distance from the municipality centroid to the nearest U.S. entry point.

²⁶ Except for a weakly identified positive relation in one of the specifications, the poppy suitability index is not associated with deforestation.

Table 3: Impact of OxyContin reformulation on eradication in Mexico

	Poppy		Cannabis	
	(1) Manual	(2) Aerial	(3) Manual	(4) Aerial
Poppy suit. X P.(2010-2017)	0.030*** (0.011)	0.017** (0.007)	-0.006 (0.014)	0.008 (0.009)
Poppy suit. X P.(2018-2021)	0.015 (0.010)	0.017 (0.010)	-0.015 (0.014)	-0.007 (0.008)
Cannabis suit. X Post2010	0.004 (0.005)	0.001 (0.002)	-0.026*** (0.007)	-0.000 (0.002)
Observations	13,302	13,302	13,302	13,302
Mean Y(pre-norm.)	13.15	2.02	9.45	1.47
R^2	0.002	0.004	0.003	0.002
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The sample consists of municipalities suitable for poppy and/or cannabis cultivation. The period of analysis is from 2005 to 2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are excluded in all specifications (Correia, 2015). All dependent variables are normalized for the period 2005-2021.

Second, I estimate the relationship between poppy suitability and agricultural area using the same estimation strategy as outlined in Equation 1 but with two period dummies. Specifically, I replace the dependent variables with normalized total agricultural area and sown area by crop type. I include only the seven most produced crops in the sample over the study period. Additionally, I retain two treatment variables representing high and low poppy price periods. Table 4 presents these results. Crops are sorted from left to right by their area size in 2009, pre-OxyContin reformulation. In my sample, maize area has the highest coverage, followed by other annual crops like sorghum, beans, and sugarcane. The most planted pluriannual crops are avocado, agave, and coffee (see Table C1 for summary statistics).

Even though the coefficients for the total agricultural area are negative for the poppy suitability index, they are not statistically significant. On the other hand, cannabis suitability is associated positively with agricultural area after 2010, implying a return to legal agricultural crops in more cannabis-suitable areas after the decline in cannabis demand.

I do not observe a change in maize area in more poppy-suitable municipalities, as shown in column (2). Maize is the primary subsistence crop in Mexico and is also used to conceal opium poppy cultivation. Therefore, it is expected that there would be no reduction in maize area, as farmers would likely continue to produce it for self-consumption while concealing poppy plants. However, all other significant annual crops, and some of the perennial ones, saw a decrease, particularly during the low poppy price period, which may be explained by a decrease in agricultural activity.

This result aligns with the findings of Tamariz et al. (2023), which reported a permanent decrease in agricultural land after 2018 in a municipality that practiced “milpa” before transitioning to poppy cultivation. Beans, a part of “milpa” crops, are used by farmers both as a subsistence crop and a cash crop for local markets or nearby cities. However, beans are much smaller than maize and are not as effective in concealing poppy plants. Additionally, bean cultivation requires a significant amount of labor compared to maize, which may be diverted to poppy harvesting. Consequently, either due to the shift from agricultural activities to off-farm work or out-migration, there has been no agricultural expansion, thereby reducing the pressure on forests.

Table 4: Change in agricultural landscape after the OxyContin reformulation

	Total		Annual crops			Perennial crops		
	(1) Area	(2) Maize	(3) Sorghum	(4) Sugarcane	(5) Bean	(6) Avocado	(7) Agave	(8) Coffee
Poppy suit. X P.(2010-2017)	-0.003 (0.011)	-0.004 (0.013)	0.002 (0.010)	-0.022*** (0.007)	-0.006 (0.012)	-0.003 (0.009)	-0.029*** (0.010)	0.003 (0.003)
Poppy suit. X P.(2018-2021)	-0.007 (0.014)	0.018 (0.016)	-0.023*** (0.011)	-0.019** (0.007)	-0.022* (0.013)	0.006 (0.010)	-0.024** (0.010)	-0.005 (0.004)
Cannabis suit. X Post2010	0.014* (0.008)	0.013* (0.007)	0.005 (0.005)	0.010*** (0.003)	0.005 (0.006)	0.009* (0.005)	0.004 (0.004)	-0.008*** (0.002)
Observations	14,114	14,114	14,114	14,114	14,114	14,114	14,114	14,114
Mean Y(pre-norm.)	8,116.13	3,830.74	848.81	390.38	367.09	161.07	121.58	260.06
R ²	0.000	0.001	0.001	0.002	0.000	0.001	0.001	0.001
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The sample consists of municipalities suitable for poppy and/or cannabis cultivation. The period of analysis is from 2005 to 2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are excluded in all specifications (Correia, 2015). All dependent variables are normalized for the period 2005-2021.

Third, I employ the same specification to analyze the impact of poppy prices on the livestock sector. I observe a reduction in the volume and value of livestock production associated with the poppy suitability index in the post-OxyContin period (columns 1-2 of Table 5).²⁷ However, the estimated coefficient for total livestock volume is not significant for the period 2010-2017, even though it is negative. The overall reduction appears to be driven by the years 2018-2021, for which the coefficient is statistically significant at the 1% level. This trend is similar to that observed for agricultural crops, where the decline in agricultural area occurs mostly in 2018-2021. The total reduction is driven by bovine, goat, and porcine categories, while poultry and sheep have a positive but not significant coefficient. It is plausible to suggest that animals requiring more labor, like bovine and porcine, decreased. This could be interpreted as labor being allocated to poppy farming and/or a reduction in agricultural activity. Furthermore, it can also be interpreted as increasing out-migration, where farmers sell their livestock before leaving.

Table 5: Change in livestock volume and value after the OxyContin reformulation

	Aggregated:			Volume by livestock type:			
	(1) Volume	(2) Value	(3) Poultry	(4) Bovine	(5) Goat	(6) Sheep	(7) Porcine
Poppy suit. X P.(2010-2017)	-0.018 (0.013)	-0.031*** (0.009)	0.017 (0.015)	-0.007 (0.013)	-0.029** (0.014)	0.001 (0.013)	-0.015 (0.014)
Poppy suit. X P.(2018-2021)	-0.041*** (0.014)	-0.043*** (0.010)	0.012 (0.016)	-0.035** (0.015)	-0.037** (0.015)	0.002 (0.015)	-0.020 (0.014)
Cannabis suit. X Post2010	0.001 (0.009)	0.008* (0.004)	-0.004 (0.009)	0.001 (0.010)	0.003 (0.006)	-0.005 (0.009)	-0.003 (0.008)
Observations	12,168	12,168	12,168	12,168	12,168	12,168	12,168
Mean Y(pre-norm.)	3,766.69	79,112.27	1,513.58	1,482.34	35.50	40.17	695.11
R ²	0.001	0.003	0.000	0.001	0.001	0.000	0.000
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The sample consists of poppy and/or cannabis suitable municipalities. The period of analysis is 2006-2021. Poppy and cannabis suitability indices are measured in hundreds of square kilometers. Singleton observations are dropped in all specifications (Correia, 2015). All dependent variables are normalized for the 2006-2021 period.

²⁷ Volume in column (1) indicates the sum of all livestock in kilograms, and value in column (2) is its corresponding value in pesos.

4.2.2 Heterogeneity by cartel presence/number

This section, closely related to the study by [Sobrinho \(2020\)](#), where the author analyzes the cartels' reaction to the heroin demand shock, aims to investigate heterogeneities concerning cartel number and presence. [Sobrinho \(2020\)](#) employs a novel method to measure cartel indicators at the annual and municipality levels. The author gathers news reports from Google News and uses a semi-supervised classification algorithm to obtain information on cartel c being in municipality i for the period 1990 to 2016 ([Sobrinho, 2020](#)). [Sobrinho \(2020\)](#) finds an increasing association between cartel presence and numbers with the poppy suitability index in an event study design. This increase is larger and precisely estimated for the period 2014-2016. Then, the author focuses on the timing of violence increase and finds more violence only when a second or a third cartel enters a municipality. Overlapping with [Daniele et al. \(2023\)](#), the author also finds increased homicides during the period 2010-2013.

The interplay between cartel activities, illicit crop cultivation, and drug policies has been shown to play an important role in deforestation. The phenomenon, known as *narco-deforestation* ([McSweeney et al., 2014](#)), can manifest in various forms ([Devine et al., 2021](#)). First, cartels may directly cause deforestation to facilitate drug trafficking activities by constructing airstrips and roads in isolated areas or by clearing land for cattle ranching, palm oil cultivation, or timber extraction, which can be used for generating income and money laundering. Second, cartel-related activities may indirectly influence deforestation by creating a demand for illicit crops, altering farmers' incentives and socio-economic factors, such as increasing violence and generating out-migration ([Daniele et al., 2023](#)), eroding local institutions and forest governance ([Devine et al., 2021](#); [Wrathall et al., 2020](#)), increasing corruption and influencing local elections ([Trejo and Ley, 2021](#)).

To test the influence of cartel presence and cartel number, I employ the OCVED data, which contains the location and date of violent events related to a cartel for the period 2000-2018 (see Appendix G for a detailed discussion). A violent event includes both lethal and non-lethal events such as assassinations, armed clashes, threats, displacement, beatings, kidnappings ([Osorio and Beltrán, 2020](#)). The cartel presence variable equals one if such an event happened in a given year at a given municipality, and the cartel number counts the number of distinct cartels participating in such events. [Osorio and Beltrán \(2020\)](#) warn that cartel presence based on violent events may not capture municipalities where one cartel exerts control, akin to a monopoly, without necessarily committing violent crimes. This may be the case in more opium poppy suitable municipalities because cartels have a trade relation with poppy farmers different from extortion or stealing type relations, which may incur more violence. This is a valid critique of indices based on news reports, and one should take this into consideration when interpreting the results.

I incorporate these two variables into a triple interaction setup, where I interact the poppy suitability index, the post-2010 dummy, and the cartel variables. Alongside deforestation-related dependent variables, I also use the homicide rate. The results are presented in Table 6. In columns 1-3, the interaction includes the cartel presence variable, while in columns 4-6, I replace it with the cartel number variable. I also include double interaction terms, as well as the cartel variables, but these are not reported for brevity. For deforestation and homicide rate outcomes, the triple interaction term is never significant, suggesting that in the case of poppy cultivation, cartels did not influence land use changes, which are primarily driven by the farmers themselves. The homicide rate is not influenced by poppy suitability in the 2010-2018 period, but this may obscure some heterogeneity, as both [Daniele et al. \(2023\)](#) and

Sobrinho (2020) point to an increasing homicide rate in the 2010-2013 period, which is reduced afterward.

Table 6: Heterogeneity by cartel presence/number - Triple DiD

	Cartel presence			Cartel number		
	(1) Def. rate	(2) Def. norm.	(3) Homicide rate	(4) Def. rate	(5) Def. norm.	(6) Homicide rate
Poppy suit. X Post2010	-0.011*** (0.004)	-0.034** (0.017)	0.287 (0.438)	-0.011*** (0.003)	-0.035** (0.014)	0.334 (0.280)
Poppy suit. X Post2010 X Cartel pr.	0.003 (0.004)	0.012 (0.020)	-0.309 (0.479)			
Cartel pr. X Post2010	-0.025 (0.021)	-0.034 (0.059)	3.076** (1.346)			
Poppy suit. X Post2010 X Cartel nb.				0.001 (0.001)	0.006 (0.006)	-0.181 (0.132)
Cartel nb. X Post2010				-0.013** (0.006)	-0.015 (0.021)	0.582 (0.522)
Cannabis suit. X Post2010	0.010*** (0.003)	0.037*** (0.007)	-0.187 (0.195)	0.010*** (0.003)	0.036*** (0.007)	-0.138 (0.194)
Observations	11,648	11,648	5,777	11,648	11,648	5,777
Mean Y	0.215	-0.000	20.483	0.215	-0.000	20.483
R ²	0.003	0.003	0.011	0.003	0.003	0.018

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The sample consists of poppy and/or cannabis suitable municipalities. The period of analysis is 2005-2018. Poppy and cannabis suitability indices are measured in hundred square kilometers. The normalized deforestation variable is normalized for the period 2005-2018. Singleton observations are dropped in all specifications (Correia, 2015).

5 Conclusion

In this study, I test how a price shock on an illicit crop influence land use decisions and deforestation. My findings reveal a decrease in deforestation in municipalities more suitable for poppy cultivation during periods of high poppy prices and afterwards. Leveraging variation in poppy prices, coupled with the geographic distribution of opium poppy suitability, I employ a difference-in-differences setup to estimate the relationship between the poppy price boom and deforestation. The decline in deforestation in more poppy suitable municipalities during the 2010-2021 period aligns with a simultaneous decrease in agricultural and livestock activities. This suggests a potential shift in labor and time allocation, where, assuming a constant farmer population and productivity, it appears that a substitution effect between illicit opium poppy and legal agricultural crops occurred during the peak farm-gate poppy price period. Deforestation decreases even more in the subsequent period when poppy prices fell, possibly because not all farmers returned to cultivating legal crops and may be related to out-migration from more poppy suitable municipalities (Tamariz et al., 2023; Daniele et al., 2023). Finally, I investigate the possible influence of cartels on deforestation and the mitigating effect of the homicide rate, where I find no significant relation between cartel presence and deforestation.

This paper contributes to several literatures. First, I analyze the crop price-deforestation relation for an illicit crop for the first time. This literature finds an overall positive relation, while my findings indicate the opposite in case of poppy. I argue that this is related to several factors, bringing rare conditions together. Second, a growing literature focuses on the relation between deforestation and illicit crops, specifically in Colombia and coca leaf cultivation. My findings suggest that this relation depends on the nature of the illicit crop, market access, violence, and prices. Finally, I contribute to the literature investigating the impact of the OxyContin reformulation on various outcomes in Mexico by analysing its impact on land use and deforestation (Daniele et al., 2023; Sobrinho, 2020).

Overall, this article analyzes an interesting context where the price boom of an illicit crop reduces deforestation. I explain the specificities of this crop and illustrate the mechanisms behind this relationship, providing valuable insights on crop price and deforestation literature. Regarding the substitution of legal agricultural areas by poppy cultivation, it appears that this phenomenon contribute to the decrease in deforestation. These findings warrant comparison with other regions in Latin America where illicit crop cultivation is prevalent.

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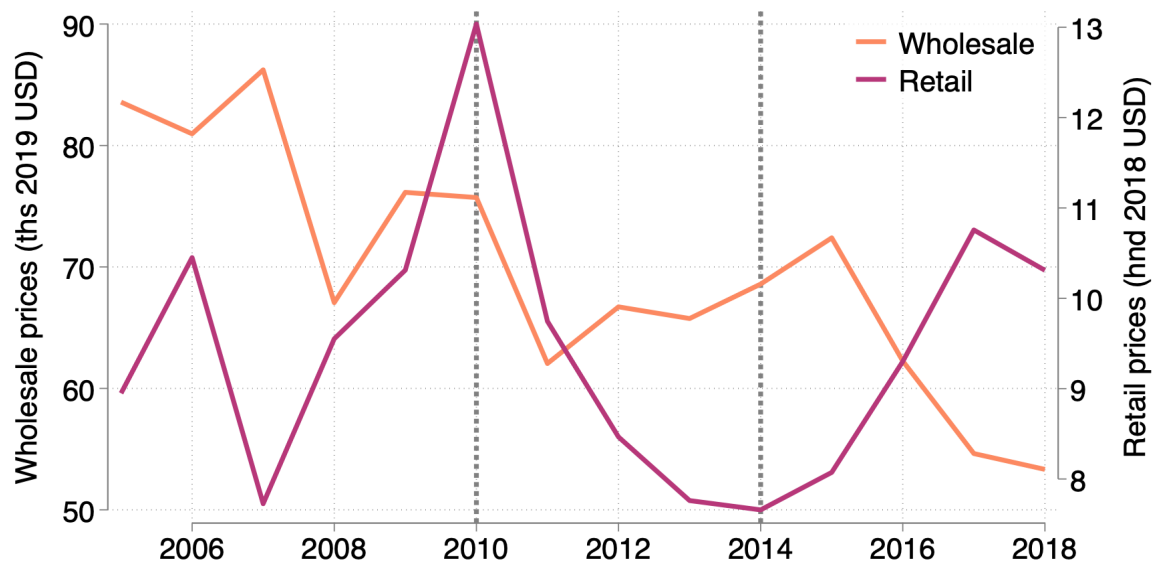
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6 Appendix

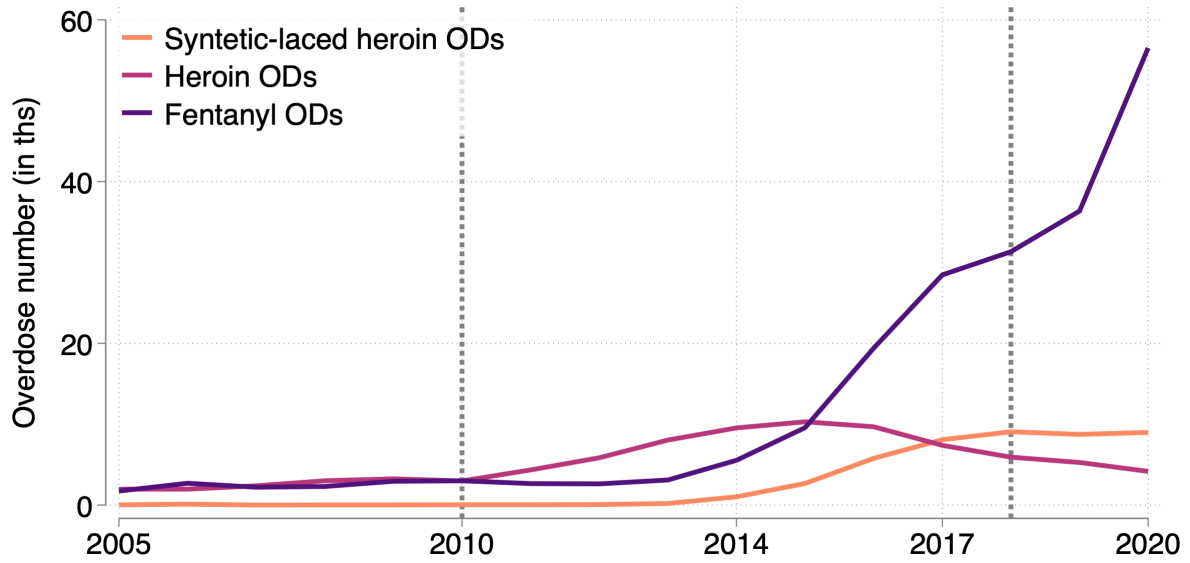
A Descriptive graphs

Figure A1: Evolution of average wholesale and retail heroin prices in the United States



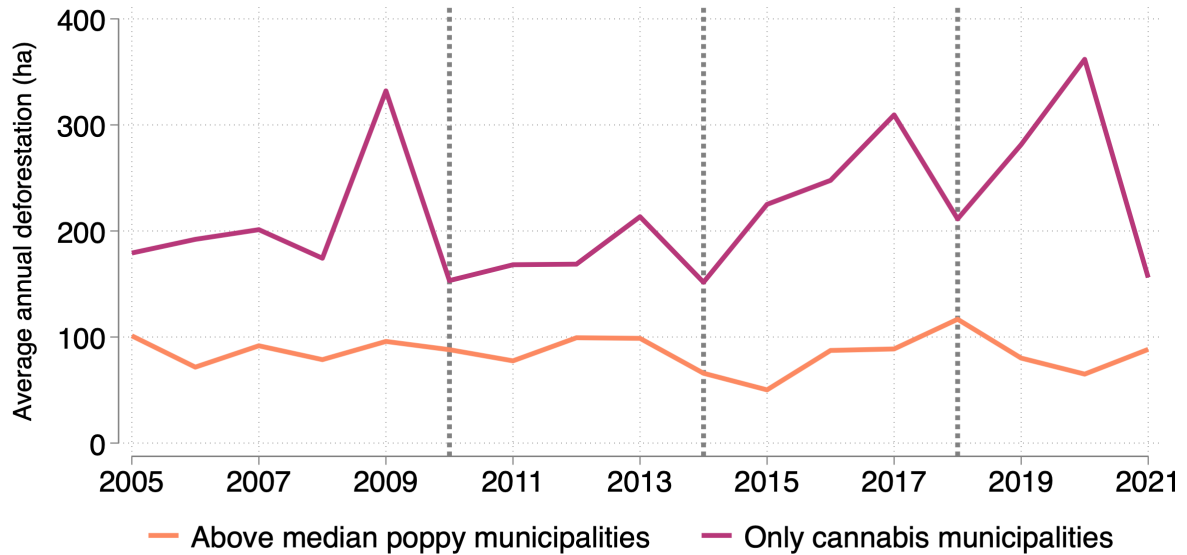
Note: UNODC calculations are based on UNODC ARQ data. Wholesale prices are adjusted for inflation and reported as USD per kg, while retail prices are adjusted for purity and inflation and reported as USD per gram. Inflation adjustments are based on the Bureau of Labor Statistics' Historical Consumer Price Index. According to UNODC, no data is available after 2018.

Figure A2: Evolution of heroin and fentanyl related overdoses between 2005 and 2020



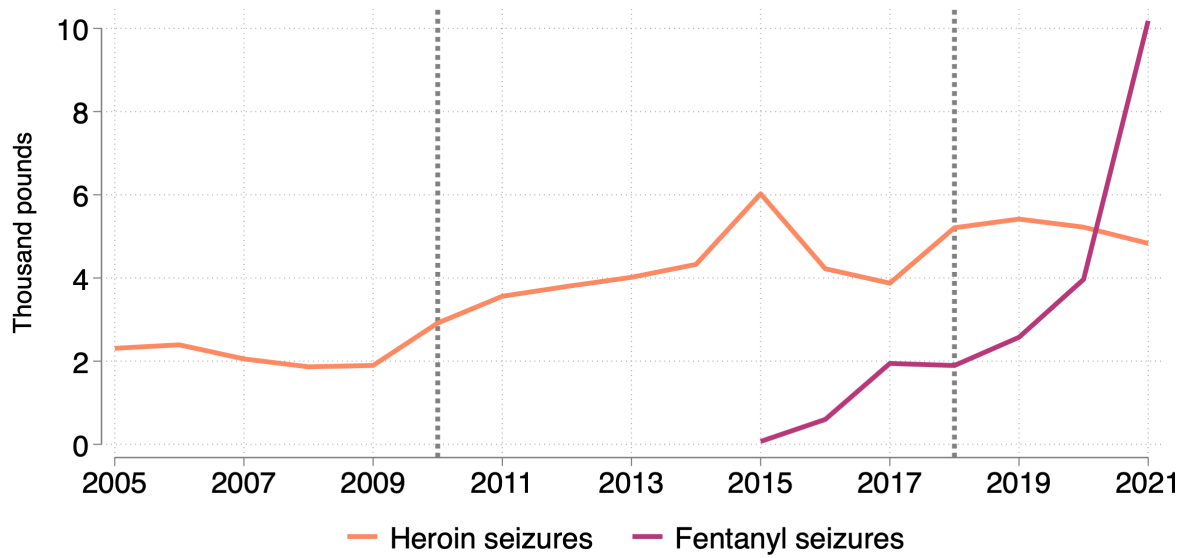
Note: Data come from the National Center for Health Statistics (NCHS). Heroin overdoses involve pure heroin and heroin laced with non-synthetic ingredients like sugar. The synthetic-laced heroin category includes heroin laced with fentanyl and/or other chemicals. Fentanyl overdoses show deaths directly related to fentanyl usage. Data is current up to 2020.

Figure A3: Evolution of annual deforestation in municipalities with above-median poppy suitability and those suitable only for cannabis production



Note: Deforestation data come from Hansen et al. (2013). The above-median poppy suitability sample consists of municipalities having more than median poppy suitability among poppy-suitable municipalities (207 units), while 'only cannabis suitability' refers to municipalities that are suitable only for cannabis production (418 units).

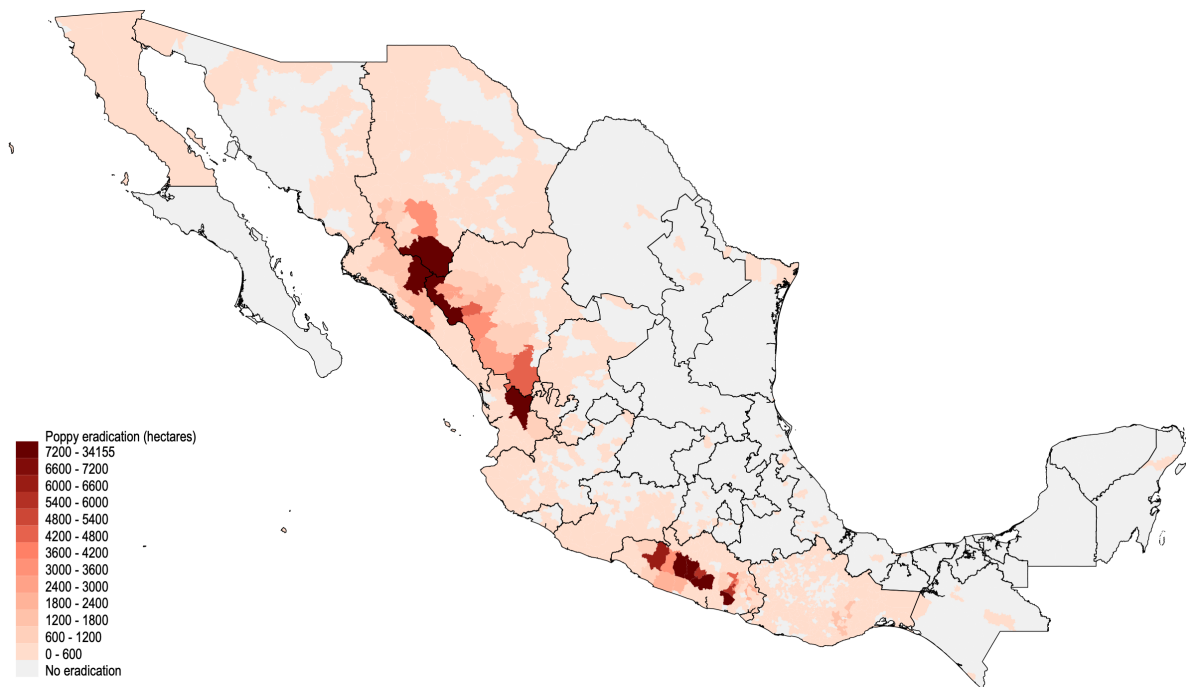
Figure A4: Evolution of annual heroin and fentanyl seizures in the United States



Note: Seizure data comes from U.S. Customs and Border Protection's (CBP) website. The amounts include seizures conducted by the Office of Field Operations (OFO). The data is presented by fiscal year, spanning from September of the given year to August of the following year. The fentanyl category has been included since 2015.

B Maps

Figure B1: Distribution of total poppy eradicated area in 2005-2018



Note: Eradication activities encompass both aerial spraying and manual eradication. The map illustrates the cumulative annual eradications for each municipality during the period 2005-2018. The data source is the Mexican military, specifically the Secretariat of National Defence (SEDENA).

C Summary statistics

Table C1: Summary statistics of all variables

	Mean	SD	Min	P50	Max	N
<i>Forests</i>						
Deforestation (ha)	144.7	789.8	0.0	7.2	22,308.1	14144
Deforestation rate (%)	0.2	0.4	0.0	0.1	11.2	14144
Normalized def.	-0.0	1.0	-2.2	-0.3	3.9	14144
Tree cover in 2000 (km. sq.)	393.2	1,002.5	1.3	103.0	13,788.1	14144
<i>Suitability indices</i>						
Poppy suitability (km. sq.)	84.5	203.7	0.0	0.0	2,830.6	14144
Cannabis suitability (km. sq.)	198.8	340.7	0.0	84.3	3,004.2	14144
<i>Agriculture (km. sq.)</i>						
Agriculture area	81.2	131.1	0.1	40.8	2,352.8	14114
Maize area	38.3	61.8	0.0	18.6	1,513.1	14114
Sorghum area	8.5	38.6	0.0	0.0	704.2	14114
Bean area	3.7	14.6	0.0	0.3	271.7	14114
Sugercane	3.9	18.8	0.0	0.0	348.5	14114
Avocado	1.6	12.5	0.0	0.0	247.3	14114
Agave	1.2	5.7	0.0	0.0	110.5	14114
Coffee	2.6	13.2	0.0	0.0	326.9	14114
<i>Livestock</i>						
Total volume (tons)	3.77	10.36	0.00	1.11	184.50	12168
Total value (ths pesos)	79.11	226.34	0.01	22.44	4163.60	12168
Poultry (tons)	1.51	7.45	0.00	0.05	132.67	12168
Bovine (tons)	1.48	3.73	0.00	0.55	112.81	12168
Goat (tons)	0.04	0.08	0.00	0.01	4.27	12168
Sheep (tons)	0.04	0.09	0.00	0.01	1.15	12168
Porcine (tons)	0.70	2.99	0.00	0.16	79.82	12168
<i>Violence</i>						
Homicide rate	10.05	22.39	0.00	0.00	366.30	14144
Cartel number	0.57	1.29	0.00	0.00	10.00	11648
Cartel presence	0.26	0.44	0.00	0.00	1.00	11648
<i>Other</i>						
Nighttime light	0.40	1.48	0.00	0.05	25.84	14144
Distance to the U.S. (km)	81.95	20.83	2.82	83.59	126.05	14144
Altitude (m)	1280.59	739.24	3.79	1414.75	3179.89	14144

Note: All data is calculated for the period 2005-2021, except for livestock, which is for 2006-2021 and cartel variables which are for 2005-2018. The sample consists of municipalities suitable for poppy and/or cannabis cultivation.

D Pre-treatment trends and characteristics

In Table D1, I estimate the presence of pre-existing differential trends with the following specification for the period 2005-2009:

$$Y_{it} = \beta_1 \text{PoppySuit}_i * \text{Year}_t + \beta_2 \text{CannabisSuit}_i * \text{Year}_t + \delta_i + \phi_t + \psi_{mt} + \epsilon_{it} \quad (3)$$

Y_{it} signifies various outcomes, PoppySuit_i and CannabisSuit_i are the suitability indices in hundred km^2 . Year_t is the linear time variable. Other controls are δ_i , the unit fixed effects for time-invariant municipality characteristics, ϕ_t year fixed effects to capture time shocks common to all municipalities, and ψ_{mt} , macro region-year fixed effects, controlling trends related to macro-ecological classifications. ϵ_{it} is the error term and standard errors are clustered at state-year level. Reassuringly, β_1 coefficients indicate a not significant differential trends for outcome variables prior to OxyContin reformulation.

Table D1: Testing pre-shock differential trends for time-varying variables - Part 1

	Deforestation			Other variables		
	(1) Rate	(2) Norm.	(3) NTL	(4) Homicide	(5) Cartel presence	(6) Cartel number
Poppy suitability x Year	0.00001 (0.00002)	-0.00009 (0.00006)	-0.00000 (0.00001)	-0.00125 (0.00139)	-0.00003 (0.00002)	-0.00001 (0.00006)
Cannabis suitability x Year	-0.00002 (0.00002)	-0.00000 (0.00003)	-0.00000 (0.00000)	0.00178** (0.00087)	0.00001 (0.00001)	0.00006 (0.00004)
Observations	4,160	4,160	4,160	4,160	4,160	4,160
Mean Y	0.223	-0.009	0.216	7.288	0.180	0.392
R^2	0.001	0.001	0.000	0.003	0.001	0.002
Macro region-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. NTL represents the average nighttime lights. The homicide variable is per hundred thousand persons. Cartel presence equals one if at least one cartel is present in a municipality, and cartel number indicates the number of cartels present in a municipality.

Table D2: Testing pre-shock differential trends for time-varying variables - Part 2

	Total	Livestock		Eradication	
	(1) Area	(2) Volume	(3) Value	(4) Poppy	(5) Cannabis
Poppy suitability x Year	-0.00002 (0.00006)	-0.00005 (0.00007)	-0.00002 (0.00004)	-0.00008 (0.00005)	-0.00010 (0.00007)
Cannabis suitability x Year	0.00003 (0.00003)	0.00004 (0.00004)	0.00003 (0.00002)	0.00002 (0.00002)	0.00005 (0.00004)
Observations	4,160	3,328	3,328	4,160	4,160
Mean Y	0.168	-0.369	-0.580	0.046	0.219
R^2	0.000	0.001	0.001	0.001	0.001
Macro region-Year FEs	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. All outcomes are normalized.

In a complementary analysis, I test the association of selected pre-treatment municipality characteristics with the poppy suitability index (Daniele et al., 2023). Objective, similar to the balance tests in binary treatment setup, is to test if results are driven by pre-treatment differences. More specifically, I estimate following equation in a cross-sectional setup:

$$Y_i = \beta_1 \text{PoppySuit}_i + \beta_2 \text{CannabisSuit}_i + \beta_3 \text{Area}_i + \psi_m + \epsilon_i \quad (4)$$

Y_i represents various pre-shock characteristics of municipalities. These characteristics include tree-covered area in square kilometers in 2000 (column 1), average deforestation from 2005-2009 (column 2), average agricultural area from 2005-2009 (column 3), altitude (column 4), distance to the closest U.S. entry point (column 5), and population in 2010 (column 6). PoppySuit_i and CannabisSuit_i are the poppy and cannabis suitability indices measured in hundred square kilometers, respectively. I control for municipality area in square kilometers (Area_i) and state fixed effects (ψ_m). The standard errors are robust to heterogeneity.

In [Daniele et al. \(2023\)](#), the municipality area variable, when used as a dependent variable instead of a control, is the only characteristic associated with poppy suitability. I include this variable as a control to better isolate the effect of poppy suitability, independent of the area. The pre-shock characteristics of municipalities do not differ significantly, except for the distance to the U.S. border variable as presented in [Table D3](#).²⁸ The latter is negatively associated with poppy suitability, indicating that more poppy-suitable municipalities are closer to the U.S. border. The inclusion of unit fixed effects in the main estimation addresses concerns related to the time-invariant characteristics of municipalities. Additionally, in the robustness section, I control for distance-year linear trends by introducing an interaction term between distance and year variables. It is particularly reassuring to observe that poppy suitability is not associated with land use-related variables.

Table D3: Pre-shock municipality characteristics and their relation to the opium poppy suitability index

	Municipality characteristics:					
	(1) Tree cover (km)	(2) Deforestation (ha)	(3) Sown area (ha)	(4) Altitude (m)	(5) Distance (km)	(6) Pop.
Poppy suit.	0.165 (0.152)	-0.158 (0.102)	2.999 (4.865)	0.034 (0.095)	-0.431** (0.189)	-26.219 (18.043)
Cannabis suit.	0.068 (0.109)	0.152 (0.142)	1.635 (2.969)	-0.237*** (0.071)	0.174 (0.159)	9.157 (16.165)
Area (km)	0.592*** (0.067)	0.153*** (0.044)	4.048*** (0.852)	0.000 (0.017)	0.145*** (0.054)	5.621 (4.122)
Observations	832	832	832	832	832	832
Mean Y	393.15	142.64	8,330.77	1,280.59	8,195.48	33,059.24
R^2	0.767	0.233	0.160	0.016	0.048	0.009
State FEs	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust to heterogeneity. State fixed effects are included. The outcomes for deforestation and sown area represent average values for the period 2005-2009. The tree cover variable is for the year 2000 and is sourced from [Hansen et al. \(2013\)](#). Mean altitude data is from [JPL \(2020\)](#). Population data is for 2005 and is obtained from the Mexican census. Nighttime light (NTL) data is from [Chen et al. \(2021\)](#). The distance variable comes from [Castillo et al. \(2020\)](#) and measures the distance from the municipality centroid to the closest U.S. border entry point.

To test the classical (or weak) parallel trend assumption, I perform an event study analysis. While the weak parallel trend assumption is sufficient for obtaining causal estimates in the case of a binary treatment variable, a stronger parallel trend assumption becomes necessary when the treatment is continuous due to treatment effect heterogeneity ([Callaway et al., 2024](#)). However, practically testing this assumption is challenging, involving the calculation of “...for all doses, the average change in outcomes over time across all units if they had been assigned that amount of dose is the same as the average change in outcomes

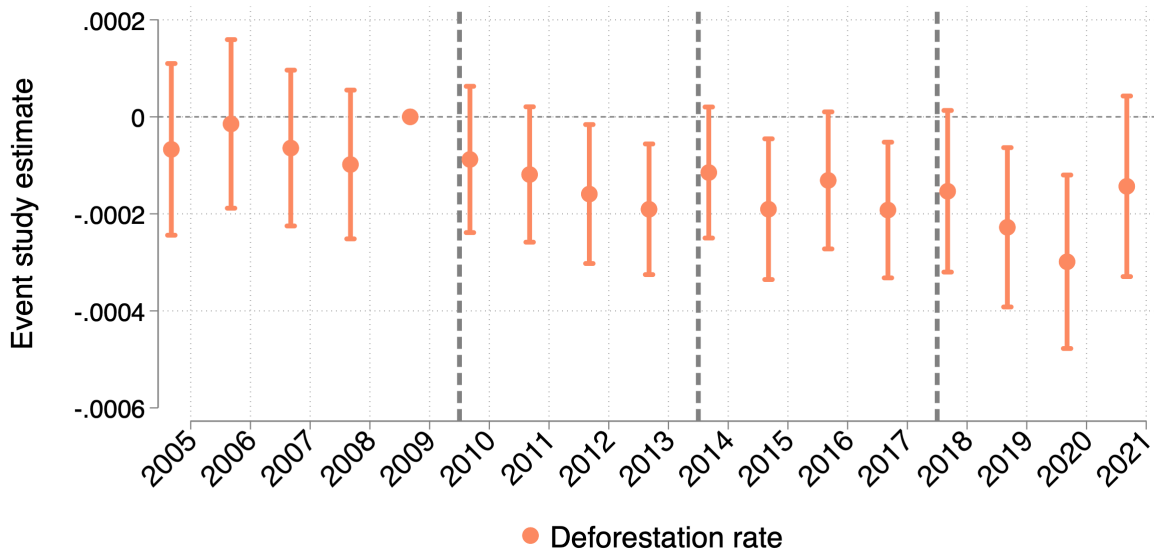
²⁸ This variable is derived from [Castillo et al. \(2020\)](#) and measures the distance from the municipality centroid to the closest U.S. border entry point.

over time for all units that experienced that dose” (Callaway et al., 2024). Therefore, I conduct the following exercise solely for demonstration purposes to get insights into dynamic patterns of outcomes. The event study specification is adapted to test parallel trends prior to 2010, the year of OxyContin reformulation, by omitting the 2009 event year dummy. The event study specification is as follows:

$$Y_{it} = \sum_{k=2005, k \neq 2009}^{2021} \beta_{1,k} \text{PoppySuit}_i \times \text{Year}_k + \sum_{k=2005, k \neq 2009}^{2021} \beta_{2,k} \text{CannabisSuit}_i \times \text{Year}_k + \delta_i + \phi_t + \psi_{mt} + \mu_{it} + \epsilon_{it} \quad (5)$$

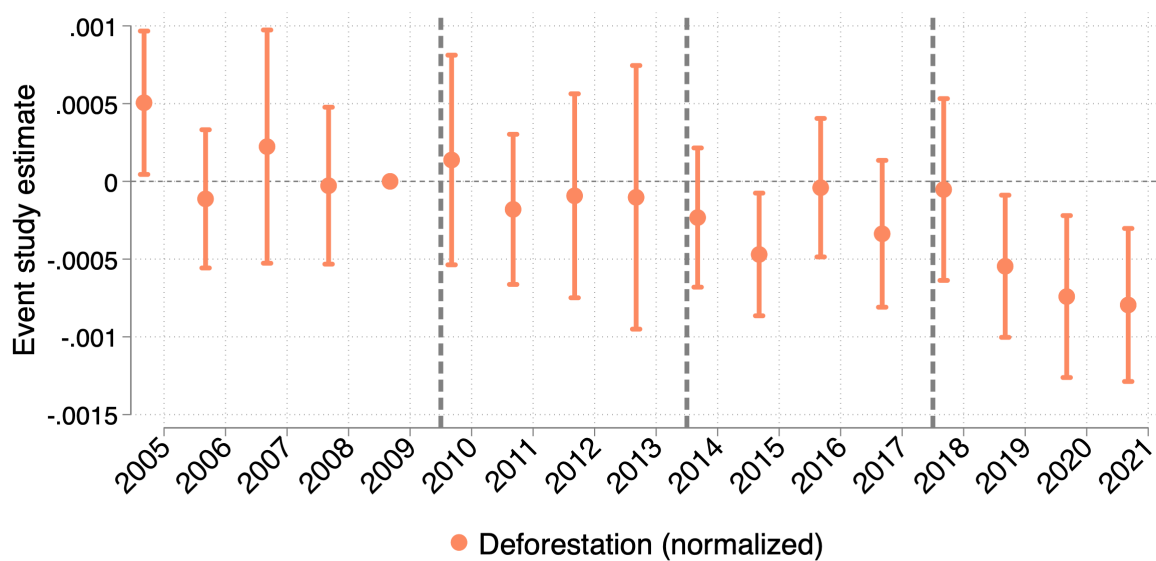
The poppy suitability index and cannabis index are interacted with year dummies from 2005 to 2021, with the exception of the 2009 dummy, which is omitted. The rest of the equation (fixed effects structure and standard errors) is identical to the main specification (Equation 1). In an alternative specification, I also replace the continuous poppy suitability variable with a median binary variable. All results are presented in Figure D1, D2, D3, and D4 and they are very similar. The weak parallel trends test holds for both specifications. Deforestation starts to reduce after 2014, and the magnitude increases after 2018.

Figure D1: Event study - Continuous treatment variable - Deforestation rate



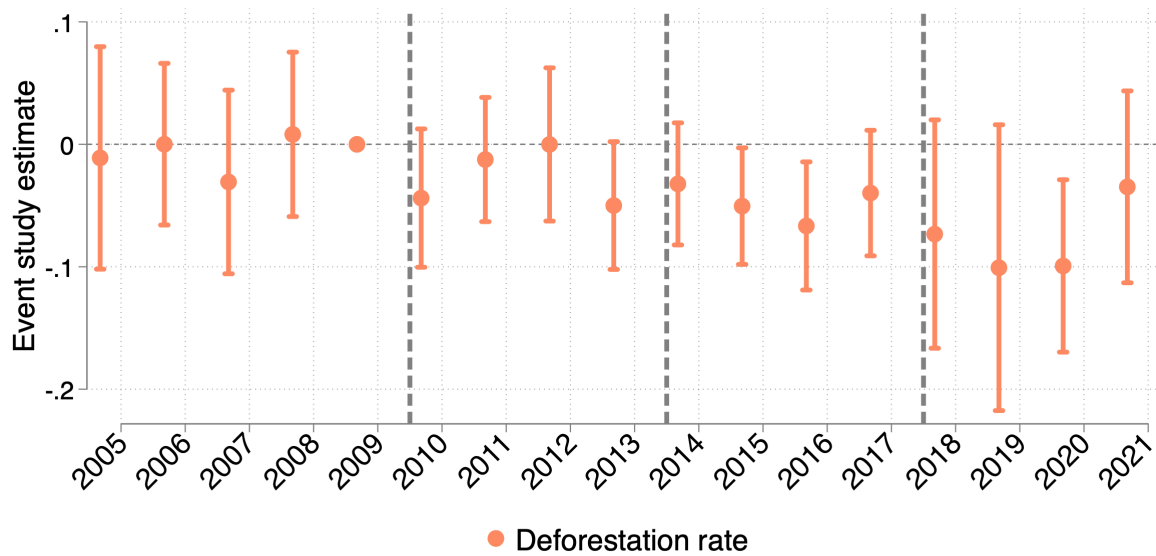
Note: This figure presents event study coefficient of deforestation rate outcome. Confidence intervals are at 95% and are based on standard errors clustered at the Mexican state-year level.

Figure D2: Event study - Continuous treatment variable - Normalized deforestation



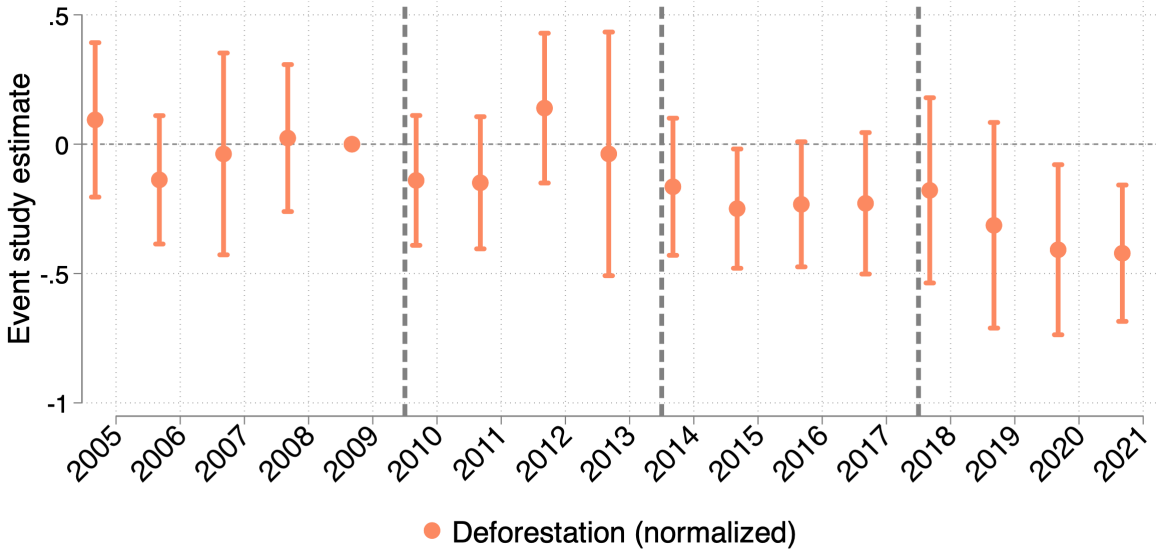
Note: This figure presents event study coefficient of normalized deforestation outcome. Confidence intervals are at 95% and are based on standard errors clustered at the Mexican state-year level.

Figure D3: Event study - Median binary treatment variable - Deforestation rate



Note: This figure presents event study coefficient of deforestation rate outcome. Confidence intervals are at 95% and are based on standard errors clustered at the Mexican state-year level.

Figure D4: Event study - Median binary treatment variable - Normalized deforestation



Note: This figure presents event study coefficient of normalized deforestation outcome. Confidence intervals are at 95% and are based on standard errors clustered at the Mexican state-year level.

E Robustness tests

E.1 Robustness - Various specifications of the baseline

Table E1: Robustness tests of baseline estimate - Deforestation rate (%) - Period: 2005-2021

	Dep. variable: Deforestation rate (%)				
	(1)	(2)	(3)	(4)	(5)
Poppy suit. X Post2010	-0.012*** (0.003)	-0.012*** (0.003)	-0.011*** (0.003)	-0.012*** (0.003)	-0.012*** (0.003)
Cannabis suit. X Post2010	0.011*** (0.003)	0.011*** (0.003)	0.011*** (0.004)	0.010*** (0.003)	0.010*** (0.003)
Distance X Post2010					0.001 (0.002)
Observations	14,144	12,563	9,996	14,144	14,144
Mean Y	0.219	0.243	0.280	0.219	0.219
R ²	0.003	0.002	0.003	0.003	0.003
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes	Yes
Sample	Baseline	TC >= 10%	TC >= 20%	Baseline	Baseline
Distance-Year linear trend	No	No	No	Yes	No

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The distance variable comes from [Castillo et al. \(2020\)](#) and measures the distance from the municipality centroid to the closest U.S. border entry point. The period of analysis is 2005-2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are dropped in all specifications ([Correia, 2015](#)).

Table E2: Robustness tests of baseline estimate - Normalized deforestation - Period: 2005-2021

	Dep. variable: Normalized deforestation				
	(1)	(2)	(3)	(4)	(5)
Poppy suit. X Post2010	-0.041*** (0.012)	-0.043*** (0.012)	-0.032*** (0.012)	-0.040*** (0.012)	-0.040*** (0.012)
Cannabis suit. X Post2010	0.039*** (0.007)	0.036*** (0.007)	0.030*** (0.007)	0.041*** (0.007)	0.042*** (0.007)
Distance X Post2010					-0.008** (0.003)
Observations	14,144	12,563	9,996	14,144	14,144
Mean Y	-0.000	-0.000	-0.000	-0.000	-0.000
R ²	0.004	0.003	0.003	0.004	0.005
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes	Yes
Sample	Baseline	TC >= 10%	TC >= 20%	Baseline	Baseline
Distance-Year linear trend	No	No	No	Yes	No

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The distance variable comes from [Castillo et al. \(2020\)](#) and measures the distance from the municipality centroid to the closest U.S. border entry point. The period of analysis is 2005-2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are dropped in all specifications ([Correia, 2015](#)).

E.2 Robustness - Randomly reshuffling suitability indices

Table E3: Placebo test: Randomly reshuffling opium poppy and cannabis suitability indices

	Def. rate			Normalized		
	(1) Shuffle 1	(2) Shuffle 2	(3) Shuffle 3	(4) Shuffle 1	(5) Shuffle 2	(6) Shuffle 3
Poppy suit. X Post2010	-0.003 (0.004)	0.003 (0.003)	-0.006 (0.005)	0.014* (0.008)	0.006 (0.008)	0.001 (0.009)
Cannabis suit. X Post2010	-0.002 (0.001)	0.001 (0.002)	0.002 (0.001)	-0.013** (0.005)	-0.004 (0.005)	0.013*** (0.004)
Observations	14,144	14,144	14,144	14,144	14,144	14,144
Mean Y	0.219	0.219	0.219	-0.000	-0.000	-0.000
R ²	0.000	0.000	0.000	0.001	0.000	0.000
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included. Each column represents the same specification but with randomly shuffled opium poppy and cannabis suitability indices.

E.3 Robustness - Clustering at the municipality level

Table E4: Impact of OxyContin reformulation on deforestation in Mexico - Clustered at municipality level

	Continous treatment		Median treatment	
	(1) Def. rate	(2) Normalized	(3) Def. rate	(4) Normalized
Poppy suit. X Post2010	-0.012*** (0.003)	-0.041*** (0.013)		
Median dummy X Post2010			-0.041** (0.018)	-0.240*** (0.065)
Cannabis suit. X Post2010	0.011*** (0.003)	0.039*** (0.008)	0.010*** (0.003)	0.036*** (0.007)
Observations	14,144	14,144	10,625	10,625
Mean Y	0.219	-0.000	0.230	-0.000
R ²	0.003	0.004	0.003	0.005
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the municipality level. Municipality and year fixed effects are included in all specifications. The sample consists of poppy and/or cannabis suitable municipalities in columns 1-2. In columns 3-4, municipalities with lower than median poppy suitability are dropped. The period of analysis is 2005-2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are dropped in all specifications (Correia, 2015).

E.4 Robustness - PPML estimator

Table E5: Impact of OxyContin re-formulation on deforestation in Mexico - PPML estimator

	Raw deforestation (ha)	
	(1)	(2)
Poppy suit. X Post2010	-0.019* (0.011)	
Median dummy X Post2010		-0.181** (0.092)
Cannabis suit. X Post2010	0.011 (0.009)	0.010 (0.009)
Observations	14,042	10,557
Mean Y	145.739	160.816
R^2 (pseudo)	0.935	0.940
Macro Reg.-Year FEs	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the state-year level. Municipality and year fixed effects are included in all specifications. The sample consists of municipalities suitable for poppy and/or cannabis cultivation in column 1. In column 2, municipalities with lower than median poppy suitability are excluded. The period of analysis spans from 2005 to 2021. Poppy and cannabis suitability indices are measured in hundred square kilometers. Singleton observations are excluded in all specifications (Correia, 2015). Coefficients are estimated by (Correia et al., 2019). The dependent variable is deforestation in hectares.

F Choice of treatment variable from

I chose to change the specification of [Daniele et al. \(2023\)](#) by replacing the inverse hyperbolic sine (IHS) transformed treatment variable with its raw form. My concerns related to the IHS transformation stem from the study by [Chen and Roth \(2023\)](#) where the authors state that regression results depend on the scale of the untransformed variable. I test this hypothesis to justify the choice of the treatment variable. In column 1 of Table F1, I re-run regressions from Equation 1 by replacing the raw treatment variable with the IHS transformed one, where the unit of raw suitability indices is in hundred km^2 . In column 2, I convert the indices to km^2 before transforming with IHS. In column 3, I convert the indices to ha , and in column 4, to m^2 before transforming with IHS.

Coefficients for poppy suitability differ both in magnitude and significance across all columns, indicating that the estimated coefficients depend on the unit of the raw variable. The magnitude of coefficients for the cannabis index also changes between columns. Therefore, I use raw poppy and cannabis suitability indices (in hundred km^2) instead of the IHS transformation to avoid this problem.

Table F1: Sensibility check for IHS transformed treatment variable

	Deforestation rate (%)			
	(1)	(2)	(3)	(4)
Ihs(Poppy suit.) X Post2010	-0.029*** (0.009)	-0.005* (0.003)	-0.002 (0.001)	-0.001 (0.001)
Ihs(Cannabis suit.) X Post2010	0.037*** (0.012)	0.013*** (0.004)	0.009*** (0.002)	0.005*** (0.001)
Observations	14,144	14,144	14,144	14,144
Mean Y	0.219	0.219	0.219	0.219
Mean Ihs(Poppy suit.)	0.336	1.687	3.286	6.520
Mean raw poppy suit.	0.845	84.522	8,452.164	84521639.080
R^2	0.002	0.002	0.002	0.002
Macro Reg.-Year FEs	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the municipality level. Municipality and year fixed effects are included in all specifications. The sample consists of poppy and/or cannabis suitable municipalities. The period of analysis is 2005-2021. In column (1), indices are in thousand square kilometers; in column (2), in square kilometers; in column (3), in hectares; and in column (4), in square meters. Singleton observations are dropped in all specifications ([Correia, 2015](#)).

G Comparing cartel data

The Mexican government and other official sources do not provide time-varying data on cartel presence at the municipality level. As a result, research on cartel presence often relies on data from news reports, organized crime blogs, and expert analysis. While state-level data provides richer information and is more readily available, this study requires an annual municipality-level cartel indicator. In this section, I briefly discuss the construction of cartel databases used in the literature and conduct a comparability analysis between recent OCVED data (Osorio and Beltrán, 2020), used in this study, and widely-used data from Coscia and Rios (2012).

Coscia and Rios (2012) data is one of the earliest attempts to quantify cartel presence by using big data and machine learning algorithms. It is widely used in the literature studying organized crime in Mexico (Castillo et al., 2020; Murphy and Rossi, 2020; Lindo and Padilla-Romo, 2018). It covers the period 1990-2010 and provides information at the municipality level on annual cartel presence, the number of present cartels, and the name of the cartel (Coscia and Rios, 2012). Coscia and Rios (2012) employed the MOGO framework consisting of three steps: (1) defining query terms such as cartel names, municipality names, and actors; (2) sending queries to Google News; and (3) identifying the year and municipality that matched the queries (Coscia and Rios, 2012).

Sobrinho (2020) elaborates on her own cartel indicator tracking the presence of nine cartels over 1990-2016. The author uses a web crawler to gather articles that include a municipality and cartel name pair for any year between 1996-2016 from Google News Mexico. Then, with a sentence extractor, the author collects all sentences that include the municipality-cartel pair, resulting in 2.8 million sentences. Finally, the author uses semi-supervised convolutional neural network (CNN) algorithms to classify each sentence as “cartel c being in municipality m” (Sobrinho, 2020). The author finds a 0.38 correlation between her data and Coscia and Rios (2012) data and argues that changes in Google’s algorithm may be causing differences.

Organized Criminal Violence Event Data (OCVED) (Osorio and Beltrán, 2020) provides information on the existence of violent events and the names of the involved cartels. OCVED collects information from 36 federal and local government agencies and 69 national and local news outlets for the period 2000-2018. The authors use the EMIS²⁹ database as a news aggregator. First, OCVED chooses reports from EMIS data by using queries for some keywords and criteria.³⁰ Selected documents are then classified by first a manual process and then with automated algorithms relying on machine learning (Osorio and Beltrán, 2020). During the manual process, research assistants assess manually whether a report is relevant using predefined inclusion and exclusion criteria. In the second step, authors train machine learning algorithms, choose the one with the highest precision, and apply it to the pool of reports. As a result, 43,681 news articles are classified as relevant to organized criminal violence. Then, authors employ Eventus ID software (Osorio and Reyes, 2017) which creates an event study data by conditioning on some coding rules based on actors and locations³¹ in Spanish. Finally, OCVED presents the date and municipality of a violent event induced by a cartel and the cartel’s name.

I conducted a comparability analysis between two open-access datasets, namely Coscia and Rios (2012)

²⁹ “A large collection of newspapers containing indexed news articles.” (Osorio and Beltrán, 2020)

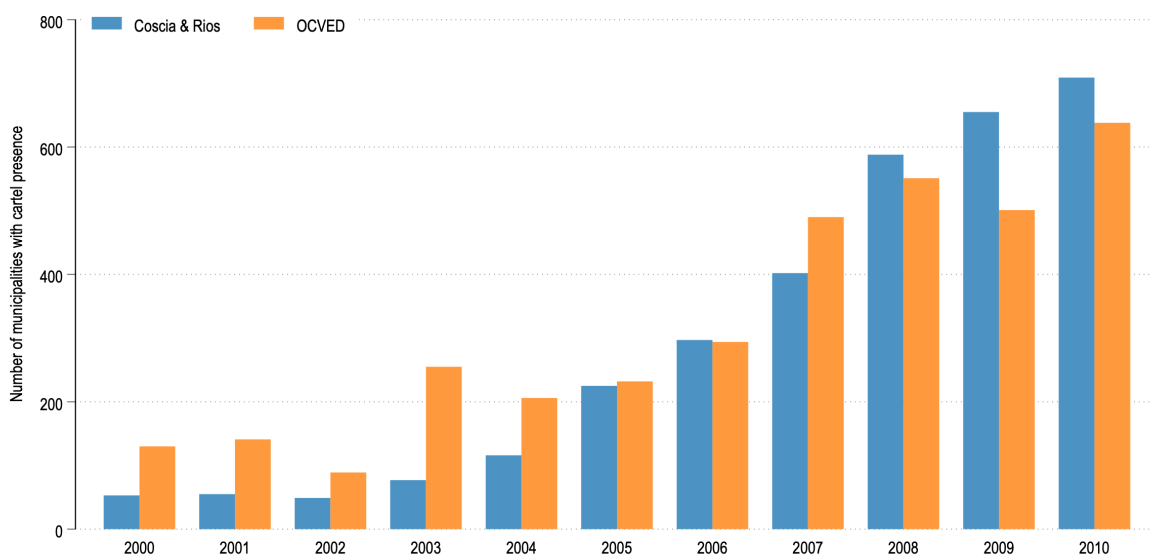
³⁰ Some keywords: “crimen organizado,” “narco,” “amapola,” “marihuana,” etc. Additional criteria include not being a sports article (similar terms used such as “attack”), not related to a conflict in Iraq or natural disasters, etc.

³¹ See website for detailed information: https://github.com/javierosorio/OCVED_2.0

and OCVED (Osorio and Beltrán, 2020), for the period of 2000-2010. In both datasets, I created two variables, a cartel presence dummy which equals 1 if a municipality has a cartel and cartel number variable which shows the number of cartels in a municipality in a given year. Evolution of these two variables is shown in G1 and G2, respectively. Coscia and Rios (2012) estimates systematically more municipalities with cartel presence than OCVED before 2005. After 2005, the estimates become quite comparable. The same observation can be made for the number of cartel quantity. Overall, in terms of annual dynamics, the variables based on the two databases show similar trends. Pearson's correlation coefficients are 0.50 for the cartel presence dummy and 0.46 for the cartel quantity variable.

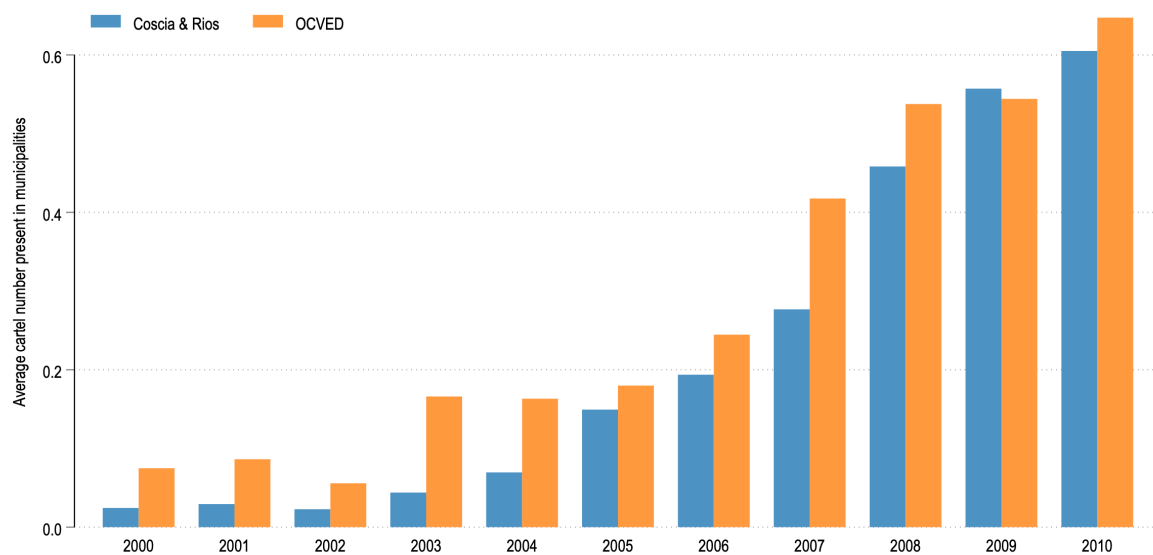
Differences between Coscia and Rios (2012) and OCVED (Osorio and Beltrán, 2020) are expected since their outcomes differ. Coscia and Rios (2012) attempts to find cartel-present municipalities without conditioning on any violent event, while OCVED captures the name of the cartel committing a violent crime. Both methodologies, including that of Sobrino (2020), rely on news outlets and machine learning algorithms to convert news reports to event studies. Based on the tests above, which indicate significant similarities between Coscia and Rios (2012) and OCVED (Osorio and Beltrán, 2020) for the period of 2000-2010, and because of OCVED's coverage (which goes up to 2018), I use OCVED (Osorio and Beltrán, 2020) in my analysis.

Figure G1: Evolution of cartel present municipality numbers in Coscia and Rios (2012) and OCVED (Osorio and Beltrán, 2020) databases



Note: Bars show number of municipalities with at least one cartel present for each year. Data come from Coscia and Rios (2012) and Osorio and Beltrán (2020).

Figure G2: Evolution of average cartel presence in municipalities [Coscia and Rios \(2012\)](#) and [OCVED \(Osorio and Beltrán, 2020\)](#) databases



Note: Bars show average of municipality cartel quantities. Data come from [Coscia and Rios \(2012\)](#) and [Osorio and Beltrán \(2020\)](#).