Mexican Cartel Wars: Fighting for the Opioid U.S. Market

Fernanda Sobrino*†

This version: October 22, 2019

Click here for the latest version

Abstract

The number of major Drug Trafficking Organizations in Mexico increased from four to nine over the last two decades. This was accompanied by an increase in drug trade related violence. This paper examines the relationship between competition and violence in illegal drug markets. In particular, I exploit an external demand shock to the heroin market. The 2010 OxyContin reformulation made the pill harder to abuse and led some opioid abusers to switch to heroin. I construct a novel data set of cartel presence across Mexican municipalities by scraping Google News and using natural language processing. I exploit within municipality variation by combining agro-climatic conditions to grow opium poppy with heroin prices in the United States across time. Event study estimates suggest that cartel presence increases substantially after 2010 in municipalities well suited to grow opium poppy. Homicide rates increase along with the number of active cartels per municipality, with higher increases when a second, third, fourth and fifth cartel become active in the territory. These results suggest that some of the increase in violence that Mexico experienced in the last fifteen years could be attribute to criminal groups fighting for market shares of heroin and not only changes in government enforcement.

*I am very grateful to Thomas Fujiwara, Micaela Sviatschi and Esteban Rossi-Hansberg for their invaluable support and guidance. For helpful comments, I thank Janet Curie, Anne Karing, Alicia Adsera, Leonard Wantchekon, Swati Bhatt, Eduardo Morales, Matteo Bobba, and other visitors and participants to the Health and Development Student Seminar Series. I also thank Patrick Signorent, Bogdan Popescu, Nikita Melnikov, Faizaan Kisat, Patrick Agte, and all the other visitors and participants to the weekly Development Tea. Thank to Hannah Rubinton, Jenny Shen, Chrissy Ostrowsky, Mauricio Matsumoto and Fabiola Alba for continuous support and encouragement. Comments are welcomed and all errors are my own.

†Department of Economics, Princeton University: mmacias@princeton.edu

1 Introduction

They understand the prescription drug issue here, and that is one of the major reasons why you are seeing the expansion of poppy production.[1]
-Jack Riley,former DEA special agent in charge of the Chicago field office, when asked about cartel expansion and the opioid crisis in the U.S.

Very much like any corporation. They judge the market demand and they shift accordingly, and I would have to say the cartels shift much more efficiently and quickly than any major corporation, because they don't have to deal with the bureaucracy.[2]
-Mile Vigil, former chief of international operations of the DEA, when asked about Mexican cartels business strategies.

Drug trafficking is the second most lucrative illegal activity with an estimated global revenue of $539 billion dollars each year.[3] Mexican Drug Trafficking Organizations are some of the most notorious criminal groups, they are the largest foreign suppliers of heroin, marijuana, methamphetamines and cocaine to the United States. The number of major drug cartels [4] in Mexico increased from four in the early 2000s to nine organizations by 2016. These cartels are usually in constant flux and have splintered, forged alliances, and battle each other for territory. This increase in the number of organizations has been accompanied by a peak in violence across Mexico with 250,547 homicides, as well as 330,000 displaced and 37,400 missing persons that can be directly attributed to organized crime.

Understanding how these organizations operate, compete and react to different policies is the key to creating and implementing strategies that might reduce the negative externalities from organized crime. Yet there is limited causal evidence on how these organizations react to market shifts and the relationship between market structure, institutional context and violence. This paper contributes to exploring these complex relationships. First, I create two novel data sets: one that uses online news articles and natural language processing to measure cartel presence across municipalities and a second one that creates an index of how well suited a municipality is for growing opium poppy. Opium poppy cultivation is illegal in Mexico so any production goes to the illegal market and opium is the main precursor for morphine, codeine, heroin and oxycodone. Second, I use an external demand shock to the heroin market to estimate the effect of this market shift on cartel entry. Third, I estimate the relationship between entry and violence and finally, I identify the Drug Trafficking Organizations that expanded into the heroin market and document

1 Ahmed (August 2015)
2 Woody (November 2017)
3 Mavrelli (2017)
4 Through this paper I will use the word cartel and Drug Trafficking Organizations as interchangeable. This does not mean that drug traffickers collude to diminish supply or set drug prices to increase profits.

how the market became less concentrated.

This paper finds evidence that an increase in the demand for heroin in the United States increased cartel presence and violence across Mexico. There are four main results. First, using an exogenous demand shock to the heroin market, the 2010 reformulation of OxyContin in the United States. The reformulation made the pill difficult to crush or dissolve, thus deterring the most-dangerous methods of abuse by injection or inhalation. I show that when the value of suitable land for growing opium poppy goes up, cartels enter into these territories. The probability of having at least two cartels present increases. After 2010 a highly suitable municipality is 10% more likely to have two or more cartels in its territory compared to a less suitable municipality. Second, I find evidence that the relationship between cartel entry, exit and the homicide rate is non linear. The presence of a single cartel does not increases the homicide rate in a significant way but the entry of the second, third, fourth and fifth cartel increases the homicide rate. The highest increase happens when the fifth cartel enters a municipality with an increase of 17.53 in the homicide rate per 100,000 inhabitants. There is no evidence that the exit of cartels reduces violence, except when a municipality with two cartels experiences the exit of one of them. The homicide rate decreases by 6 homicides per 100,000 inhabitants after this exit. Third, I show that the demand shock had a direct effect on demographics. There is out migration from the most affected municipalities after 2010 especially of the more educated and wealthier members of these communities. Finally, I identify five cartels that enter, exit or expanded into the heroin market.

To establish these results, I use as a source of plausible exogenous variation the 2010 reformulation of OxyContin in the United States. Between 1996 and 2010 supply and demand for legal opioids shot up in the United States. To reduce the increasing misuse of these legal opioids in 2010 the FDA approved the reformulation of OxyContin to make it harder to abuse. The reformulation shifted demand from legal opioids to heroin. Increasing the heroin overdose related deaths Abby et al. (2018) and the number of users, it is estimated that around 80% of heroin users started with a legal opioid Muhuri et al. (2013). This resulted in higher heroin prices in the United States and a subsequent increase in heroin production by Mexican cartels. Mexican Drug Trafficking Organizations have historically produced some opium for the US market but the amount of heroin of Mexican origin seized by the DEA increased from 19% in the early 2000s to more than 90% by 2016 DEA (2018).

This shock allows me to use two different sources of variation, agro-climatic conditions to cultivate opium poppy and the change of the heroin prices in the United States. The main outcome variable used in this paper is cartel presence across municipalities over time. Data on illegal economic activities, such as drug trafficking are sparse, so that this analysis is subject to significant data restrictions. Official data does not exists on the cultivation or distribution of drugs nor does a complete panel of which trafficking organizations operate in each territory. To deal with this problem I used several machine learning techniques that allow me to approximate measures for illegal drug trafficking.

First, I build an opium suitability index for Mexican municipalities. Ideally I would like to observe opium yields from each Mexican municipality. Unfortunately Mexico is a relatively new player in the mass production of opium. As a result, historical data on opium yields does not exist by municipality in Mexico. I use yields from Afghanistan and a rich set of agro-climatic conditions to build a suitability index using an elastic net.[5] The agro-climatic variables chosen through the optimal elastic net were then employed to built the suitability index for Mexican municipalities which is highly correlated with eradication data from the Mexican military. Time variation comes from the price of heroin in the United States. These two variables together define a municipality time specific shock which leads to differential exposure from the shock that depends on geographic and climatic characteristics of each municipality.

Cartel presence data exists from different sources, such as the Mexican prosecutor's office, the Mexican military, federal police and the DEA, but the problem with these data sets is that they are usually at the state level and report for sparse time spans. Inspired by Coscia and Rios (2017), I use web-content to obtain information of an otherwise hard to measure phenomena. The idea of using web content in particular Google-News to generate full panel data of cartel presence by municipality is motivated by the assumption that local and national newspapers combined probably contain more regular, detailed and systematic coverage of when and where criminal organizations are operating. I use a web crawler to extract articles related to a municipality and cartel pair and then used natural language processing to validate whether an article is actually talking about the cartel being active in that municipality. I use a semi-supervised convolutional neural network, that was trained manually using 5,000 sentences. The resulting data set is highly correlated with Coscia and Rios (2017), two data sets collected by hand from local newspapers and State level data from the DEA.[6]

The above data sets are complemented by official data from the Mexican Military on eradication and seizures, official data on homicide rates, law enforcement and demographic characteristics of each municipality. These data allows me to observe how Drug Trafficking Organizations react to the municipality time specific shock. An event study specification is used to measure how this shock affected different outcomes.
First, I show that the increase in the price of heroin encouraged Drug Trafficking Organization to expand their operations into high suitable municipalities. In 2004 there was just one cartel present in territories where opium poppy was eradicated, by 2016 the nine major cartels can be found in at least one municipality producing opium poppy. Before 2010, the number of municipalities with at least two cartels numbered 31, after 2010 this increases to 172 municipalities. The probability of having at least two cartels present for the mean suitable municipality when the price of heroin doubles increases by 10% after 2010. The result for the number of cartels is similar with the entry of .46 cartels each year

[5] Afghanistan is the world largest producer of opium and the United Nations have data on yields and hectares cultivated since the 1990

[6] These two data sets can be find here: Sánchez Valdés (March 2015) and Sánchez Valdés (July 2017)

after 2010. These results are in line with the intuition that Drug Trafficking Organizations adapt and react to external market pressures. In particular, the cartels will enter new valuable markets or expand production along with the increase in demand. These results are robust to different sets of controls and fixed effects. These results contrast with results found for Colombia Millán-Quijano (2019) where the Drug Trafficking Organizations rarely fight over production sites and prefer to fight for the trafficking networks.

Second, I explore the relationship between cartel entry, exit and violence. A positive demand shock will increase the value of controlling drug production and drug trafficking but it is not obvious that this should increase violence. In the absence of conditions for revenue sharing through peaceful agreements Drug Trafficking Organizations will fight for bigger market shares Castillo and Kronick (2019). Mexico lacked the infrastructure that would facilitate non-violent agreements. The relationship between the number of cartels and the increase in homicides is not linear. While the first cartel does not increase violence, it is when there are more than two cartels in the same place when violence increases. The second cartel increases the homicide rate per a 100,000 inhabitants by 7, the third and fourth cartel by 13 each of them, the fifth cartel by 17 and the sixth cartel by 10. There does not seem to be any effect after the seventh cartel enters a municipality, but there are too few municipalities with more than six cartels to fully assess this dynamic. The exit of cartels from a location is just significant when a municipality goes from two cartels to one, as the homicide rate decreases by six. This result suggests that is not the presence of illegal activities that generates violence but the presence of more than one criminal organizations fighting for profits.

Third, I ask how different demographic outcomes reacted to the external demand shock. There is an increase in the homicide rate of 24 more homicides per 100,000 inhabitants after 2010. This is consistent with increased entry as cartels compete for heroin profits. I find that the demand shock leads to a decrease in population and average years of education and an increase in the number of households with dirt floors and with women as the head of the household. These results suggest that there was outmigration from the exposed municipalities of the more educated and wealthier of their members. Finally, I observe that the military is eradicating more opium and less marijuana in these municipalities, which is consistent with the value of opium going up as the value of marijuana decreases.

Finally, the data set built for this paper allows me to observe which particular cartel operates in each municipality over time so I can examine how each cartel expanded into the newly valuable heroin market. Before 2010 the production of heroin was highly concentrated, with just the Sinaloa Cartel present in municipalities where opium poppy was eradicated by the military. By 2016 nine organizations are present in opium producing municipalities. I am able to identify two expanding cartels, Sinaloa and Los Zetas, two newly created cartels that immediately entered the heroin market, Jalisco New Generation and the Templar-Knights and one contracting cartel, La Familia Michoacana. These results are consistent with information from the Mexican Military and the DEA.

There are three main potential concerns with the data and the identification strategy that I am using. First, the measure of cartel presence uses news articles. This could be potentially misleading due to the violence experienced by journalists in Mexico. Since 2000, more than 200 journalists have either disappeared or been killed by criminal organizations. Anecdotal evidence and the subset of news articles used to train the neural network suggest that as long as journalists either just mention large organizations or inform on official data provided by the government, they are safe from cartels' violence. To provide external validity of this data set I use official DEA data and find them to be highly correlated. I also use the official data set of killed and missing journalists and no particular patterns seem to bias reporting towards any subset of cartels. Second, these results could be driven by changes in policing and military enforcement and not necessarily from the increase in heroin demand. Previous work shows that between 2006 and 2010 some of the increase in homicides in Mexico can be attributed to police enforcement strategies Atuesta and Ponce (2017),Phillips (2015) and political party alliance Dell (2015). Despite the change in the federal government in the middle of my sample the strategy against drug trafficking did not change.[7] I am able to control for both police presence and military activity across the sample in order to isolate the effect of the demand shock from any effect related to law enforcement. I also control for political party of the mayors and state governors. The results are robust to these controls and to an extended set of fixed effects. The last potential concern is that the increase in heroin prices is generated by the cartels and not by the demand shift from legal to illegal opioids. There was a sharp jump in the number of heroin users and overdose deaths in the United States;Abby et al. (2018) show that the reformulation made people switch from legal opioids to heroin. Furthermore, the increase in heroin of Mexican origin seized by the DEA goes from 19% before 2010 to 51% in 2011 and reaches 94% by 2016. Suggesting that there is no reverse causation and that the cartels reacted to the increase demand.

These results provide novel evidence that external policies that shift demand or supply of illegal drugs have direct effects on criminal organizations activity and subsequent effect on violence and other outcomes. This paper speaks to several literatures. First, this paper complements the literature studying the recent increase in violence in Mexico. Most of this literature examines how law enforcement strategies and political alliances increase violence Osorio (2015), Phillips (2015), Atuesta and Ponce (2017), Rios (2013), Holland and Rios (2017), Dell (2015). This study provides evidence of an alternative channel, increase in heroin demand, that might explain some of the increasing violence in Mexico.

This paper also speaks to the recent literature that tries to explain how Drug Trafficking Organizations organize, interact, and generate violence Biderman et al. (2018), Acemoglu et al. (2009), Murphy and Rossi (2017). In particular, I focus on how the entry of multiple Drug Trafficking Organizations to valuable territories increases violence. These results are in line with theoretical models of how increasing value of territories leads to turf wars between cartels Mesquita (2018),Castillo and Kronick (2019). These results also add to

[7] In 2012,Enrique Peña Nieto from the Revolutionary Party (PRI) was elected president

the literature studying how external demand and supply shocks in illegal markets affect violence Millán-Quijano (2019), Mejía and Restrepo (2013), Castillo et al. (2015).This paper contributes to the literature on illegal markets and its effects on different outcomes Dell et al. (Forthcoming), Dube et al. (2016), Sviatschi (2018). I add to this the effect of how the number of competing cartels affects main demographics across municipalities.

Second, this paper contributes to the literature that explores the curse of suitability for crops for which there exists a substantial black market and its relationship to armed conflict and violence. Most of this literature has either focused on cocaine in Colombia Dube and Vargas (2013), Angrist and Kugler (2005) or opium in Afghanistan Gehring et al. (2018), Bounadi (2018). I complement this literature by adding Mexico to the list of countries subject to this kind of illegal suitability curse. Mexico's location as the bridge between Latin America and the United States can also be considered part of this curse if we consider location as a natural asset.

Finally this paper is related to the increasing social science literature that uses text and images as data to measure otherwise hard to quantify phenomena. Gentzkow et al. (2017) provide an introduction of the techniques and previous work in the economics and politics literature that has used text as data. The data set and techniques used here can be use in several other applications to create measures of other types of illegal activities across the world.

The rest of the paper is organize as follows. In the next section, I provide the institutional background for my analysis. In section 3, I present the data, in Section 4, I provide a theoretical model and the main econometric specification. Sections 5 and 6 present the results and in the final section I conclude.

2 Background

This section provides background on three contextual facts for my analysis. First, I lay out an overview of the history of drug trafficking in Mexico. Despite the fact that drug trafficking organizations were prominent they were not the main producers of heroin before the relevant period of study. Second, I summarize the war on drugs and its effects on violence and Drug Trafficking Organizations. Finally, I give an overview of the opioid crises in the United States and its relationship with the heroin market. This is key for my identification strategy.

2.1 Drug Trade in Mexico

Mexico's location has make it a key country in transporting goods between Latin America and the United States, including narcotics and contraband. The origin of the Drug Trafficking Organizations of today can be traced back to the Prohibition era in the United States, when the first criminal organizations established several routes from Mexico to the US border in order to smuggle alcohol Grillo (2011).

At the beginning of the twentieth century the US and Mexican governments slowly started prohibiting the production and consumption of some substances that included marijuana, opium and cocaine. Mexican traffickers saw this as an opportunity, and start smuggling illegal drugs through the same routes they used to smuggle alcohol. Timidly the drug traffickers expanded across Mexico and the United States. The increased demand of marijuana during the sixties in the United States, combined with lax laws regarding cultivation in Mexico, drove the Mexican production of marijuana up and the consolidation of big trafficking organizations begun. The United States government did not like the careless attitude of their Mexican counterpart and launched the first big anti-drugs campaign know as operation Intercept. This operation nearly shut down the US-Mexican border to stop marijuana shipments but did not had any significant effect on the amount of marijuana crossing the border. The Mexican government launched its first big anti-drug operation, known as operation Condor which used the military to eradicate illegal crops in the Golden Triangle.[8] These two operations reduced the drug traffickers revenue from marijuana and made them shift into the cocaine market. During the late 1980s, the US authorities started breaking the Colombian Drug Trafficking Organizations and closed the Caribbean route between Colombia and Miami. The Mexican traffickers slowly took over the transportation of cocaine between Colombia and the United Stated. They already had established routes for transporting marijuana and used them to cross cocaine across the border. The share of cocaine arriving to the US moving through Mexico grew from 50% in the early 1990s to almost 100% by 2000 O'Neil (2009).

The origin of most of the current Drug Trafficking Organizations in Mexico can be trace back to the Guadalajara Cartel consolidated during the 1980s by Miguel Angel Felix Gallardo, a former police officer. He established the connection between the Colombian and Mexican organizations and expanded the routes between Mexico and the United States. Mexican Drug Trafficking Organizations have become multi-product firms with differing levels of vertical integration, they own or control the whole supply chain for several drugs, from the farmland to the gangs that sell the product to the final consumers. Since their origins the Drug Trafficking Organizations have retained close relationships with the authorities. These strong ties survived for decades while the PRI was in power. During the late 1980s the PRI started loosing its hegemonic power across the country which lead to a crack on the previous agreements between the government and criminal organizations. This generated territorial battles between former allies. Drug related violence increased across the country.

2.2 The War on Drugs

Former Mexican President Felipe Calderon, in office between 2006-2012 from the conservative party PAN, declared the war on drugs in 2006; the Drug Trafficking Organizations

[8] region known for its high production of marijuana and opium located where the states of Sinaloa, Durango and Chihuahua come together.

violently resisted this war. Violence between drug traffickers has escalated particularly in Michoacan, where the government decided to deployed military and federal police in order to reduce the cartel violence. At the beginning of the twentieth first century there were just four major Drug Trafficking Organizations; sixteen years later the DEA and the Mexican military identified at least nine major actors. Drug Trafficking Organizations (DTOs) have displayed their violence with the public beheading of corpses, car bombs, and the murders of journalists and public officers. For example, they shot down a military helicopter in May 2015.[9]

Violence spread quickly beyond the US-Mexican border and into the whole country. Since 2006, there has been an estimated of 250,547 homicides related to organized crime. These account for 50% of the country homicides. The number of missing people is up to 37,400, and the number of displaced people due to violence is estimated to be around 380,000. The number of missing or killed media workers exceeds 200. Despite President Enrique Peña Nieto's (2012-2018) efforts to reduce violence, his strategy towards Drug Trafficking Organizations did not change from the one established by Calderon. Violence decreased a little during the first year of his administration but went up again immediately after this year. The government strategy of beheading organizations by targeting high rank kingpings generated a lot of instability inside the cartels which led to more violence Jones (2013), Calderón et al. (2015),Espinosa and Rubin (2015). The extent of corruption and political instability in Mexico adds to the difficulty of fighting these criminal organizations. The list of former governors, majors, members of congress, policemen and military authorities that had some relationship with drug traffickers is extent and shows how difficult fighting these organizations can be.[10] The War on Drugs led to a spike in homicides and increased violence particularly between 2008 and 2010, less explored is the period just after 2010. This paper adds to the discussion of what generated the increase in violence. The mechanism proposed here is the external demand shock increasing violence.

2.3 The Opioid Crises

It is estimated that everyday 130 people in the United States die from overdosing on opioid-based drugs.[11] The rate of drug overdose deaths tripled between 1999 and 2010 the rate related to opioid deaths six-folded during the same period. At the beginning of the 1990s, pharmaceutical companies developed several opioid-based painkillers. Through marketing campaigns and two misleading research articles. They assured the medical community that patients would not become addicted to these drugs.[12] Prescriptions of opioid base painkillers shot up and eventually led to diversion and misuse. Pharmaceuticals companies knew that their products were addictive, as admitted by Purdue Pharma in a

---

9 Woody2018

10 Feuer (December 2018)

11 https://www.cdc.gov/drugoverdose/images/data/OpioidDeathsByTypeUS.PNG

12 DeWeerdt (September 2019)

lawsuit in 2007. The number of people accumulating pills and reselling them on the black market rapidly increased between the mid-1990s and 2010. In 2010 physicians organizations pressured the government to make it harder to accumulate pills, and the federal and state governments started to crack down on pill mills and Purdue Pharma introduced an abuse deterrent version of OxyContin designed to make it harder to crush or dissolve,thus deterring the most-dangerous methods of abuse by injection or inhalation. The restriction in the legal supply drove some users to switch to the illegal counterpart, heroin. Abby et al. (2018) use cross sectional variation in OxyContin availability across states and find a clear relationship between the reformulation of OxyContin and the increase in heroin deaths. It has been estimated that about 80% of people who use heroin first misused some prescription opioid Muhuri et al. (2013). This reformulation provides plausible exogenous variation for cartel activity in Mexico, particularly their reaction towards the heroin market.

3 Data

The main goal of this paper is to document how Mexican Drug Trafficking Organizations reacted to the opioid crisis and disentangle the relationship between market structure and violence in illegal markets. To answer these questions ideally I would like to observe when each cartel enters a municipality, raw opium production by cartel, and homicides and violence related to drug trafficking. Due to the illegality of the market these data either do not exist or are reported in aggregate geographical levels and across sparse times. To proxy for cartel presence and opium suitability, I use web scraping and machine learning. These techniques can be used to measure other usually hard to quantify phenomena such as illegal crop suitability and cartel presence by municipality. The data sets and how they were built are described below.

3.1 Cartel Presence

The Mexican prosecutor's office, military and federal police have their own data on presence, but usually at the state level and they are not published every year. The same is true of the DEA. To measure cartel presence, I construct a novel data set. This data set tracks presence of the nine mayor Drug Trafficking Organizations in each Mexican municipality between 1990 and 2016.

I follow and extend Coscia and Rios (2017): they tracked the presence of nine criminal organizations at the municipal level between 1990 and 2010. They used a search algorithm that codes a cartel as being present if the frequency of hits for a particular municipality-organization exceeds a certain threshold. I follow their idea and then use natural language processing to classify the articles.

First, I use a web crawler to scrape Google News though the Google interface.[13] The assumption behind scraping web content is that local and national newspapers combined contain a more systematic, regular and detailed coverage of cartel activity within Mexico. This web crawler looked for any news articles between 1990 and 2016 that contained the pair of municipality-organization. The organizations included in the list are the nine organizations, identified by the Mexican prosecutor's office as major actors in the drug trafficking business.[14] These nine are organizations are: the Sinaloa Cartel, the Beltran-Leyva Organization, the Golf Cartel, CNJG(Cartel de Jalisco Nueva Generacion), the Juarez Cartel, Los Caballeros Templarios, La Familia Michoacan, Los Zetas and the Tijuana Cartel. The DEA identifies six of them as major trafficking organizations DEA (2018). Then, I keep the sentences from these articles that contain the pair of words and use natural language processing to classify each sentence as indicating valid presence or not. The algorithm used for this was a semi-supervised Convolutional Neural Network (CNN) that I trained manually by reading 5,000 of these sentences. The particular CNN used has an out of sample accuracy of 0.8644. Finally, each sentence classified as valid was assigned to a pair or pairs of municipality-organization. A full detailed explanation of the algorithm and the particular CNN used can be found in Appendix A.1.

To validate this data set as a proxy for cartel presence, I use two data sets that also use news articles to measure cartel presence and DEA aggregated data by state.

3.1.1 Comparison between this data and other datasets that used news articles to measure cartel activity:

These two data sets are: Coscia and Rios (2017) time series and data collected by Professor Victor Manuel Sanchez from the Autonomous University of Coahuila in Sinaloa Mexico. The correlation between these two data sets and mine is positive and statistically significant. In particular, correlation between my data set and Coscia and Rios (2017) is 0.3810879 for the whole sample where the data intersects between 1990 and 2010.[15] The fact that this correlation is not high can be explained by the change in the Google algorithm between 2012 and 2019. The difference can also come from the differences in the validation techniques, number of hints versus natural language processing. The second data set was generated by Professor Sanchez: he manually recorded data from local and national newspapers for the state of Michoacan between 2011 and 2013 and for the Mexico City Metropolitan Area between 2014 and 2017. The correlation between this data set and the one used here is 0.7092723.

[13] Google News has change since Coscia and Rios (2017) scrape their data in 2012, Google News API not longer allows you to go back in time so I use the crawler in the Google interface instead.

[14] https://www.scribd.com/document/286347648/Organizaciones-criminales-EPN?ad_group=xxc1xx&campaign=VigLink&medium=affiliate&source=hp_affiliate

[15] All hints before 2000 come from a Google project that digitized newspapers.

3.1.2 External validation of this data set:

The DEA has published a biannual map of cartel presence across Mexico, since 2009. In 2009, they published a complete map of cartel presence which turns to be highly correlated with my data set at 0.69. For the years 2011, 2013 and 2015 the DEA just recorded the presence of dominant cartels and the correlation with my data sets goes down to 0.35. The DEA documents do not explain what they mean by dominant presence, and the news articles might be catching non-dominant presences. Finally, the increase violence that media workers and specially journalists experience from Drug Trafficking Organizations might affect the measure of cartel presence. The data on missing and killed media workers is public, and there does not seem to be any particular bias towards reporting or misreporting a particular organization. Anecdotal evidence shows that as long as journalists use data coming from the police or the military, they are safe from the violence of the cartels. These provides evidence that the proxy use here for cartel presence is close to data from Mexican authorities, given that journalist are just reporting on police and military reports. The measure use here might be underestimated actual cartel presence. Journalist are just reporting when something happens related to the cartel either a violent event, captures, or seizures. Therefor I will not observe cartels just operating without being detect by the authorities. Then the results were the dependent variable is cartel presence will not be biased and the results when the independent variable is cartel activity will be biased towards zero. Then, these results can be see as a lower bound to the effect of cartels on violence.

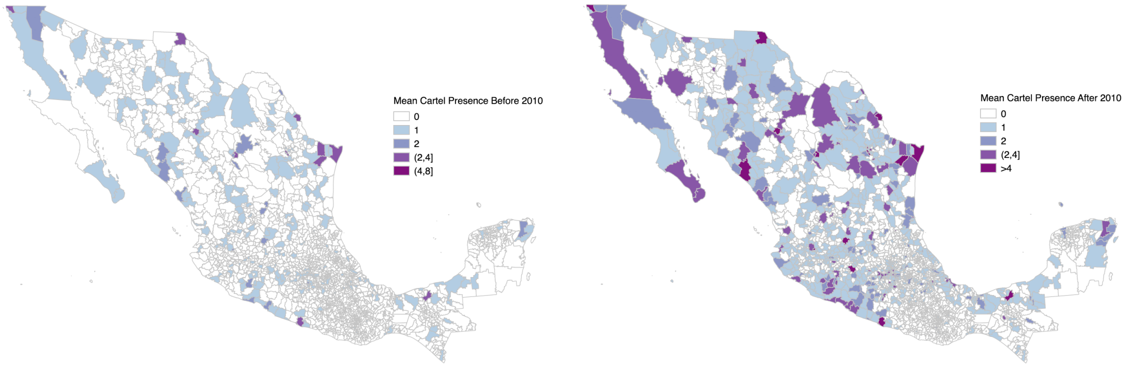
Figure 1 shows the evolution of cartel presence between 2004 and 2016. Panel (a) shows the mean average number of active cartels between 2004 and 2009 and panel (b) shows the mean number of active cartels between 2010 and 2016. The maps show the increase in the number of municipalities with a cartel active and also the increase in the number of municipalities with multiple cartels presents.

3.2 Agro-ecological data

The geographic variation in opium poppy suitability is draw from multiple data sets. A suitability index measures an area comparative advantage for crop cultivation base on geographic and climatic characteristics. While these indexes exist for almost all legal crops, they do not exist for *papaver somniferum* commonly know as opium poppy. The only available measure is the FAO overall characteristics for *papaver somniferum* to survive.[16] Suitability indexes are built using agro-climatic characteristics and crop yields. Unfortunately, there does not exist historical data on opium production in Mexico.[17]

[16] `http://ecocrop.fao.org/ecocrop/srv/en/dataSheet?id=8296`

[17] UNDOC just started collecting these data in 2014 but they are still unable to provide accurate measures for opium yields at the municipality level



(a) Mean Cartel Presence 2004-2009 (b) Mean Cartel Presence 2010-2016

Figure 1: Cartel Presence

The suitability index that I build here is constructed using Afghanistan data, the world's number one opium producer. The UN has been collecting data (surveys and satellite images) on opium yields and hectares cultivated since the early 1990s.[18] I use yields by district between 2000 and 2019 plus 45 agro-climatic characteristics and all their interactions.[19] The main agro-climatic variables I use are temperature, precipitation, elevation, terrain ruggedness, soil quality and river density. A full description of this variables and the data sets they came from can be found in Appendix A.2.

The suitability index is build by regressing log productivity of opium on the geo-climatic characteristics by district and year. The number of total regressors will be 903, so I use an elastic net, a penalized OLS regression, Zou and Hastie (2005) to reduce the number of regressors. A 10 fold cross-validation is use to validate the model and the final chosen model has an out of sample accuracy of 0.7535.[20] This model is used to predict log productivity of opium in Mexican municipalities given its agro-climatic characteristics.[21] This measure is then standardized and its range set between 0 and 1 for interpretation reasons, so that 1 means perfectly suitable and 0 means not suitable to grow opium poppy. The correlation between the suitability index and the opium poppy eradication data from the Mexican Military between 2000 and 2005 is 0.451248.
Figure 2 shows the suitability index for each municipality. The darker the tone shown the more suitable the area is to grow opium poppy. This map and the maps in Figure 1 show similar patterns. Mostly all the states in the Pacific coast; Sinaloa, Nayarit, Jalisco,

[18] https://www.unodc.org/unodc/en/crop-monitoring/index.html?tag=Afghanistan

[19] The suitability index built here is similar to the ones used by Kienberger et al. (2017),Sonin et al. (2019),Bounadi (2018) and Gehring et al. (2018)

[20] k-fold cross validation generally results in a less biased and less optimistic estimate. It consist on splitting the data into k groups and use this to train and test the model.

[21] The shrinking and mixing parameters used can be found in Appendix A.2

Colima, Michoacan and Guerrero, are highly suitable to grow opium and the number of active cartels increased after 2010. Table 1 shows the relationship between the suitability index and eradication data. This table confirms that highly suitable municipalities have eradications which imply that some opium is being produce there.

Table 1: Suitability Index and Eradication

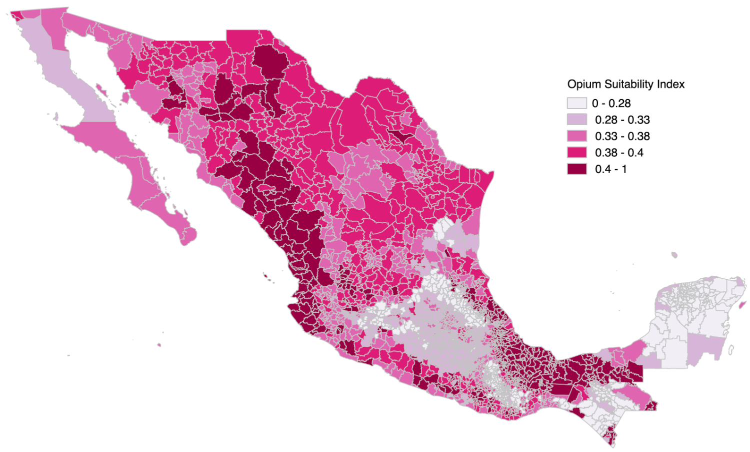
	Post2010	Pre2010	All Years
SuitIndex	401.025***	386.471***	788.409***
	(137.447)	(194.678)	(283.476)
Constant	−85.514	−75.265	−160.993
	(59.360)	(69.883)	(101.758)
Observations	2,455	2,455	2,455
R^2	0.003	0.002	0.003
Adjusted R^2	0.003	0.001	0.003
Residual Std. Error	642.414 (df = 2453)	908.534 (df = 2441)	1,322.943 (df = 2441)
F Statistic	8.513*** (df = 1; 2453)	3.941** (df = 1; 2441)	7.735*** (df = 1; 2441)

Notes: This table presents the results of a ordinary least square model where the dependent variable is the mean eradication of opium poppy. Controls for police and military presence, and political party. Municipality fixed effects.$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

3.3 Municipality level data

There does not exist a full panel of homicides related to organized crime. I use the total number of homicides by municipality and year from INEGI. This data set includes all the deaths in the country for which a death certificate was generated, then they are classified the cause of death and one of the classifications is intentional deaths. Data on population, average years of education, percentage of indigenous population, illiterate population, unemployment. Other basic characteristics of the households that includes houses with dirt floors, percentage of houses without electricity, sewage or running water and percentage of houses with TV, refrigerator, washer machine, phone, Internet and car come from INEGI 2000, 2005, 2010 and 2015 censuses and intercensal surveys. Data in marginalization by municipality are from CONEVAL and data on the affiliated political parties of mayors and governors is drawn from CIDAC and INAFED.

Figure 2: Opium Poppy Suitability Index



3.4 Drugs Time Series

The Mexican National Defense Office publishes data each year on how many hectares of opium and marijuana are eradicated by municipality and the amount of drugs seized by the military and marines. The data on heroin prices come from the UNDOC data set; data on heroin overdose deaths from the national CDC wonder data set, and data on heroin users each year from the National Survey on Drugs and Health.

4 The effect of external demand shocks on cartel presence

In this section I examine the casual effect of a plausible external demand shock to the heroin market on the presence of Drug Trafficking Organizations across Mexico. First, I describe the theoretical framework for the mechanism behind the relationship between the increase in the value of certain territories, entry, and violence. Second, I introduce the main econometric specification and address possible threats to my identification strategy. Last, I present the effect of the shock on the probability of having more than one cartel active and in the number of active Drug Trafficking Organizations per municipality.

4.1 Theoretical Framework

In this section I provide a theoretical model that relates cartel entry, investment in military capacity and violence. The mechanism behind the analysis is the following: a positive demand shock to the heroin market increases the value of controlling drug production and drug trafficking routes. In the absence of conditions to reach peaceful agreements to share the market, drug traffickers will fight each other to gain as much market shares as possible.

The following model is a two-stage entry game, a variant of the endogenous sunk cost models in Schmalensee (1992), with the addition of a success function that determines the proportion of the total shares that each organization will win. To simplify the model, I assume that each municipality is an independent production site, an extension of this model will take into account the geographic location of the cartel headquarters and include spill over effects. I will also assume that the government actions are completely known by the cartels and that they have already internalized any possible seizures or extra costs that government interventions might generate.[22] Finally, the only way a Drug Trafficking Organization can gain market power is through investing in military capacity.

There are N potential cartels that want to enter a production site, each of them invest M_i in military capacity, and the total military presence in the municipality will be $M = \sum_{i=1}^{N^*} M_i$. The potential crop production of the site is given by R and that military capacity has no dynamic effect.

In the first stage, cartels decide whether to enter or not a site and pay fixed cost F, think of this as an exploration fixed cost. Cartels need to make sure the site is productive and also know who else is in that territory. In the second stage, they decide how much to invest in military capacity.

The contest function is given by:

$$s_i = \frac{M_i^\eta}{\sum_{j=1}^{N^*} M_j^\eta}$$

In the data I observe multiple Drug Trafficking Organizations in one site, so this success function can be interpreted as the proportion of the total share that each cartel gets from its investment. Here η describes the returns to military efforts, if $\eta \leq 1$ there are decreasing returns to effort if $\eta > 1$ the returns are increasing.
The profit for a cartel entering a municipality is given by:

$$\pi_i = Rs_i - M_i - F$$

where R is the total revenue from this production cite.
There will be a byproduct from military expenditure, a negative externality, that I will call violence. Violence will be a function of the total military investment of all the cartels $V(\sum_{i=1}^{N} M_i)$. The only assumption about this function is that it will be zero if there is zero investment in military capacity and increases with military expenditure.
As long as $\eta \leq 2$ there will be well-behaved symmetric Nash equilibria in M_i with non-negative profits.
The Cournot symmetric NE in military expenditure will be:

[22] For a model on how the government interdictions affect violence see Castillo and Kronick (2019)

$$M = R\eta\frac{n-1}{n^2}$$

and the free entry condition is :

$$n^{*2}\frac{F}{R} + n^*(\eta - 1) - \eta = 0$$

The parameter η will determine the relationship between the total revenue from a site and the number of cartels that enter:

- If $\eta < 1$ then when $R \to \infty$ so does $N \to \infty$. There are decreasing returns to military effort.
- If $\eta = 1$ then $n^* = \left(\frac{F}{R}\right)^{1/2}$ In this case military expenditure is increasing in the size of the prize as long as $F \geq 9/4R$, the military expenditure per cartel needs to grow as the market grows in order to keep the free entry condition active.
- If $\eta \in (1, 2]$ then when $R \to \infty$ the number of cartels is bounded by $n^{**} = \frac{\eta}{\eta - 1}$ here competition is tough and military expenditure increases more than in the previous case.

In all the cases above the number of cartels and the military investment will be increasing with the size of the revenue. This models predicts that an external demand shock that increases the revenue of some production sites (R) will increase cartel entry and their investment in military capacity to capture higher market shares. More cartels and higher investment in military capacity will lead to increase in violence.

4.2 Empirical Strategy

4.2.1 Baseline Econometric Specification

To estimate the causal effect of competition between Drug Trafficking Organizations on violence. I ideally need a policy change or external shock that shifts demand or supply but that does not directly affect violence. This directly disqualifies any shift that might happen through law enforcement, as this kind of shock will have two different effects on violence: a direct one from the change in law enforcement and an indirect one from market pressures. Throughout this paper I use the reformulation of OxyContin in 2010 into a form that made the pill harder to abuse.[23] This was followed by an increased in heroin overdose deaths and a spike in heroin prices in the US. This seems like a plausible exogenous shock to the heroin

[23] The ADF pill is difficult to crush and snort, and several studies have found that the move led to a rapid drop in illicit use of the drug.

market that might affected the decision of the Drug Trafficking Organizations to entry into new territories that are suitable for opium production. I exploit within-municipality variation from combining the suitability index and heroin prices in the United States. The main specification is an event study analysis, where the relevant event is the OxyContin reformulation in 2010.

$$Y_{mt} = \sum_{t=2004}^{2016} \beta_t Suit_m * PriceHer_t + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_s t + \epsilon_{mt} \tag{1}$$

$Suit_m$ is a measure of opium poppy suitability of municipality m, this measure is between 0 and 1, where 1 means perfectly suitable and 0 not suitable. $PriceHer_t$ is the retail price of a milligram of heroin in the US adjust by purity and inflation in 2016 dollars and normalized to 2002. The Y_{mt} will be the probability of having more than one cartel and the number of active cartels. The α_m are municipality fixed effects, γ_t year fixed effects and $\sigma_s t$ state specific time trends. These fixed effects control for invariant differences between high-suitable and low-suitable municipalities and changes in time trends across years. The controls include police presence, military presence, a dummy if the mayor is from the conservative party PAN and a dummy if both the state governor and the mayor are from the conservative party.[24]

The only difference between this specification and an standard event study is that here the treatment is a continuous variable.[25]

The main results are presented by plotting the coefficients β_t to show the evolution of the outcome variables relative to the reformulation in 2010. The year 2009 was normalized to zero and the plots show two different coefficients: the simple post average from the event study coefficients and the difference-in-difference coefficient. These difference-in-difference results are estimated using the same specification as equation (1), but with the event dummy years replace by $PostRef_{mt} = Suit_m * PriceHer_t * \mathbb{1}[t >= 2010]$. Standard errors are clustered using Conley (1999) with a radius of 500 Km. This is used to address the fact that there is spatial correlation in the suitability index, and clustering by municipality might be a too small geographic variation.

4.2.2 Threats to Identification

Here I address some potential concerns regarding the main identification strategy. I provide evidence that measuring cartel presence using news articles is not biased towards any particular cartel. I also discuss the validity of the reformulation as an external demand shock. Finally, I present a series of robustness checks that address the potential of violence

[24] Dell (2015) finds that drug related violence increases after close elections of PAN mayors. There is also evidence that PAN mayors and governors cooperate more easily with the federal government on the efforts against drug dealers.

[25] Strategy commonly use to estimate the effect of commodity shocks Dube and Vargas (2013)

and cartel activity being completely driven by the war on drugs and government action and not by market pressures.

The main threat to identification is building the cartel presence data set using news articles. I already showed in the data section that this data set is highly correlated with other data sets on cartel presence build through news papers and also aggregate data from the DEA. Despite this, it could be that this measure is biased. Mexico is known for being one of the most dangerous countries in the world to be a journalist. More than 200 media workers have disappeared or been killed since 2000. Anecdotal evidence from other journalists shows that some of them had stop reporting cartel activities that are not first reported by the police or the military. To train the neural network used to validate the data I read 5,000 sentences to classify them as either presence or not, this sub-sample confirms that most of the journalists are either not reporting names of particular cartel members, just the bigger organizations, or that they are just reporting using official data from local and federal police or the military.[26] Examples of these sentences can be found in the Appendix. The data set that includes the location, date and media where these journalists either were killed or disappeared is public.[27] I use this data to test if there are particular regions of the country or years when crimes against the media happen more often. The most lethal state in Mexico to be a journalist is Veracruz: I ran all the analysis excluding this state and all the results of the paper still hold. All the other attacks against the media are distributed mostly evenly across 23 states. States with low cartel or no cartel presence do not experience any attacks against the media. All this provides evidence that the cartel presence measure use here is a good proxy for cartel activity across Mexico.

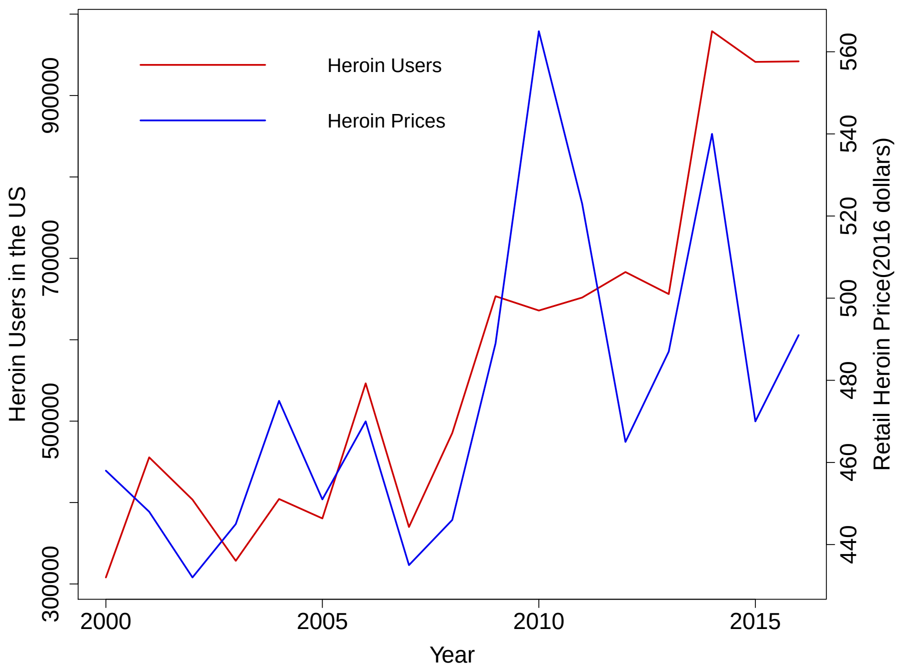
The second potential concern with this identification strategy is that Drug Trafficking Organizations had a direct impact in the price of retail heroin in the United States. Then the price will not be exogenously changing but will be reacting to supply changes. The sharp increase in the heroin of Mexican origin seized by the DEA in the United States from 19% in 2009 to 51% in 2011 and 95% by 2016, suggests that the cartels adapted after the increase in demand in the United States. The Drug Trafficking Organizations reacted by producing more heroin as the demand increased. Figure shows the increase in heroin users and heroin prices in 2010. Abby et al. (2018) and Muhuri et al. (2013) have shown that the reformulation drove up the demand for heroin and the overdose deaths from it. Then, it is reasonable to assume that the increase in demand and the subsequent increase in prices attracted more drug traffickers to the heroin market.

Finally, one last concern is that the increase in violence and the multiplication of Drug Trafficking Organizations is a direct effect from the war on drugs. To address this I use several controls that include police presence, military bases, garrisons and ports, if the mayor of the municipality is from the conservative party PAN, if the mayor and

[26] The police reports are not public so I could not use them to create a data set.

[27] The data set of missing and killed journalist can be found here https://en.wikipedia.org/wiki/List_of_journalists_and_media_workers_killed_in_Mexico

Figure 3: Heroin Users and Heroin prices in the United States



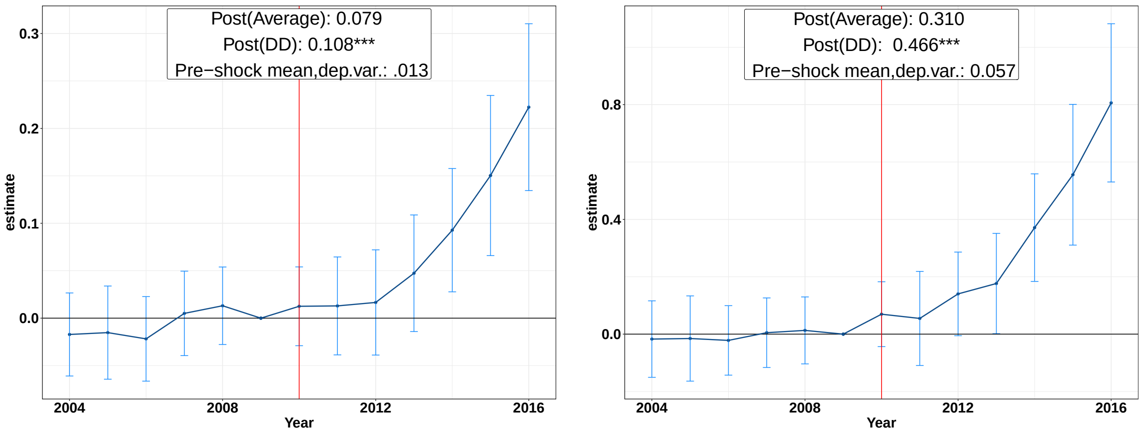
Note: Heroin prices are from UNDOC data set and heroin users come from National Survey on Drugs and Health.

governor are both from the PAN party. I also add baseline controls for the municipality characteristics interacted with year fixed effects. I also add state-specific time trends to control for any other government policies that might affect cartel activity. The results seem to be robust to all of these different specifications.

One last identification concern is the fact that marijuana legalization and the opioid crisis happened at the same time. This does not seem to be a big problem because both of these external shocks increase the value of opium and drive cartels to switch to the heroin market and leave the less profitable marijuana market.

4.2.3 Results

The section below shows the cartel presence reaction to the 2010 shock. First, I show how the probability of having more than one cartel active changes after the shock and then how the number of cartels affects this. The results are robust to including the set of covariates described in the section above; all the fixed effects and also the baseline characteristics interacted with fixed effects.



(a) More than one cartel active

(b) Number of active cartels

Figure 4: Event Study on cartel presence

Cartel Activity: Figures 1 and 2 in the data section show the increase in the number of municipalities with more than one cartel after 2010 in specially the most suitable areas for opium poppy cultivation. Next, I estimate the casual effect of heroin prices in cartel presence, particularly the price spike experienced in 2010. Figure 4 shows the event study coefficients from equation (1) where the dependent variable is one if the municipality has more than one cartel and zero otherwise. The figure shows that the pre-shock probability of having more than one cartel present is just 0.013. The event study post event average is 0.079 and the difference-in-difference coefficient is 0.108. To understand the magnitude of these coefficients consider the effect of an increase in the price of heroin of 30%,(this was the price increase between 2009 and 2010). The probability of having more than one cartel will be 14% higher in a high suitable municipality compared to a low suitable one.

Figure 5 shows the coefficients from specification (1), where Y_{mt} is the number of active cartels in municipality m at time t. As in the case for the probability of having more than one cartel present. These coefficients are close to zero before the shock and start slowly increasing in 2010. The figure shows the average post-shock event study coefficient that is 0.310, the difference-in-difference coefficient is 0.466 and highly significant and the pre-shock average number of cartels that was just 0.05 cartels. To understand the magnitude of these coefficients, lets compare the high and low suitable municipalities when there is a heroin price increase of 30%. The number of active cartels will increase by 0.6 more cartels each year after the shock.

Robustness Checks: Table 2 addresses some concerns presented in section 4.2.2. The first column uses the specification in equation (1), but just includes municipality and year fixed effects. The second column includes the same set of fixed effects plus a set of controls that are police presence, military presence, distance to military bases, garrisons and ports interacted with year fixed effects, a dummy if the mayor is from the conservative party PAN and a dummy if both the mayor and the governor are from the conservative party. These controls for potential biases coming from the war on drugs acting differently across municipalities with different political alliances or municipalities with a higher presence of authorities. Columns 3 and 4 add a set of baseline time trends. These baseline characteristics are population, years of education, poverty index, hectares of drugs cultivated and kilos of drugs-seized all of these variables are from 2000 and are interacted with year fixed effects. Column 4 just adds the same set of controls as Column 2 to the set of baseline controls. The estimates are robust to all these controls. Finally, Column 5 includes linear time trends by state and all the covariates from the previous columns. The results for both having more than one cartel active and the number of cartels are robust to all these controls and fixed effects. The standard errors are clustered using Conley (1999) with a radius of 500 Km.

Table 2: The effect of the reformulation on cartel activity

	Cartel Activity									
	More than one					Number of Cartels				
PshockInst(dd)	0.108***	0.121***	0.064***	0.044***	0.049 ***	0.466***	0.537***	0.292***	0.227***	0.241***
Radius 500 km	(0.011)	(0.014)	(0.012)	(0.012)	(0.012)	(0.002)	(0.049) (0.038)	(0.039)	(0.039)	
Observations	32,202	31,752	32,202	31,752	31,752	32,202	31,752	32,202	31,752	31,752
Pre-shock mean, dep. var.	0.012	0.012	0.012	0.012	0.012	0.057	0.057	0.057	0.057	0.057
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓		✓	✓	✓	
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the results of the difference-in-difference model for the dependent variables: more than one cartel active and number of cartels. These results are estimated using the the same specification as Equation 1, but with the event dummy years replace by a post shock dummy interacted with suitability and heroin prices. The first four columns show the results for the probability of having more than two cartels active. The next four columns show the coefficients for the number of cartels. Columns (1) and (6) present the results with municipality and year fixed effects. Columns (2) and (7) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (8) control for baseline characteristics interacted by year such as population, drug activity in 2000 and marginalization rate. Columns (4) and (9) add to the baseline trends, the set of controls from Column (2) & (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

In sum, patterns of cartel entry are consistent with the theoretical model presented in section 4.1. The increase in the value of some production sites encourage more cartel activity in these places. When the prices of the final product is high more Drug Trafficking Organizations will try to enter the market. These results are also consistent with anecdotal evidence of increased cartel presence in municipalities were cartels where not active before and that now produce most of the opium Ahmed (August 2015). The results above do not show a sharp jump in 2010, this is consistent with cartels slowly realizing that these sites are now more valuable. The production process from plating the opium to getting heroin takes at least four month, the time the crop need to grow. This supports the casual mechanism used in this paper. An explanation of how opium is transformed into heroin can be found in Appendix A.2.

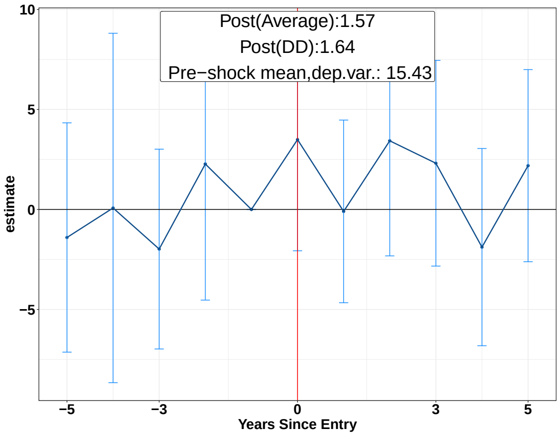
5 Entry, Exit and Violence:

This section provides evidence of the relationship between cartel entry, exit and the homicide rate. I use an event study specification that exploits heterogeneity on the time of entry and exit across municipalities. The relevant event of study is the entry or exit of the cartels. The relationship between the number of cartels and violence is not obvious. The presence of illegal activities does not necessarily breeds violence.Snyder and Duran-Martinez (2009) and Castillo and Kronick (2019) show that the ability to reach peaceful agreements to share profits between criminal organizations relies on how strong national institutions are. Mexico during this period of time lacked such conditions so I expect to see the criminal organizations fighting over potential profits. The main econometric specification used in this section is the following one:

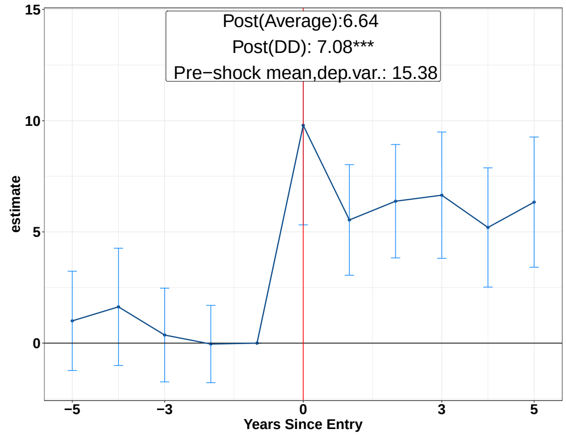
$$Y_{mt}^{n} = \sum_{\tau=-5}^{5} \beta_\tau \mathbb{1}\{\tau = t - e_m\} + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_e t + \epsilon_{mt} \tag{2}$$

The time relative to the entry of the cartel is indexed by τ. The variable e_m denotes the calendar year in which municipality m experience the entry of cartel number n, so $\mathbb{1}\{\tau = t - e_m\}$ is an indicator of municipality m in year t having experience the entry of the cartel number n τ years ago. In the summation $\tau = -5$ (or $\tau = 5$) term includes all the years greater than or equal to five years before (or five years after) the entry of the first cartel. This specification normalizes the year $\tau = -1$ to zero. I control for a vector of municipality fixed effects α_m, calendar year fixed effects γ_t, the same controls as before X_{mt} and linear state time trends $\sigma_e t$.

The results are presented by plotting the β_τ coefficients, to show the within municipality evolution of the homicide rate relative to the event of the entry or exit of the nth cartel. The graphs also show difference-in-difference results which are estimated with the



(a) First Cartel Entry



(b) Second Cartel Entry

Figure 5: Cartel Entry[28]

same specification as equation (2) but with the event time year dummies replaced by a dummy variable $PostEntry_{mt}$ (indicating that in year t municipality m has the entry of the nth cartel). The standard errors are clustered using Conley (1999) error with a radius of 500Km.

5.1 Results

This section shows three main results. First, the presence of a single cartel does not increases violence. Second, there seems to be a non linear relationship between the number of cartels and the increase in the homicide rate. Last, the only significant effect from the exit is when a municipality goes from two to one cartel only.

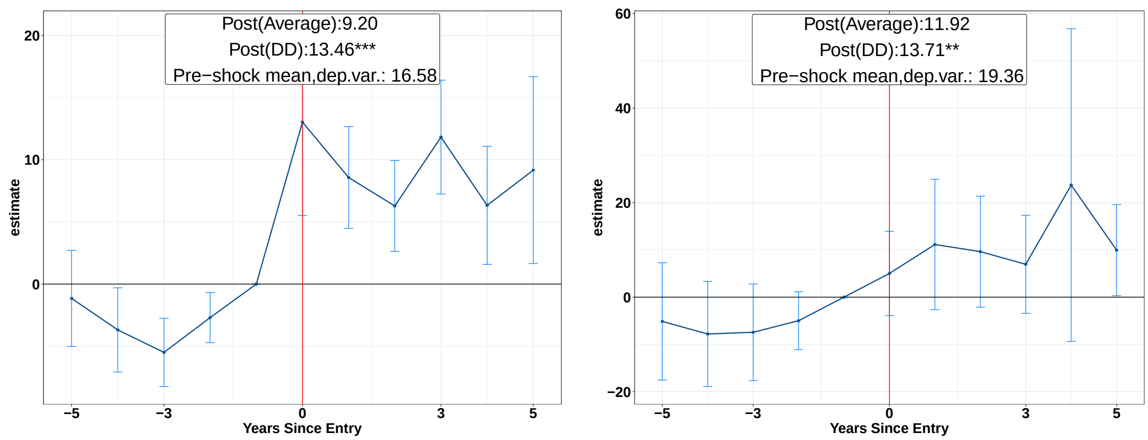
Figure 7 presents the coefficients from equation (2) where the relevant event is the entry of the first cartel to a municipality. There does not seem to be a significant effect from this entry. This result is consistent with Biderman et al. (2018), that find a decrease in violence in São Paulo when a single gang gains monopoly power. This result suggests that is not criminal activity alone that generates violence but is the interaction between different actors that increases violence. It might indicate that as long as a single group can maintain monopoly power in a location there should not be an increase in violence regardless of the illegality of their activity. This result is robust when adding controls for police and military presence, political party affiliations, municipality baseline characteristics interacted with time trends and state specific time trends.

The second result from this analysis is the increase in the homicide rate from cartel entry. Figure 6, panel (a) shows that when a municipality goes from having one to two cartels the homicide rate per 100,000 inhabitants increases by 7 homicides. The increase peaks at the year the second cartel enters but stays high for the next five years. The entry of the third and fourth cartel both increase the homicide rate by 13 homicides. From Figure 6, panel (b) there is an sharp increase the year the third cartel enters but the effect in the homicide rate after five years is less stable than for the entry of the second cartel. Figure 7, panel (a) shows that before the fourth cartel enters a municipality, with already three active cartels there is a pre-trend. The homicide rate increases by 13 homicides and there is some effect that last for the next couple of years. The entry of the fifth cartel increases the homicide rate by 17 homicides. This is the biggest increase and Figure 7, panel (b) shows that the biggest increase in the homicide rate occurs the year after the fifth cartel enters and not simultaneously with the entry. There is not as sharp an increase as there is for the entry of the second and third cartel. The coefficients are increasing and then get noisier. The last significant effect that I find is from the entry of the sixth cartel, the homicide rate increases by 10 extra homicides. There is not significant effect after the sixth cartel, but the number of municipalities with more than 6 cartels is only 14. These sets of results are robust to including controls for police presence, military presence, political party, baseline trends and state specific linear time trends. The tables that show the difference-in-difference coefficients from specification (2) can be found in the Appendix A.3

The last result is related to the exit of cartels from a municipality. There does not seems to be any significant effect when a cartel leaves a municipality. The only clear effect is when a municipality goes from two to one cartels. Figure 8 shows the coefficients from the specification (2) when the relevant event is a municipality with two cartels that experiences the exit of one of them. This graph shows a sharp drop of the homicides after the exit of the cartel and the homicides keep going down for a couple of years. The homicide rate per 100,000 inhabitants decreases by 6 homicides after the exit. This result is robust to including the different controls and fixed effects. The three results presented in this section are consistent with the theoretical model from section 4. The model predicts that when there exists a single criminal organization, violence should be zero and that violence is an increasing function of the number of cartels. The first and last result from this section suggest that when a single organization has the monopoly power of a territory violence should be low. It is not the presence of drug traffickers or their illegal activities that generate violence but the competition in which these organizations engage to win market power that generates the increase in violence.

Figure 9 shows the difference-in-difference coefficients from equation (2) but with the

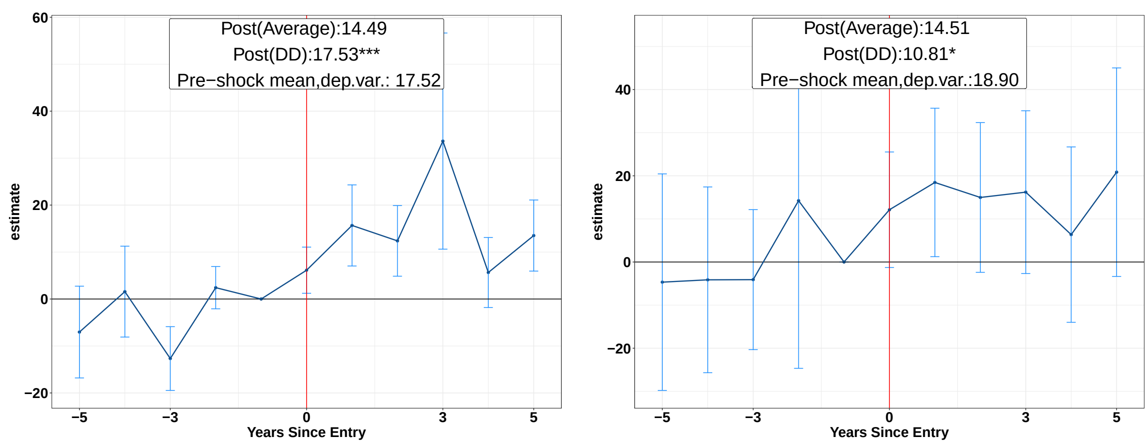
[28] All the coefficients graphs show through the paper have the event study coefficients for the basic specification with municipality and year fixed effects. The difference-in-difference results for all the different specifications can be found in the Appendix. Standard errors are clustered using a 500Km radius.



(a) Third Cartel Entry

(b) Fourth Cartel Entry

Figure 6: Cartel Entry

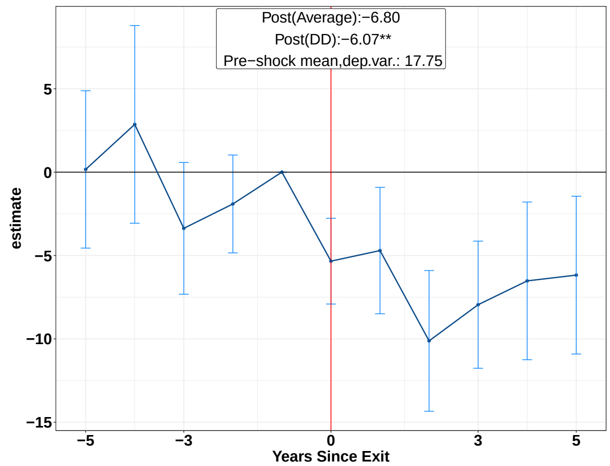


(a) Fifth Cartel Entry

(b) Sixth Cartel Entry

Figure 7: Cartel Entry

Figure 8: Going from two to one active cartel

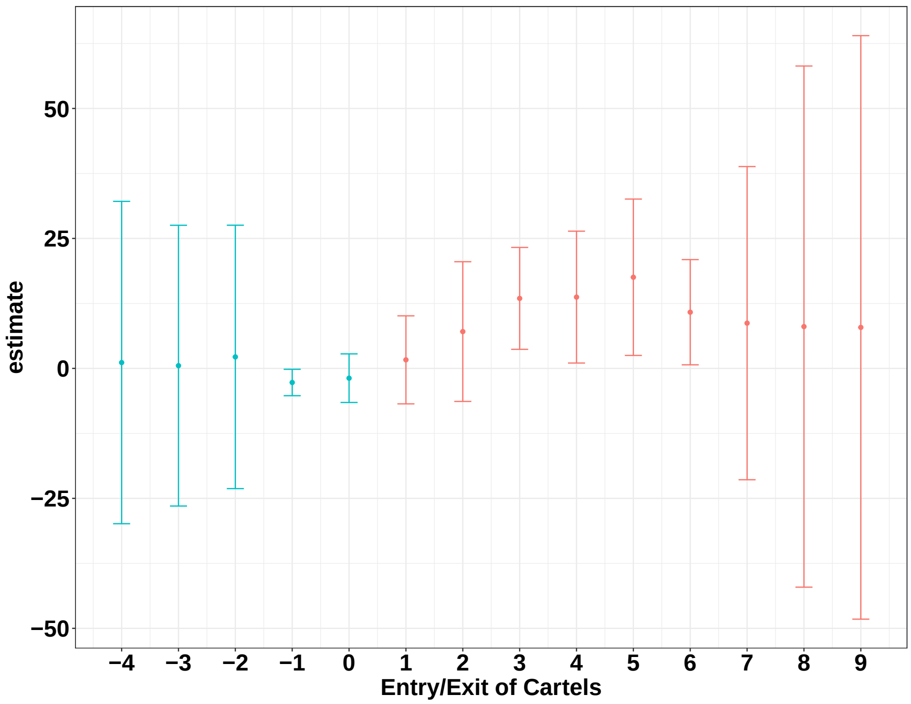


event time year dummies replace by a dummy variable $PostEvent_{mt}$ using just municipality and calendar year fixed effects. The coefficients and error bars in red , 1-9, show the effects of the entry of the first, second and so on cartel. From this graph there is the non-linear relationship between the entry of the cartels and the homicide rate per 100,000 inhabitants. The standard errors of these estimates get bigger as the number of active cartels increases in a municipality. This is because there are not that many municipalities with more than five cartels active in their territory. The coefficients and error bars in blue account for the exit of cartels. The coefficient in zero measures the effect in the homicide rate in municipalities that go from having one to zero cartels. The coefficient in -1, is the effect of a cartel leaving a municipality that previously had two cartels. The other three coefficients are the effects from a municipality that experience the exit of one cartel and previously had three of them, -2. The effect of a municipality that goes from four to three cartels, -3, and the first bar shows the coefficient and standard errors from municipalities that had five cartels and experience the exit of one of them. This figure summarizes the relationship between cartel entry, exit and the homicide rate. The significant effects occur when a municipality goes from one to two or two to one, this confirms that when there is just one criminal organization present in one place there is no notorious increase in violence. The rest of the graph shows that there are not significant effects of exit if there are at least two cartels left and that violence seems to be increasing in the number of cartels.

5.2 The effect of the shock on other outcomes

In this section I analyze the effect that the external demand shock had on other outcomes. I use the first specification (1) where the relevant event happens in 2010. First, I

Figure 9: Entry and Exit of Cartels



show that there was an increase in the homicide rate after 2010. Second, I ask how demographics such as population, average years of education and the percentage of households with dirt floor change after the shock. Finally, I see how the government data on eradication confirms that after 2010, the suitable municipalities were producing more opium than before. These results show that the shock had a direct impact on other outcomes across Mexican municipalities.

Homicide Rate per 100,000 inhabitants: Figure 14 shows the coefficients from the event study (1) where Y_{mt} is the homicide rate per a 100,000 inhabitants. There is an increase in the number of homicides after 2010 and it stays high after the shock. The difference-in-difference coefficient is an increase of 24 homicides in the homicide rate. This means that a high suitable municipality will have a homicide rate with 24 more homicides per 100,000 inhabitants compare to a less suitable one. Table 3 shows the results for different specifications. The results are robust to all the different controls and fixed effects. The model that includes all the controls and state specific time trends has an increase of homicides per 100,000 of 11 extra homicides after 2010.

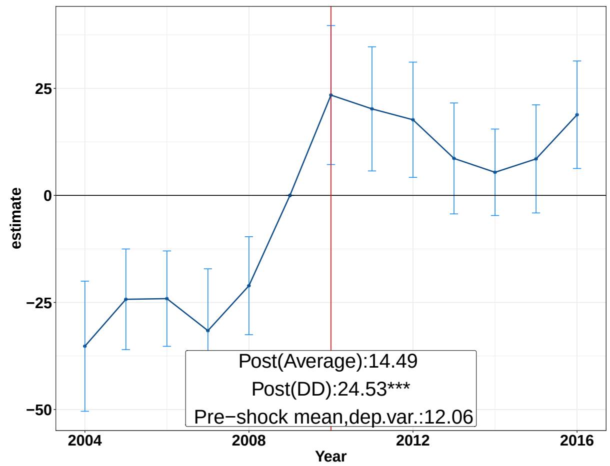
Change in demographics: This section analyses the effect of the shock on different demographic outcomes. First I ask if the shock had any effect on the population and households composition. The variables used are log of the population, mean years of

Table 3: Homicides per 100,000

	Homicides per 100,000 inhabitants				
Post-shock	24.53***	20.60***	22.19***	15.61***	11.13***
	(8.72)	(2.87)	(2.94)	(2.84)	(2.54)
Observations	32,202	31,752	32,202	31,752	31,752
Pre-shock mean, dep. var.	12.06	12.06	12.06	12.06	12.06
Municipalities FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Covariates		✓		✓	✓
Baseline trends			✓	✓	✓
State trends					✓

Notes: This table presents the results of the difference-in-difference model for the dependent variables: homicide per 100,000 inhabitants. This results are estimated using the the same specification as Equation 1, but with the event dummy years replace by a post shock dummy interacted with suitability and heroin prices. Column (1) presents the results with municipality and year fixed effects. Columns (2) adds controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) controls for baseline characteristics interacted by year such as population, drug activity in 2000 and marginalization rate. Columns (4) adds to the baseline trends, the set of controls from Column (2) & (7). Columns (5) adds state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 10: Homicides per 100,000 inhabitants

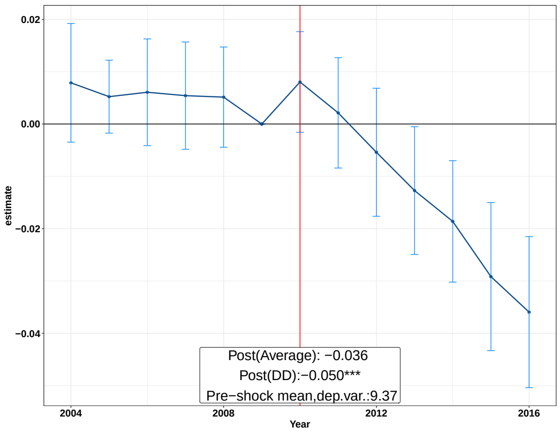


education, percentage of households with women as the head of the household and mean number of occupants per dwelling.[29] The second set of variables that I analyze suggest that there was probably an income boost in the municipalities exposed to the shock. These variables are the percentage of households without dirt floor and percentage of households that do not have access to basic services (water,electricity and sewer).[30] Figure 11, panel (a) shows an steady decrease in the log of the population after 2010 and Figure 11, panel (b) has a similar steady decrease in the average years of education. Figure 12, panels (a) and (b) show an increasing share of households with women as the head of the household and an increasing number of occupants in the same dwelling. All these results are consistent with out migration of the more educated and wealthier members of these communities. The Tables that show all the difference-in-difference coefficients for the different specifications can be found in Appendix A.3. To understand the magnitude of these coefficients I will compare a high-suitable municipality with a low-suitable one. A high-suitable municipality will have -0.050 less log of population and -0.4180 years of education compare to a low-suitable one. The number of occupants per dwelling will increase by 4.45 and the percentage of households with a woman as the head will be 1.5% higher in a perfectly suitable municipality compare to one that is not suitable.

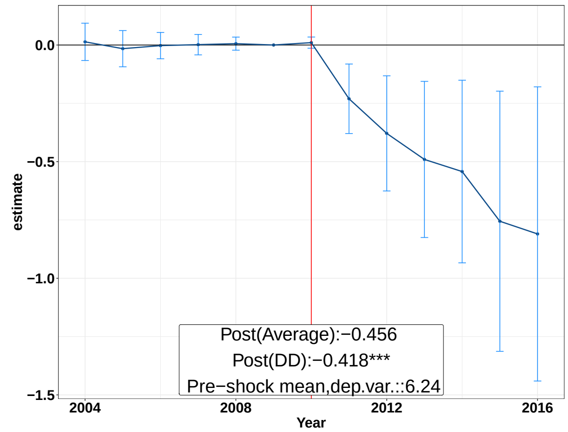
Economic Outcomes: The next set of results suggest that the shock might have had a

[29] The other variables analyzed are percentage of indigenous population, percentage of people with social security and adult illiteracy. These three does not show significant changes during the time of the analysis.

[30] The other variables that I analyzed were percentage of households that own TV,Fridge,washer,car,phone and computer non of these show any change after the shock. They either have an increasing trend or are completely flat during the years analyzed.

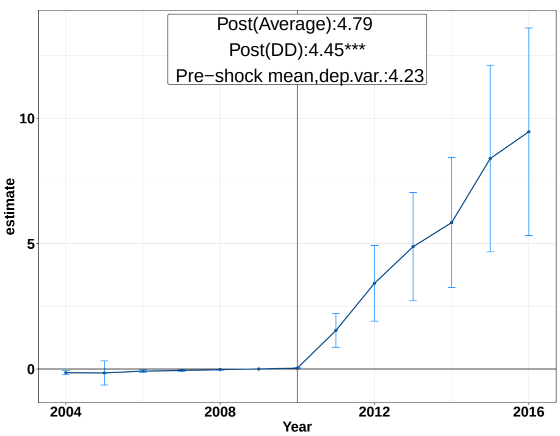


(a) Log of Population

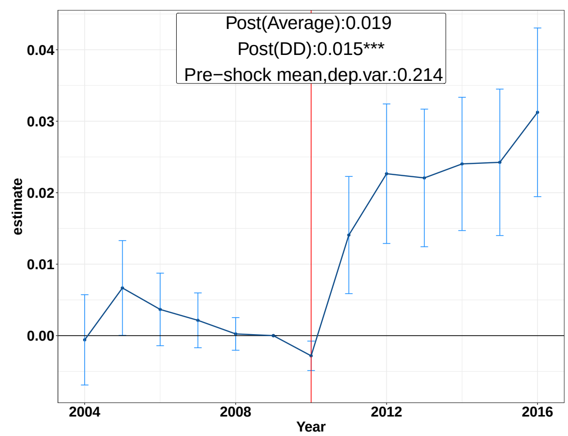


(b) Mean Years of Education

Figure 11: Demographic outcomes

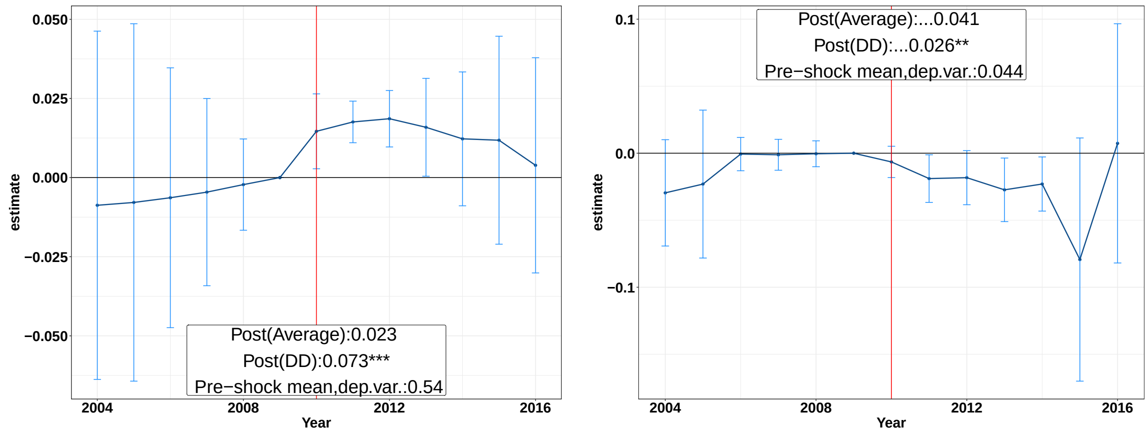


(a) Occupants per dwelling



(b) Percentage of households with women as a head

Figure 12: Demographic outcomes



(a) Households with Non Dirt Floor

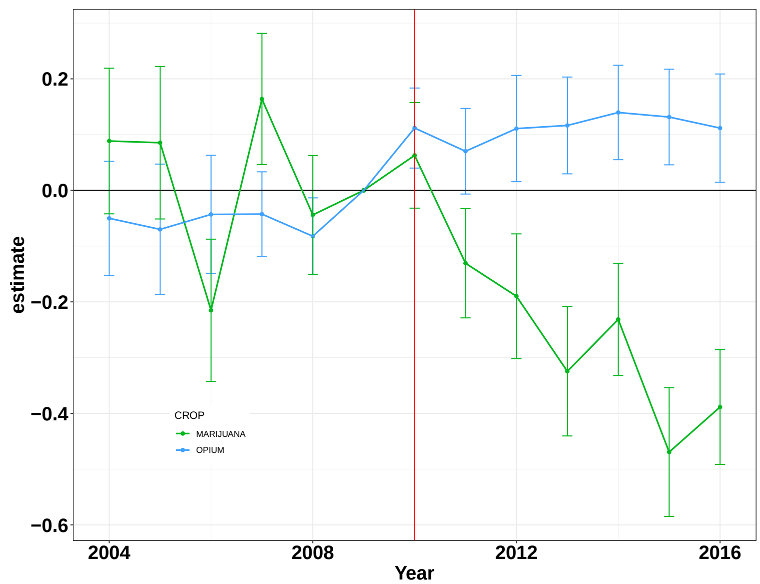
(b) Households without Basic Services (water/sewer/electricity)

Figure 13: Economic outcomes

positive impact in some socio-economic outcomes. Figures 20 and 21 show the coefficients from the event study specification (1). From Figure 13, panel (a) there was an increase in the percentage of houses that had floors made of any other material different from dirt. Figure 13, panel (b) shows a steady decrease in the percentage of households without any basic service. These services are access to piped water, access to sewers and access to electricity. The percentage of households without dirt floor after the shock will be 7.3% higher in a high-suitable municipality compare with a low-suitable one when the price of heroin remains constant. The percentage of households without services will go down by 2.6% in a high-suitable municipality compare to a non-suitable one. The difference-in-difference coefficients for the different specifications can be found in Appendix A.3. These results suggest that there was an income boost from the increase in opium cultivation and that it is probably increasing the quality of the houses of the poorest members of these communities.

Military eradication In this section I use the eradication data from the Mexican military to see if the shock affected the type of crops the government was finding and eliminating. I assume that the military did not became better at eradicating one particular crop during this period and that eradication can be seen as a proxy of total production. Figure 14 shows the coefficients for specification (1) for the log hectares eradicated of marijuana and opium. There is a clear jump in the amount of eradication of opium and an slowly decline in the eradication of marijuana after 2010. There does not seem to be any particular pre-trend for any of the crops. Table 4 shows the difference-in-difference coefficients with the different controls and fixed effects, the results are robust to all of these different specifications. These results confirm that after the shock the value of cultivating opium increase while the value of marijuana was decreasing, which lead to the farmers to switch crops.

Figure 14: Log of Hectares eradicated



6 Cartel Competition and concentration in the heroin market

In this section I provide evidence of the expansion of several cartels into the heroin market after the increase demand in the United States. Historically, Mexico has produced some opium and exported it to the United States since the beginning of the XX century. Opium poppy, native to the eastern Mediterranean area, was introduced to Mexico by Chinese immigrants in the late XIX century and proved to be well-suited to cultivation. The prohibition laws in the United States regarding psychedelic substances and the political chaos in Mexico after the Mexican Revolution lead to the proper environment for the creation of the first Drug Trafficking Organizations. During the XX century Mexican traffickers mostly produced and trafficked marijuana and eventually entered the cocaine and methampethamine business. They exported some heroin but it was never their main activity. Until 2006 there was just one cartel, the Sinaloa Cartel; in areas where opium poppy was eradicated by the Mexican government. By 2016 the nine main organizations can be found in municipalities where opium poppy was eradicated by the military. Figure 20 shows the Herfindahl–Hirschman Index for the raw opium market. The index was calcu-

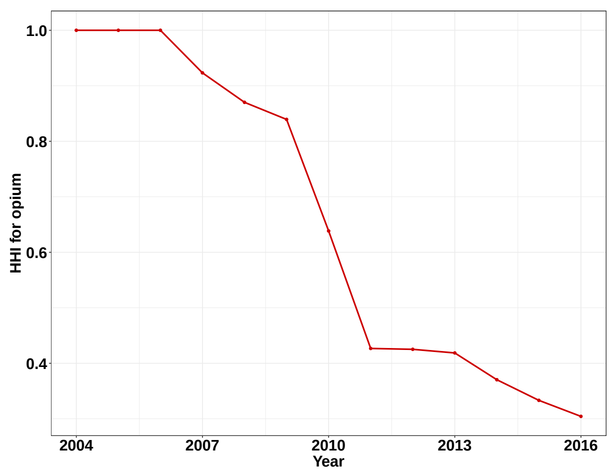
Table 4: Opium and Marijuana Eradication

	Eradication									
	log(Hectares Opium Poppy)					log(Hectares Marijuana)				
Post-shock	0.198^{***}	0.157^{***}	0.088^{*}	0.033^{*}	0.040^{***}	-0.220^{***}	-0.192^{***}	-0.235^{***}	-0.210^{***}	-0.166^{**}
Radius 500 Km	(0.001)	(0.045)	(0.038)	(0.008)	(0.004)	(0.002)	(0.048)	(0.047)	(0.047)	(0.054)
Observations	32,202	31,752	32,202	31,752	31,752	32,202	31,752	32,202	31,752	31,752
Pre-shock mean, dep. var.	0.130	0.130	0.130	0.130	0.130	0.295	0.295	0.295	0.295	0.295
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓		✓	✓	✓	
State trends					✓					✓
F-test pre-trends	2.51	2.40	0.516	0.256	0.476	0.027	0.848	1.13	0.782	0.124

Notes: This table presents the results of the difference-in-difference model for the dependent variables: log of hectares of opium poppy and Marijuana eradicated by the Mexican military.These results are estimated using the the same specification as Equation 1, but with the event dummy years replace by a post shock dummy interacted with suitability and heroin prices. The first four columns show the results for the probability of having more than two cartels active. The next four columns show the coefficients for the number of cartels. Columns (1) and (6) present the results with municipality and year fixed effects. Columns (2) and (7) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (8) control for baseline characteristics interacted by year such as population, drug activity in 2000 and marginalization rate. Columns (4) and (9) add to the baseline trends, the set of controls from Column (2) & (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

lated using the cartel presence and the eradication data set. I used the military eradication as a proxy for total production and the cartels present in those municipalities to assign market shares. In municipalities where there was more than one active cartel, I equally split the production between them. From the image the HHI drops from 1 in 2004 to around 0.3 in 2016. The graph also shows that the biggest jump occurs in 2010, after the reformulation of OxyContin this measure confirms the rest of the paper findings, when the demand for heroin increased in the United States the cartels decided to enter or expand their operations into this market.

Figure 15: HH1 Opium



6.1 Identifying Expanding and competitive cartels

This paper considers nine main Drug Trafficking Organizations recognized by the Mexican Military and the DEA as the major actors. The interactions between these organizations are complex with them expanding, fragmenting and disappearing. The last decade saw some of them fragmenting due to the government strategy of capturing kingpings. These strategies left power gaps that lead to internal disputes in these organizations Phillips (2015). Less explored is fragmentation due to market pressures. The increase in the market value of certain territories might incentivize drug traffickers to break from their main organizations or stop previously pacific agreements with former allies to capture higher market shares. In the early 2000s, the only organization producing and trafficking heroin was the Sinaloa Cartel. Around the time of the shock the Jalisco New Generation Cartel split from the Sinaloa Cartel Crime (2019) and took some of its former parent organization's territory suitable for growing opium poppy. The second fragmentation that happened around the time of the shock is the Templar-Knights Cartel splitting from La Familia Michoacana. The group that started as a self-defense group in order to defend Michoacan against criminal organizations rapidly became a criminal organization itself. These two groups have been fighting with each other for the control of the state of Michoacan. I used the specification below to quantify the effect that the shock had on the presence of each of the nine organizations.

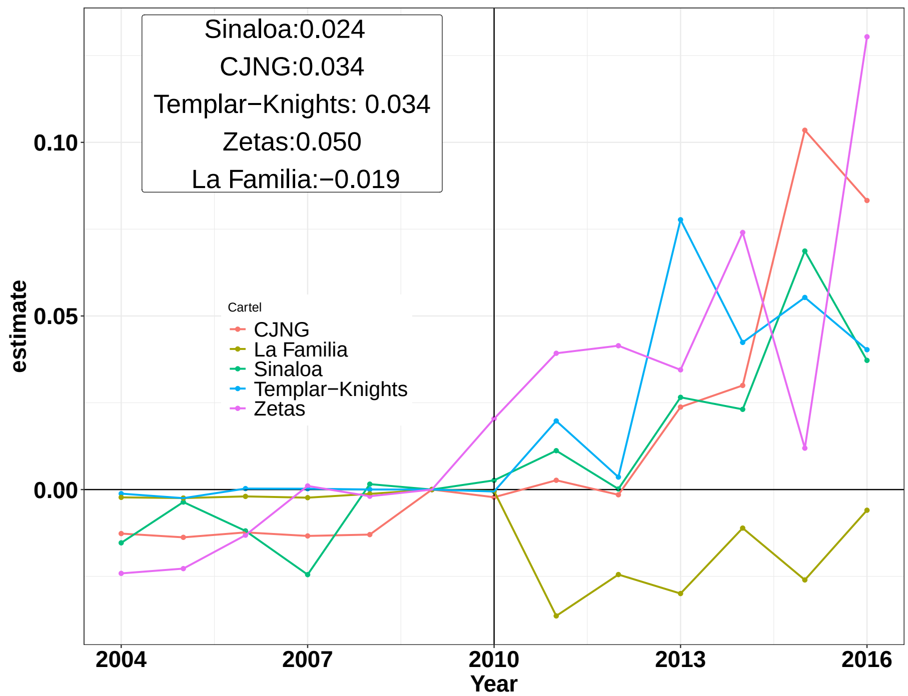
Econometric Specification:

$$Y^c_{mt} = \sum_{t=2004}^{2016} \beta_t Suit_m * PriceHer_t + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_e t + \epsilon_{mt} \tag{3}$$

where Y^c_{mt} is the probability of having the cartel c active in municipality m and time t. $Suit_m$ is the measure of suitability in the municipality m, $PriceHer_t$ is the retail price of heroin in the United States per milligram of heroin adjust by purity in 2016 dollars, X_{mt} is a set of controls that includes: police presence, military presence, political party of the mayor and political party of the governor of the state. α_m are municipality fixed effects, γ_t year fixed effects and $\sigma_e t$ are state specific time trends.

Results The nine major organizations studied in this paper show at least some presence in municipalities well suited to grow opium poppy. Figure 16 shows the coefficients from equation (3) with municipality and year fixed effects, controls for police presence, military presence and political affiliation of the major and governor of the state, baseline characteristics interacted with year and state specific time trends. The standard errors are clustered using a 500Km radius. The dependent variable is a dummy that is one when the particular cartel is present and zero otherwise. The graphs presents the results for the five main cartels that have activity in the heroin market. There are two cartels expanding into the heroin market, the Sinaloa Cartel and Los Zetas, two cartels splitting from existing ones and immediately entering the heroin market, Jalisco New Generation and the Templar Knights and one cartel loosing presence, La Familia Michoacana. The difference-in-difference coefficients for the different specifications can be found in the Appendix A.3. To interpret these results lets compare a high-suitable municipality with a low-suitable one when the price of heroin increased by 30%,this was the actual price increase between 2009 and 2010, in the United States. The probability of the Sinaloa Cartel being present in a high suitable municipality is 3.12% higher each year after the shock compare to a low suitable municipality. The probability of the Jalisco New Generation or the Templar Knights being present increases by 4.42% each year after the shock and the probability of Los Zetas increases by 6.5%. Finally, the probability of La Familia being present decreases by −2.47% each year after the shock. The other fours cartels, Tijuana, Golf, Juarez and the Beltran-Leyva Organizations do not show a significant increase in the probability of being present in high-suitable municipalities despite the fact they do enter and expand during this period of time to opium producing territories. A detailed analysis of what happened too this other four cartels and the coefficients can be found in Appendix A.3. These results suggests that market pressures can also lead criminal organizations to split and fight with previous allies to get control of valuable territory.

Figure 16: Cartel Presence by Cartel



7 Conclusion

This paper provides evidence of the relationship between market structure and violence in illegal markets. I contribute to the literature by adding market pressures and external demand shocks as factors that increase violence and the number of Drug Trafficking Organizations. I also provide two new data sets that can be used elsewhere to have a better understanding of how Drug Trafficking Organizations interact. The techniques used to create these data sets can be easily extended to other settings and used to understand other illegal markets.

The results from this paper suggest that a shift in the demand for drugs in consuming countries have direct effects in producing and trafficking countries. Particularly, I emphasize that criminal organizations are profit-maximizing players that will decide to enter and expand into profitable markets, and in the absence of a strong institutional setting usually they will use violence to win market power. Though the Mexican context and the interaction with the opioid crises is unique in some ways, there are many other example of illegal markets which might have similar unintended consequences from shifts in demand. For example, policies in order to reduce similarly overused legal opioids in Europe might have similar violent effects in Afghanistan on the restructuring of criminal organizations. Although, the levels of violence and drug crime related homicides in Mexico are an exception and not the rule, some other local illegal markets might experience similar market pressures and lead to spurs of violence or the surge of numerous criminal organizations. Understanding how criminal organizations organize and how their market structures interact with violence is key to implementing policies that aim not just to reduce illegal activities like drug trafficking but the negative externalities associated with them.

Overall, this paper provides evidence of how criminal organizations market structures interact with violence, motivating future research on understanding their structure, competition practices, and relationships with the legal economy.

References

Abby, A., Powell, D. and Pacula, R. L. (2018), 'Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids', *American Economic Journal: Economic Policy* **10(4)**, 1–34.

Acemoglu, D., Robinson, J. A. and Santos, R. (2009), 'The Monopoly of Violence: Evidence from Colombia', (15578).

Agencias (April 2016), 'Cae 'El Gringo Payán', presunto operador de El Mayo Zambada', Zocalo.
URL: *https://www.zocalo.com.mx/new_site/articulo/cae-el-gringo-payan-presunto-operador-de-el-mayo-zambada-1435099245*

Ahmed, A. (August 2015), 'Young Hands in Mexico Feed Growing U.S. Demand for Heroin', The New York Times.
URL: *https://www.nytimes.com/2015/08/30/world/americas/mexican-opium-production-rises-to-meet-heroin-demand-in-us.html*

Angrist, J. D. and Kugler, A. (2005), 'Rural Windfall or a New Resource Curse? Coca, Income, and Civil Conflict in Colombia', (11219).

Atuesta, L. H. and Ponce, A. F. (2017), 'Meet the Narco: increased competition among criminal organisations and the explosion of violence in Mexico', *Global Crime* **18**(4), 375–402.

Biderman, C., Mello, J. M., De Lima, R. S. D. and Schneider, A. (2018), 'Pax Monopolista and Crime: The Case of the Emergence of the Primeiro Comando da Capital in São Paulo', *Journal of Quantitative Criminology* **35**(3), 573–605.

Bounadi, M. E. (2018), 'Weather and Conflicts in Afghanistan', *EBA Working Paper,Expert Group for Aid Studies, Sweden.* .

Calderón, G., Robles, G., Díaz-Cayeros, A. and Magaloni, B. (2015), 'The Beheading of Criminal Organizations and the Dynamics of Violence in Mexico', *Journal of Conflict Resolution* **59**(8), 1455–1485.

Castillo, J. C. and Kronick, D. (2019), 'The logic of violence in turf war', *Working paper* .

Castillo, J. C., Mejía, D. and Restrepo, P. (2015), 'Scarcity without Leviathan: The Violent Effects of Cocaine Supply Shortages in the Mexican Drug War', *The Review of Economics and Statistics* .

Conley, T. G. (1999), 'GMM estimation with cross sectional dependence', *Journal of Econometrics* **92**(1), 1 – 45.

Coscia, M. and Rios, V. (2017), 'Knowing where and how Criminal Organizations Operate using Web Content', *Proceedings of the 21st ACM international conference on Information and knowledge management* pp. pp. 1412–1421.

Crime, I. (2019), Jalisco Cartel New Generation, Technical report, InSight Crime.
URL: *https://www.insightcrime.org/mexico-organized-crime-news/jalisco-cartel-new-generation/*

DEA (2018), 2018 National Drug Threat Assessment, Technical report, U.S. Department of Justice Drug Enforcement Administration.

Debate, E. (Febrero 2017), 'Así era el H9, heredero del Cártel de los Beltrán Leyva', El Debate.
URL: *https://www.debate.com.mx/mexico/Asi-era-el-H9-heredero-del-Cartel-de-los-Beltran-Leyva-20170212-0068.html*

Dell, M. (2015), 'Trafficking Networks and the Mexican Drug War', *American Economic Review* **105**(6), 1738–1779. .

Dell, M., Feigenberg, B. and Teshima, K. (Forthcoming), 'The Violent Consequences of Trade-Induced Worker Displacement in Mexico', *American Economic Review: Insights* .

DeWeerdt, S. (September 2019), 'Tracing the US opioid crisis to its roots', Nature Outlook: Opioids.
URL: *https://www.nature.com/articles/d41586-019-02686-2*

Dube, O., García-Ponce, O. and Thom, K. (2016), 'From Maize to Haze: Agricultural Shocks and the Growth of the Mexican Drug Sector', *Journal of the European Economic Association* **14**(5), 1181–1224.

Dube, O. and Vargas, J. F. (2013), 'Commodity Price Shocks and Civil Conflict: Evidence from Colombia', *The Review of Economic Studies* **80**(4), 1384–421.

Espinosa, V. and Rubin, D. B. (2015), 'Did the Military Interventions in the Mexican Drug War Increase Violence?', *The American Statistician* **69**(1), 17–27.

Feuer, A. (December 2018), 'El Chapo Trial Shows That Mexico's Corruption Is Even Worse Than You Think', The New York Times.
URL: *https://www.businessinsider.com/mexico-catch-cjng-jalisco-cartel-gunmen-who-shot-down-army-helicopter-2018-8*

FOROtv (May 2017), 'Vinculan a proceso a 'El Garo', operador del Cártel del Golfo en NL', Noticieron Televisa.
URL: *https://noticieros.televisa.com/ultimas-noticias/vinculan-proceso-el-garo-operador-cartel-golfo/*

Frick, S., Kramell, R., Schmidt, J., Fist, A. J. and Kutchan, T. M. (2005), 'Comparative Qualitative and Quantitative Determination of Alkaloids in Narcotic and Condiment Papaver somniferum Cultivars', *Journal of Natural Products* **68**(5), 666–673.

Gehring, K., Langlotz, S. and Stefan, K. (2018), 'Stimulant or Depressant?: Resource-Related Income Shocks and Conflict', *Household in Conflict (HiCN) Working Paper* (286).

Gentzkow, M., Kelly, B. and Taddy, M. (2017), 'Text as Data', (23276).

Grillo, I. (2011), *El Narco: Inside Mexico's Criminal Insurgency*, Bloomsbury Publishing.

Holland, B. E. and Rios, V. (2017), 'Informally Governing Information: How Criminal Rivalry Leads to Violence against the Press in Mexico', *Journal of Conflict Resolution* **61**(5), 1095–1119.

Jones, N. (2013), 'The unintended consequences of kingpin strategies: kidnap rates and the Arellano-Félix Organization', *Trends in Organized Crime* **16**(2), 156–176.

Karina (May 2015), 'Declaran tres presuntos delincuentes detenidos tras balacera Tanhuato', Sdpnoticias.
URL: *https://www.sdpnoticias.com/estados/delincuentes-detenidos-presuntos-declaran-tres.html*

Kienberger, S., Spiekermann, R., Tiede, D., Zeiler, I. and Bussink, C. (2017), 'Spatial risk assessment of opium poppy cultivation in Afghanistan: integrating environmental and socio-economic drivers', *International Journal of Digital Earth* **10**(7), 719–736.

Lopez, M. and Kalita, J. (2017), 'Deep Learning applied to NLP'.

Mavrelli, C. (2017), Transnational Crime and the Developing World, Technical report, Global Financial Integrity.

Mejía, D. and Restrepo, P. (2013), 'Bushes and Bullets: Illegal Cocaine Markets and Violence in Colombia', (011934).

Mesquita, E. B. d. (2018), 'Territorial Conflict over Endogenous Rents', *The Journal of Politics* **0**(ja), null.

Millán-Quijano, J. (2019), 'Internal Cocaine Trafficking and Armed Violence in Colombia', *Economic Inquiry* **0**(0).

Mosso, R. (April 2015), 'Detienen a operador de 'Los Zetas' en Culiacán', Milenio.
URL: *https://www.milenio.com/policia/detienen-a-operador-de-los-zetas-en-culiacan*

Muhuri, P., Gfroerer, J. and Davies, C. (2013), 'Associations of Nonmedical Pain Reliever Use and Initiation of Heroin Use in the United States', *CBHSQ Data Review* .

Murphy, T. E. and Rossi, M. (2017), 'Following the Poppy Trail: Causes and Consequences of Mexican Drug Cartels', (130).

O'Neil, S. (2009), 'The Real War in Mexico: How Democracy can Defeat the Drug Cartels', *Foreign Affairs* .

Osorio, J. (2015), 'The Contagion of Drug Violence: Spatiotemporal Dynamics of the Mexican War on Drug', *The Journal of Conflict Resolution* **59**(8), 1403–432.

Phillips, B. J. (2015), 'How Does Leadership Decapitation Affect Violence? The Case of Drug Trafficking Organizations in Mexico', *The Journal of Politics* **77**(2), 324–336.

Rios, V. (2013), 'Why did Mexico become so violent? A self-reinforcing violent equilibrium caused by competition and enforcement', *Trends in Organized Crime* **16**(2), 138–155.

Schmalensee, R. (1992), 'Sunk Costs and Market Structure: A Review Article', *The Journal of Industrial Economics* .

Shaver, A., Carter, D. and Shawa, T. W. (2019), 'Terrain Ruggedness and Land Cover: Improved Data for Most Research Designs', *Conflict Management and Peace Science* **36**(2), 191–218.

Snyder, R. and Duran-Martinez, A. (2009), 'Does illegality breed violence? Drug trafficking and state-sponsored protection rackets', *Crime, Law and Social Change* **52**(3), 253–273.

Sonin, K., Wilson, J. and Wright, A. (2019), 'Rebel Capacity and Combat Tactics', *Becker Friedman Institute , working paper No. 2018-74* .

Sviatschi, M. M. (2018), 'Making a Narco: Childhood Exposure to Illegal Labor Markets and Criminal Life Paths', (2018-03).

Sánchez de Tagle, O. (January 2014), 'Las autodefensas nos dieron un respiro', Animal Político.
URL: *https://www.animalpolitico.com/2014/01/michoacan-entre-balazos-la-pgr-y-detenidos-por-incendio-una-farmacia/*

Sánchez Valdés, V. M. (July 2017), 'Los cárteles que operan en el centro de México', Animal Político.
URL: *https://www.animalpolitico.com/el-blog-de-causa-en-comun/las-organizaciones-criminales-operan-centro-mexico/*

Sánchez Valdés, V. M. (March 2015), 'La nueva configuración del crimen en Michoacán', Animal Político.
URL: *https://www.animalpolitico.com/el-blog-de-causa-en-comun/la-nueva-configuracion-del-crimen-en-michoacan/*

Woody, C. (November 2017), 'Mexican heroin is flooding the U.S., and the Sinaloa cartel is steering the flow', Business Insider.
URL: *https://www.businessinsider.com/sinaloa-cartel-sending-mexican-herion-to-the-us-2017-11*

Young, T., Hazarika, D., Poria, S. and Cambria, E. (2017), 'Recent trends in deep learning based natural language processing', *CoRR* .

Zou, H. and Hastie, T. (2005), 'Regularization and Variable Selection via the Elastic Net', *Journal of the Royal Statistical Society. Series B (Statistical Methodology)* **67**(2), 301–20.

A Appendix

A.1 Cartel Presence

The algorithm use during the web scraping and the natural language techniques are describe here:

- Web scraping: a unique set of key words that include a Drug Trafficking Organization and municipality was send to the Google News interface to look for any article containing both key words. To reduce ambiguities regarding municipality or DTOs names I followed the same rules as Coscia and Rios (2017). I used the 9 main active cartels that both the Mexican prosecutor's and the DEA recognized. The queries were passed to the crawler that saved all the articles that included the query between 1990 and 2016. The algorithm found 2'249,561 news articles.[31] The next step consists on validating which of these articles actually is talking about a cartel being present in some municipality.

- Natural Language Processing: to validate the presence of the cartel-municipality pair I used the approach of using text as data describe in Gentzkow et al. (2017). The first step was to extract and curate each news article, doing this is not trivial and there exists several python libraries that use algorithms plus web scraping to extract the main article from the whole html. This was done in order to prevent false positives, some newspapers htmls include links to other articles that might be the source of Google finding the query in that particular link. After extracting the main article a word recognition algorithm was use to keep the articles that mention the DTO-municipality in their main body. The number of remaining articles after this process is 1'201,483. I used a sentence extraction algorithm to keep each sentence of the articles that contains the cartel and municipality pairs. There are 2'802,224 of this sentences.
  Next, I manually classified 5,000 sentences as either presence or not to train the algorithm. The following sentences are examples classified as presence. Most of this sentences are journalist reporting on police reports, this reduces the risk that media workers might experience from organized crime.

  Examples classify as presence:
  -*The attorney general in Nayarit started some operations that end up with the capture of two Beltran-Leyva operators in Tepic Debate (Febrero 2017).*
  -*Apatzingan, the most dangerous place for the self defense groups is still controlled by Knights Templar Cartel Sánchez de Tagle (January 2014).*
  -*Mexican Marines caught Hugo Cesar Roman Chavarria, alleged Zetas operator in*

[31] I restricted the search for articles in Spanish and appearing in Google News Mexico

charge of trafficking drugs through Coahuila and Nuevo Leon Mosso (April 2015).
-*Gerardo Payan alleged operator of the Sinaloa Cartel was caught by marines las Thursday in Mocorito, Sinaloa Agencias (April 2016).*
-*El Garo, operator of the Gulf Cartel in the municipalities of Apodaca, Garcia and Santa Catarina is waiting for trial FOROtv (May 2017).*
-*Yesterday, while investigating a trespassing case federal police had a confrontation with members of the Jalico New Generation Cartel in Tanhuato Karina (May 2015).*

As mention early in the paper most of this news either talk about official reports from the police or the military or do not mention particular members of the cartels. This due to how dangerous is to report on cartel activity for journalist. Again it might be that the measure of cartel entry is bias down but as long as there is no one particular cartel that is not being report or being under report this should not affect the general interpretation of the results.
In order to classify the presence of cartel c in municipality m I use a semi supervised convolutional neural network (CNN) Young et al. (2017). A CNN is a deep learning algorithm which can take as an input a sentence/phrase or article. It has several layers of convolutions with non linear activation functions applied to the results. The convolutions are use over the input layer to compute the output. This results in local connections, where each region of the input is connected to a neuron in the output. Each layer applies different filters and combines their results.Lopez and Kalita (2017). The input use here are sentences represented as a matrix, each word is represented by a vector and each of these vector is a word embedding, low dimensional representations. I use a pre-trained embedding in Spanish, trained using Wikipedia articles. A word embedding maps meaning into a geometric space. This transforms each sentence into the vector space and takes into account the relative position of each word in a sentence. The filters of the CNN slide over word windows, here I use sequences of 5 vectors of dimensions 128 for the consolutional part and 10 layers of the ReLU function plus a last layer that uses the sigmoid function to classify. A less technical explanation of what the CNN does is the following one. Sentences are first tokenized into words, then transform into a word embedding matrix, then the filters are applied on this embeddings. The filters consist on applying different window sizes to produce a feature map. TThis is followed by a max-pooling operation that applies the max operator to each filter to obtain a fixed length output and reduce dimensionality of the output. This produces the final sentence representation that is classified. To train this model I manually classified 5,000 sentences and then use bootstraping to calculate the network weights. Once the sentences were classified as presence or not presence, I use a word extraction algorithm to assign each sentence to a municipality-organization pair or pairs.
Table 11 shows the first appearance of each cartel in the data set use here. Some

of this Drug Trafficking Organizations are older than 1990 but I just scrape data starting in 1990.

Table 5: Summary of cartel presence

Cartel	First Year Appear	First Mun	Mun Active 1990	Mun Active 2000	Mun Active 2010	Mun Active 2016
Juarez	1990	Chihuahua/Juarez	3	5	42	79
Tijuana	1990	Tijuana/Mexicali	9	2	22	42
Sinaloa	1990	Sinaloa/El Fuerte	9	4	88	160
Beltran Leyva	2004	Sinaloa	0	0	85	118
Fam Mich	1990	Mujica/La Piedad	3	2	47	101
Golf	1990	Matamoros	1	2	36	89
Zetas	1999	Matamoros	0	9	100	227
CJNG	2010	San Juan de los Lagos	0	0	12	211
Templar Knights	2011	Acuitzio	0	0	0	107

A.2 Agro-ecological data

From opium to heroin: *papaver somniferum* is an annual crop with a short productive cycle that can be harvested 4 times a year. The main product extract from it is raw opium. Raw opium contains between $8 - 91.2\%$ of morphine depending on the plant variation Frick et al. (2005).Opium is a low cost crop that does not requires many inputs but it is land intensive. Usually an hectare of poppy flowers will produce between 8 to 15 kilograms of raw opium. Yields of heroin from raw opium are between 6 to 10 percent. To transform raw opium into heroin first the morphine needs to be extracted from the opium paste and dried. Once the morphine is dry acetic anhydride is added to create brown tar heroin, this can be smoked, inhaled or injected. To produce high purity white heroin ammonia, hydrochloric acid and acetone is added.[32]
The variables use to construct the suitability index and the data sets they came from are the following:

- Temperature and Precipitation from the WorldClim data set. This data set includes: mean annual temperature, mean diurnal range, temperature seasonality, maximum temperature during the warmest month, minimum temperature during the coldest month, mean temperature of the wettest quarter, mean temperature of driest quarter, mean temperature of warmest quarter, mean temperature of coldest quarter, annual precipitation, precipitation of wettest month, precipitation of driest month, precipitation seasonality, precipitation of wettest quarter, precipitation of driest quarter, precipitation of warmer quarter and precipitation of coldest quarter.
- Elevation data from Shuttle Radar Topography Mission (SRTM).
- Terrain ruggedness from Shaver et al. (2019)

[32] https://www.unodc.org/pdf/research/Bulletin07/bulletin_on_narcotics_2007_Zerell.pdf

- Land Cover from Globcover 2009
- Soil quality from the FAO Harmonized World Soil Database.
- River density: diva-gis data-sets weighted by Strahler stream order.
- Soil climatic characteristics from the yearly Copernicus data set. This data set includes: mean monthly precipitation, mean evaporation, soil temperature, soil water, heat flux and rain.

The suitability index was built by regressing the log of opium yields by year and district in Afghanistan between 1990 and 2018 on the 45 geo-climatic characteristics and all its interactions. To reduce the number of regressors I use an elastic net. An elastic net is a penalized OLS that combines lasso and ridge methods. The best model, chose using a 10 fold validation, has a $\alpha = .4$ and $\lambda = 0.07557243$. Here α is the degree of mixing between the ridge and the LASSO regression and the λ is the shrinkage parameter. The number of variables reduces from 903 to 50.
Variable selected:
Soil temperature, mean annual evaporation interacted with temperature seasonality, mean annual precipitation interacted with: average monthly rain, minimum temperature during the coldest month, mean temperature during the driest quarter and terrain ruggedness. Soil temperature interacted with seasonal precipitation, soil water interacted with : river density and topsoil organic carbon, ruggedness interacted with: mean temperature during the wettest quarter, topsoil grave, topsoil organic content and topsoil clay, heat flux interacted with temporal seasonality, precipitation seasonality, river density and topsoil clay, mean temperature interacted with: minimum temperature during the coldest month and ruggedness, mean diurnal range interacted with mean temperature during the driest quarter, precipitation seasonality and ruggedness, minimum temperature during the coldest month interacted with: mean temperature during the warmest month, precipitation during the wettest quarter, precipitation during the driest quarter, river density, topsoil calcium carbonate and topsoil salinity, mean temperature during the wettest quarter interacted with precipitation during the wettest quarter, precipitation during the warmest quarter, altitude and topsoil sodicity, mean temperature during the driest quarter interacted with mean temperature during the coldest quarter, precipitation during the wettest quarter and ruggedness, mean temperature during the coldest quarter interacted with precipitation during the warmest quarter, precipitation during the warmest month interacted with precipitation during the wettest quarter and ruggedness, precipitation during the driest month interacted with: precipitation during the warmest quarter and river density,precipitation seasonality interacted with precipitation during the wettest quarter, precipitation during the wettest quarter interacted with precipitation during the warmest quarter and ruggedness,altitude interacted with topsoil teb,river density interacted with topsoil organic carbon, topsoil gypsum and topsoil salinity ,

topsoil sand interacted with topsoil calcium carbonate, topsoil clay interacted with topsoil teb and topsoil cec soil interacted with topsoil teb.

A.3 Robustness checks

A.3.1 Cartel Entry and Exit:

The next tables show the coefficients for equation (2) but with the event time year dummies replaced by a dummy variable $PostEntry_{mt}$, indicating that in year t municipality m experienced the entry or exit of a cartel. The dependent variable is the number of homicides per 100,000 inhabitants. The tables present the difference-in-difference model for two set of independent variables. The first four columns show the results for the first variable and the next four for the second one. Columns (1) and (6) present the results with municipality and year fixed effects.Columns (2) and (7) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (8) control for baseline characteristics interacted by year such as population, drug activity in 2000 and marginalization rate. Columns (4) and (9) add to the baseline trends, the set of controls from Column (2) and (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The sample selection is conditional on having n cartels in $t-1$. There is selection in the sample so that the comparison group is municipalities that stay with n cartels versus the ones that go to $n+1$ or $n-1$. Tables 6 to 8 present the entry events and Table 9 present the exit ones.

Table 6: Entry of the First and Second Cartel

	Homicides per 100,000 inhabitants									
	First Carte Entry					Second Cartel Entry				
Post-entry	1.64	2.05	2.07	2.12	1.43	7.08***	8.33**	6.41**	7.61**	5.28*
	(4.23)	(2.14)	(1.98)	(2.18)	(2.05)	(2.71)	(2.71)	(2.80)	(2.68)	(2.39)
Observations	42,624	42,624	42,624	42,624	42,624	13,389	13,389	13,389	13,389	13,389
Pre-entry mean, dep. var.	15.43	15.43	15.43	15.43	15.43	15.38	15.38	15.38	15.38	15.38
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

The results presented in the core of the paper are robust to different controls and fixed effects. The number of observations is decreasing because the number of municipalities that have n cartels is decreasing on n. There are not significant results of the entry of the

Table 7: Entry of the Third and Fourth Cartel

	Homicides per 100,000 inhabitants									
	Third Cartel					Fourth Cartel				
Post-entry	13.46***	15.62***	14.70**	14.66**	12.76**	13.71**	15.59***	15.55**	15.39**	13.05***
	(4.90)	(4.55)	(5.07)	(5.05)	(4.28)	(6.34)	(4.42)	(4.90)	(4.85)	(3.69)
Observations	7,719	7,719	7,719	7,719	7,719	4,409	4,409	4,409	4,409	4,409
Pre-entry mean, dep. var.	16.58	16.58	16.58	16.58	16.58	19.35	19.35	19.35	19.35	19.35
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Entry of the Fifth and Sixth Cartel

	Homicides per 100,000 inhabitants									
	Fifth Cartel					Sixth Cartel				
Post-entry	17.53***	21.08***	19.01***	19.84**	16.41***	10.81*	14.48**	10.53*	11.62*	6.57*
	(7.52)	(6.80)	(7.19)	(7.28)	(4.34)	(5.06)	(4.52)	(4.92)	(5.95)	(3.29)
Observations	2,493	2,493	2,493	2,493	2,493	1,451	1,451	1,451	1,451	1,451
Pre-entry mean, dep. var.	17.31	17.31	17.31	17.31	17.31	18.90	18.90	18.90	18.90	18.90
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: Cartel Exit; from one to zero and from two to one

	Homicides per 100,000 inhabitants									
	Exit from 1 to 0					Exit from 2 to 1				
Post-exit	−2.01	−2.45	−1.85	−2.52	-3.62^{*}	-2.70^{*}	-3.27^{**}	-3.35^{**}	-3.23^{*}	-6.07^{**}
	(2.33)	(1.55)	(1.49)	(1.52)	(1.64)	(1.27)	(1.18)	(1.28)	(1.28)	(2.24)
Observations	12,289	12,289	12,289	12,289	12,289	2,556	2,556	2,556	2,556	2,556
Pre-entry mean, dep. var.	18.27	18.27	18.27	18.27	18.27	17.75	17.75	17.75	17.75	17.75
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓
Note:										*p<0.1; **p<0.05; ***p<0.01

seventh cartel into a municipality that already has six active cartels. There are also not significant effects of the exit of one cartel when there are more than three organizations in a municipality.

A.3.2 The effect of the shock in socioeconomic outcomes:

The next tables show the coefficients for equation (1) but with the event time year dummies replaced by a dummy variable $PostShock_{mt}$ interacted with the suitability index and the heroin price in the United States. The relevant event is again the 2010 OxyContin reformulation. Each table presents the difference-in-difference model for two dependent variables. Table 10, log of the population and mean years of education. Table 11, percentage of households with a woman as the head and the number of occupants per dwelling. Finally, Table 12 the percentage of households without dirt floor and the percentage of household without access to basic services. Columns (1) and (6) present the results with municipality and year fixed effects.Columns (2) and (7) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (8) control for baseline characteristics interacted by year such as population, drug activity in 2000 and marginalization rate. Columns (4) and (9) add to the baseline trends, the set of controls from Column (2) and (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The results for all the other outcomes that did not change significantly during this period are available upon request. The results in the main part of the paper are robust to all the controls and fixed effects added in here.

Table 10: Population and Education

	Demographics:									
	log(population)					Years of Education				
Post2010	-0.050^{***}	-0.013^{***}	-0.062^{***}	-0.076^{**}	-0.039^{***}	-0.418^{***}	-0.815^{***}	-0.085^{*}	-0.111^{**}	-0.366^{***}
	(0.008)	(0.004)	(0.012)	(0.007)	(0.009)	(0.008)	(0.095)	(0.034)	0.035)	(0.089)
Observations	32,202	31,752	32,202	31,752	31,752	32,202	31,752	32,202	31,752	31,752
Pre-shock mean, dep. var.	9.37	9.37	9.37	9.37	9.37	6.24	6.24	6.24	6.24	6.24
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Women as Head of Household and Occupants per Dwelling

	Demographics:									
	% Women Head of Households					Occupants per dwelling				
Post2010	0.015^{***}	0.011^{*}	0.011^{*}	0.010^{**}	0.021^{***}	4.45^{***}	7.57^{***}	4.31^{***}	4.87^{***}	4.01^{***}
	(0.002)	(0.005)	(0.005)	(0.005)	(0.006)	(0.364)	(0.658)	(0.334)	(0.340)	(0.526)
Observations	32,202	31,752	32,202	31,752	31,752	32,202	31,752	32,202	31,752	31,752
Pre-shock mean, dep. var.	0.21	0.21	0.21	0.21	0.21	4.23	4.23	4.23	4.23	4.23
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: No-Dirt Floor and No-Basic Services

	Economic outcomes:									
	% without Dirt Floor					% of Households without basic Services				
Post2010	0.073^{***}	0.038^{*}	0.081^{***}	0.081^{***}	0.056^{***}	-0.026^{***}	-0.013^{*}	-0.022^{**}	-0.012^{**}	-0.014^{***}
	(0.009)	(0.017)	(0.013)	(0.013)	(0.016)	(0.000)	(0.006)	(0.008)	(0.006)	(0.003)
Observations	32,202	31,752	32,202	31,752	31,752	32,202	31,752	32,202	31,752	31,752
Pre-shock mean, dep. var.	0.54	0.54	0.54	0.54	0.54	0.044	0.044	0.044	0.044	0.044
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

A.3.3 Cartel Competition:

The next tables show the coefficients for equation (1) but with the event time year dummies replaced by a dummy variable $PostShock_{mt}$ interacted with the suitability index and the heroin price in the United States. The relevant event is again the 2010 OxyContin reformulation. Each table presents the difference-in-difference model for two dependent variables. The dependent variables are dummies for cartel presence of each of the nine major organizations. Columns (1) and (6) present the results with municipality and year fixed effects.Columns (2) and (7) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (8) control for baseline characteristics interacted by year such as population, drug activity in 2000 and marginalization rate. Columns (4) and (9) add to the baseline trends, the set of controls from Column (2) and (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The results for the cartels expanding, entering and shrinking are robust to all the controls and fixed effects. The coefficients for the other four cartels are not significant for all the specifications, but all the coefficients are positive across specifications. These results and analysis of entry patterns of the cartels suggest that all of them except for La Familia expanded into territory well-suited to cultivate opium poppy. Maps of the evolution of each cartel are available upon request.

Table 13: Sinaloa and Jalisco New Generation

	Cartel Activity by Cartel									
	Sinaloa Cartel					CJNG				
Post2010	0.107***	0.102***	0.0714***	0.041***	0.03*** 4	0.080***	0.089***	0.059***	0.052***	0.039***
	(0.010)	(0.011)	(0.001)	(0.009)	(0.008)	(0.001)	(0.010)	(0.001)	(0.008)	(0.001)
Observations	32,012	31,562	32,012	31,562	31,562	32,012	31,562	32,012	31,562	31,562
Pre-shock mean, dep. var.	0.0104	0.0104	0.0104	0.0104	0.0104	0.0004	0.0004	0.0004	0.0004	0.0004
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 14: Templar-Knights and La Familia Michoacana

	Cartel Activity by Cartel									
	Templar-Knights Cartel					La Familia				
Post2010	0.022***	0.034***	0.006**	0.006**	0.032***	−0.004***	−0.004**	−0.019**	−0.023**	−0.012**
	(0.000)	(0.008)	(0.0009)	(0.0008)	(0.007)	(0.000)	(0.0007)	(0.0008)	(0.007)	(0.004)
Observations	32,012	31,562	32,012	31,562	31,562	32,012	31,562	32,012	31,562	31,562
Pre-shock mean, dep. var.	0	0	0	0	0	0.004	0.004	0.004	0.004	0.004
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15: Los Zetas

	Cartel Activity by Cartel				
	Zetas				
Post2010	0.125***	0.138***	0.104***	0.090***	0.054***
	(0.0001)	(0.014)	(0.001)	(0.012)	(0.011)
Observations	32,012	31,562	32,012	31,562	31,562
Pre-shock mean, dep. var.	0.014	0.014	0.014	0.014	0.014
Municipalities FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Covariates		✓		✓	✓
Baseline trends			✓	✓	✓
State trends					✓

Note:
*p<0.1; **p<0.05; ***p<0.01

Table 16: Juarez and Beltran Leyva Organizations

	Cartel Activity by Cartel									
	Juarez Cartel					Beltran-Leyva				
Post2010	0.041***	0.046***	0.027**	0.021	0.008	0.046***	0.063***	0.014***	0.012	0.032
	(0.008)	(0.009)	(0.001)	(0.009)	(0.009)	(0.006)	(0.008)	(0.001)	(0.007)	(0.017)
Observations	32,012	31,562	32,012	31,562	31,562	32,012	31,562	32,012	31,562	31,562
Pre-shock mean, dep. var.	0.009	0.009	0.009	0.009	0.009	0.007	0.007	0.007	0.007	0.007
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01

Table 17: Tijuana and Golf Cartels

	Cartel Activity by Cartel									
	Tijuana Cartel					Golf Cartel				
Post2010	0.018	0.019	0.009	0.003	0.011	0.029^{**}	0.040^{**}	0.019	0.021^{*}	0.023^{**}
	(0.009)	(0.009)	(0.005)	(0.004)	(0.014)	(0.001)	(0.007)	(0.000)	(0.006)	(0.007)
Observations	32,012	31,562	32,012	31,562	31,562	32,012	31,562	32,012	31,562	31,562
Pre-shock mean, dep. var.	0.004	0.004	0.004	0.004	0.004	0.005	0.005	0.005	0.005	0.005
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

Note: *p<0.1; **p<0.05; ***p<0.01