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

Fernanda Sobrino[*,†]

This version: November 1, 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 to 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 am particularly grateful to Will Lowe for helping me with the deep learning in this paper. 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 in Mexico increased from four in the early 2000s to nine organizations by 2016.[4] These cartels are usually in constant flux and have splintered, forged alliances, and battled 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 create and implement strategies that might reduce the presence of organized crime and the negative externalities associated with it. 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 explore 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 Mexican municipalities. The second one 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

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. The United States Department of Justice define a major Drug Trafficking Organization as a "complex organization with highly defined command and control structures to produce, transport and or distribute large quantities of drugs."

to the heroin market, the 2010 OxyContin reformulation, to estimate the effect of this market shift on cartel entry. Third, I estimate the relationship between cartel entry, exit, and violence. Finally, I identify the Drug Trafficking Organizations that expanded into the heroin market and document how the market became less concentrated.

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 increased in the United States. OxyContin became popular for recreational use and abuse because the drug offered much more of the active ingredient oxycodone. The pills were easily manipulate to extract their active ingredient. To reduce the increasing misuse of these legal opioid in 2010 the FDA approved the reformulation of OxyContin. The new pill was harder to crush and dissolve. This change made the drug less appealing to some users who changed to its illegal substitute, heroin. 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 percentage 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 exogenous variation, agro-climatic conditions to cultivate opium poppy and the change of heroin prices in the United States. These variation allows me to measure the effects of the demand shock on cartel presence and violence across Mexican municipalities. Differential exposure to the shock arises since municipalities with different agro-climatic conditions experienced the changes in heroin prices differently. 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 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. Hence, I use yields from Afghanistan and a rich set of agro-climatic conditions to build a suitability index using an elastic net. An elastic net is a penalized OLS that helps to reduce a model dimensionality by generating zero-valued coefficients.[5] The agro-climatic variables chosen through the optimal elastic net were then employed to build the suitability index for Mexican municipalities. This index is highly correlated with eradication data from the Mexican military. Time variation

[5] Afghanistan is the world largest producer of opium and the United Nations have data on yields and hectares cultivated since the 1990. A detailed explanation of the particular elastic net used and how it was chosen can be found in the Appendix A.2.

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.

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 regular, detailed and systematic coverage of when and where criminal organizations are operating.

To build this data set, I used a web crawler, an automated script which methodically browses the web, to extract articles related to a municipality and cartel pair. Then, I 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[6] convolutional neural network (CNN) to achieve this. A CNN is a series of algorithms primarily use to classify images but that have been proven to achieve good performance for sentence classification Kim (2014). A CNN allows more complex relationships between words in a sentence than a simple bag of words algorithm.[7] I trained the CNN by manually classifying 5,000 sentences as either cartel presence or not. The resulting data set is highly correlated with Coscia and Rios (2017). Their data set use the same web crawling technique and then classify the presence of the cartels based on the relative number of results extracted from Google. The technique proposed here extends this by actually looking into the articles and applying state of the art natural language processing techniques to validate the data. The data is also highly correlated with two data sets collected by hand from local newspapers Sánchez Valdés (March 2015), Sánchez Valdés (July 2017) and State level data from the DEA.[8]

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.

I found the following results. 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 found by the military. By 2016 the nine major cartels can be found in at least one municipality producing opium poppy. Before 2010, the number of municipalities with

[6] Semi-supervised learning uses label data and unlabeled to gain more understanding of the population structure in general

[7] A full explanation of the algorithms and the techniques used can be found in the Data Section and Appendix A.1.

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

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 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 with the increase in demand. These results are robust to different sets of controls and fixed effects.

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, however it is not obvious that this should increase violence. Cartels will decide to fight over a territory or not as a function of the expected value of entering a location. Scarcity of highly-suitable land to cultivate opium will increase the probability of clashes between cartels. 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 say this with confidence. The exit of cartels from a location has a significant effect 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 scare resources. Illegality does not necessarily is accompanied by violence, the institutional and market structures relate to the levels of violence (Snyder and Duran-Martinez 2009*a*).

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. The mean homicide rate before the shock across Mexico was 12.06 and the mean homicide rate through the whole period in municipalities without any cartel present is 11.78 homicides. This increase homicide rate is consistent with more entry and cartels competing for heroin profits. I find that the demand shock leads to a decrease in population and average years of education. The number of occupants per dwelling and the percentage of households with women as a head increased after the shock. These results suggest that there was outmigration from the exposed municipalities of the more educated and wealthier members. I also show that the percentage of households without dirt floor increases and that the percentage of households without any basic service, electricity, water and, sewage decreases. These two results suggest that there is a cash flow from the opium market that is probably being capitalized by the poorest households through investments in their homes. Lastly, I observe that the military is eradicating more opium and less marijuana in these municipalities, again consistent with the value of opium going up as the relative 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. Only the Sinaloa Cartel was 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 cartel 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.[9] 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 since 2010. 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 22% before 2010, to 51% in 2011, and reaches 86% by 2016. Mexican cartels used to produce heroin for the west coast states of the United States, while Colombian organizations supplied to the east coast. The increased demand for heroin and the already established trafficking networks of the Mexican cartels facilitate them to enter the east coast states Esquivel (March 2016). All this provides evidence that the cartels reacted to the increased

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

demand.

These results provide novel evidence that external policies that shift demand or supply of illegal drugs have direct effects on criminal organization's activity and subsequent effect on violence and other outcomes. This paper speaks to several literatures. First, it complements the literature studying the recent increase in violence in Mexico. Most of this literature examines how law enforcement strategies and political alliances increased 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 cartels 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 contribute to 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). Furthermore, contributes to the literature on illegal markets and its effects on different outcomes Dell et al. (Forthcoming), Dube et al. (2016), Sviatschi (2018), by showing how the number of competing cartels affect demographics and economics outcomes 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 consider as a natural asset.

Finally this paper contributes 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. In particular, I used state of the art deep learning techniques to generate the cartel presence data. This data set provides an example of the advantages of using more complex natural language processing techniques in economic applications. The algorithms presented here have the ability to help measure other hard to quantify variables not just related to illegal activities.

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 context essential for my analysis. My identification relies on the demand shift being exogenous to the Mexican government and cartel activity. First, I give an overview of the opioid crises and its relationship with the heroin market. Second, I provide context for the history of drug trafficking in Mexico, the main organizations and the War on Drugs. This in order to provide context of the evolution of these Drug Trafficking Organizations and the institutional background that describes the Mexican government actions against these organizations. All these provides context and evidence that the increase in heroin demand was exogenous to both the Mexican government and the cartels.

2.1 The Opioid Crises

It is estimated that everyday 130 people in the United States die from opioid-based drugs overdose.[10] The rate of drug overdose deaths tripled between 1999 and 2010 the rate related to opioids increased six-folds during the same period. At the beginning of the 1990s, pharmaceutical companies developed several opioid-based painkillers. Through marketing campaigns, and based on two misleading research articles they assured the medical community that patients would not become addicted to these drugs.[11] Prescriptions of opioid base painkillers shot up and eventually led to misuse. One of these opioids that was particularly abuse was OxyContin. OxyContin is a narcotic analgesic that due to its time-released formula contained more milligrams of its active ingredient than other similar opioids. People crushed the tablets to snort or inject them, this destroys the time-release mechanism so that the users can immediately feels the effects of the narcotic. In 2010 physicians organizations pressured the government to make it harder to accumulate pills and harder to abuse them. As a result, the federal and state governments started to crack down on pill mills, and Purdue Pharma introduced an abused deterrent version of OxyContin. This new pill was 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 its 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). Hence, the reformulation provides plausible exogenous variation for cartel activity in Mexico, particularly their reaction towards the heroin market.

[10] https://www.cdc.gov/drugoverdose/images/data/OpioidDeathsByTypeUS.PNG

[11] DeWeerdt (September 2019)

2.2 Drug Trade in Mexico

Mexico's location has made it a key country 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 started smuggling illegal drugs through the same routes they used to smuggle alcohol. Networks are a key element for illegal drug trafficking. The least cost drug transportation routes are probably different from the ones used by legal goods. Traffickers need not just to minimize distance and transport costs, also the probability of government interdictions and turf wars. Once a route has been proven effective to smuggle an illegal good it is likely that traffickers will use it for other illegal activities. 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 counterparts 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. In 1975, 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.[12] 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 moved 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.

Since their origins Mexican Drug Trafficking Organizations have retained close relationships with local authorities. These strong ties survived for decades while the hegemonic

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

party PRI was in power. During the late 1980s PRI started loosing elections across the country. This led to a crack in the previous agreements between the government and criminal organizations. In 2000, the dominant party PRI lost for the first time the presidential election. Violence across the country remained low but without the previous state sponsored protection cartels fought for valuable territory Snyder and Duran-Martinez (2009*b*). Violence between several organizations escalated quickly to levels not seen before.

2.3 The War on Drugs:

Former Mexican President Felipe Calderon, in office between 2006-2012 from the conservative party PAN, declared war on drugs in 2006. The Drug Trafficking Organizations violently fought back. Violence between drug traffickers 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.

Violence spread quickly beyond the US-Mexican border and into the whole country. Since 2006, there have been an estimated of 250,547 homicides related to organized crime. These account for 50% of the country's 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 significantly change from the one established by Calderon. Violence decreased a little during the first year of his administration but went up again immediately afterwards. 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). This strategy has led to cartel fragmentation, when the main kingpin is either detained or killed. They left an open position at the top of the organization, cartel fractions that used to operate peacefully will splintered from the parent organization and form new organization.

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 extensive and shows how difficult fighting these organizations can be.[13] The War on Drugs led to a spike in homicides and increased violence particularly between 2008 and 2010. The period after 2010 has been studied less. This paper adds to the discussion of what generated the increase in violence.

[13] Feuer (December 2018)

2.4 Mexican Cartels and the Heroin Market:

Historically, Mexico has produced some opium and exported it to the United States since the beginning of the twentieth century. Opium poppy, native to the eastern Mediterranean area, was introduced to Mexico by Chinese immigrants in the late nineteenth century and proved to be well-suited to cultivation. During the twentieth 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.

This paper considers nine main Drug Trafficking Organizations recognized by the Mexican prosecutor's office and the DEA. These organizations are the following ones:

The Gulf Cartel: founded in the 1930s as an alcohol smuggling organization. After Prohibition era it continued to operate other illegal activities like prostitution and gambling rings. By 1980s, it was one of the most powerful cartels in Mexico and had established connections with the Cali Cartel in Colombia. After the arrest of Garcí-Ábrego, the cartel kingpin, in 1996 they lost the Colombian connection and started to loose power. During the increased turf wars in the early 2000s, the cartel recruited former military special forces to form the cartel's armed wing, Los Zetas. This group will eventually separate from its parent organization and become an independent cartel. Currently, the Gulf Cartel is still fighting with Los Zetas for the controlled of Mexico east coast.

The Juarez Cartel: originated during the 1970s in the city of Juarez. During the 1980s, the Juarez Cartel worked with the Guadalajara Cartel and after this was dismantled Amado Carillo Fuentes, alias 'Lord of the Skies' assumed control. The organization grew exponentially under Carillo Fuentes. Eventually, he controlled half of the Mexican trafficking and expanded to South America. After his death in 1997 his brothers took over the organization. The Juarez Cartel has debilitated due to constant fights with the Sinaloa Cartel over the Juarez corridor. Despite this, it remains a powerful cartel because of its large and longstanding transportation, storage and security networks through the country.

La Familia Michoacana: emerged in the late 1980s as a self defense group against the drug dealers that operated in the state of Michoacán. Since then, they transformed into a criminal organization. In the early 2000s they were able to drove Los Zetas out of Michoacán and expanded their operations to neighboring states. They kept the hegemony of the region and were one of the most violent organizations. In 2011, the cartel fragmented into two organizations: La Familia and the Knights-Templar. La Familia lost almost all its territory to the Knights-Templar Cartel.

The Tijuana Cartel: after Miguel Felix Gallardo was arrested in 1989 he divided his former territory and gave it to former allies. His nephews the Arellano-Felix brothers got Tijuana. The cartel was in constant turf with the Sinaloa Cartel for the control of the border crossing. By 2013, all the Arellano-Felix brothers were death or in prison.

Enedina, the last Arellano-Felix that remains has now the command of the organization. The Tijuana Cartel loose the control of Tijuana to the Sinaloa Cartel around 2010. Since 2015, the remains of the Tijuana Cartel had been trying to re gain control of the city.

The Sinaloa Cartel: described as the largest and most powerful criminal organization in the Western Hemisphere. Joquin, 'El Chapo' Guzman a former employee of the Gudalajara Cartel kept the Sinaloa territory after Felix Gallardo was captured. El Chapo fought with his former allies in Tijuana and expand his cartel operations across the country. Since 2012, the cartel has been involved in several turf wars with all the other cartels. Despite 'El Chapo' extradition the Sinaloa Cartel has remained one of Mexico's most powerful organized groups.

Beltrán-Leyva Organization: former allies of the Sinaloa Cartel. The Beltrán-Leyva worked closely with 'El Chapo' until 2008 when one of the brothers was arrested and the other four blame their former boss for the arrest. They decided to leave the Sinaloa Cartel and founded their own organization. Since then they have been engage in several turf wars with the Sinaloa Cartel.

Jalisco New Generation Cartel(CJNG): emerged from the Sinaloa Cartel in 2010. The criminal group used to moved drug shipments and managed the finance of the Sinaloa Cartel. The cartel has been fighting Los Zetas, the Knights Templar, and the police with extreme violence. The organization expanded rapidly and became one of the most powerful cartels.

Los Zetas: former armed wing of the Gulf Cartel. Originally composed of commandos of the Mexican Army that deserted and joined the Gulf Cartel. Los Zetas won power over time and eventually outnumbered their former parent organization. They started a violent turf with the remains of the Gulf Cartel. They also started to expand to the territories dominated by other cartels and brought violence with them. Despite several internal disputes and that their main leaders have been captured or killed some cells of the organization are still active and have control of some parts of the country.

The Knights Templar: emerged in 2011 as a splinter of La Familia. They took control over La Familia operations and territory, including Mexico's second biggest port Lazaro Cárdenas. In recent years they have been fighting with the CJNG over the control of the states of Jalisco and Michoacán.

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 achieve these two goals 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 periods of time. To create a data set for cartel presence and opium suitability, I use web scraping and machine learning. 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, unfortunately they are only available at the state level and they are not published every year. The same is true for the DEA datasets. Hence, in order to measure cartel presence I need to construct a novel data set. This data set tracks presence of the nine mayor Drug Trafficking Organizations described in the background section. The data covers each Mexican municipality between 1990 and 2016.

I follow and extend Coscia and Rios (2017). They tracked the presence of the same nine criminal organizations at the municipal level between 1990 and 2010. They use a search algorithm that codes a cartel being present if the frequency of the hits for a particular municipality-cartel exceeds certain threshold. I follow their same idea of scraping news from the web. The difference is that I looked inside the articles text and used deep learning to classify them. The use of hits even proportional to the number of results may be misleading. The search engine may identify as hits news articles that do not mention the municipality-cartel pair in the core of the article. The algorithm I used is the following one.

First, I use a web crawler[14] to scrape Google News Mexico.[15] The assumption behind scraping web content is that local and national newspapers combined contain a more systemic, regular and detailed coverage of cartel activity within Mexico than available datasets. This web crawler looked for any news articles between 1990 and 2016 that contained a municipality-cartel pair. The algorithm found 2'249,561 news articles.

Second, I extract the main body of the articles and keep just the ones that mention the pair of municipality-cartel. Some news web pages include links to other articles in the side of the main content. If this side content includes the name of the cartel or the municipality sometimes the search engine will return this as a hit.[16] The number of remaining articles after this process is 1'201,483. I used a sentence extractor to keep the sentences from this articles that included the pair of a municipality-cartel.[17] To assign a year to each sentence I did the following. If the article contained a year I assign the event to that year, if no year was assigned I use the publication year. The number of sentences that I analyzed are are 2'802,224.

Next, I manually classified $5,000$ sentences as either presence or not to train a semi-supervised convulutional neural network.[18] I use 80% of this sample as the training set

[14] A bot that systematically browses the world wide web.

[15] Google News has change since Coscia and Rios (2017) scrape their data in 2012. The Google News API no longer allows you to go back in time. I ran the web crawler in the Google interface instead.

[16] In the Appendix A.1 I include a picture of an example of a news page to make this more clear.

[17] In further iterations of this project I will use the whole article as the input and not just the sentences.

[18] Examples of this sentences can be found in Appendix A.1.

and 20% as the test set. A CNN is a deep learning set of algorithms usually used for image classification but had proven effective in text classification Kim (2014), Young et al. (2017). The CNN works the following way. Sentences are first break into words, then transform into a word embedding matrix.[19] Then several filters are applied that constitute of different word window sizes that go over each sentence. This is followed by a discretization operations that reduce dimensionality of the output. This produces the final sentence representation that is classified. The particular CNN used here has an out of sample accuracy of 0.8644.[20]

In order to validate this data set 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 Validation with other data sets created from news articles:

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, 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.[21] The fact that this correlation is not larger can be explained by the change in the Google algorithm between 2012 and 2019. The low correlation can also be explained by the difference in validation techniques, number of hits 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 Michoacán 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.

3.1.2 External validation:

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 are probably catching non-dominant presence.

The high correlation between my data set and the manually collected one provide evidence that the algorithm used here has a high performance compare to an actual human manually classifying the articles. Despite the fact that probably the articles manually coded were different than the ones found by the web crawler. The deep learning techniques use to generate this data set can be use elsewhere to measure similar hard to observe outcomes.

[19] A word embedding is a learned representation of text where words that have the same meaning have similar representation.

[20] A more technical explanation of the algorithm can be found in Appendix A.1.

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

The high correlation between the DEA data and my data set shows that using news articles as a source of illegal activity might be as good as using data from the authorities. The advantage of using the news is that data are at a more disaggregated geographical level and with higher periodicity. This is particularly important in measuring drug related criminal activity. These groups continuously change their territorial dominance and knowing these fluctuations is key to understand them better.

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 present.

3.2 Agro-ecological data

The geographic variation in opium poppy suitability is drawn 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.[22] Suitability indexes are built using agro-climatic characteristics and crop yields. Unfortunately, there does not exist historical data on opium production in Mexico.[23]

I built a suitability index using Afghanistan's output data. Afghanistan is the main world opium producer and the UN has been collecting data (surveys and satellite images) on opium yields and hectares cultivated since the early 1990s.[24] I use yields by district between 2000 and 2018 plus 45 agro-climatic characteristics and all their interactions.[25] The main agro-climatic variables used are temperature, precipitation, elevation, terrain ruggedness, soil quality and river density. A full description of these 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 is 903. 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.[26] This model is then used to predict log productivity of opium in Mexican municipalities given its agro-climatic

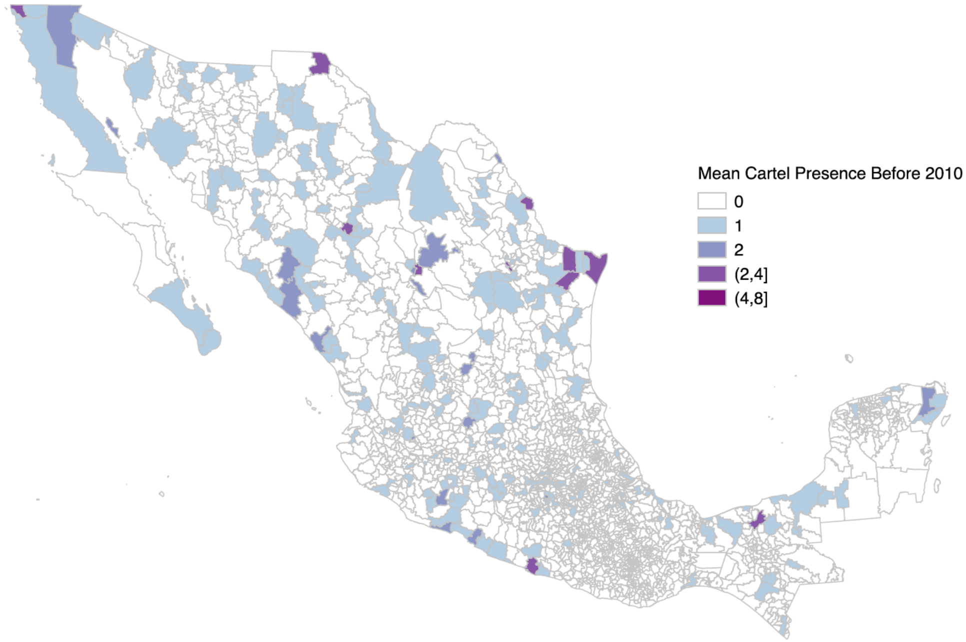
22 http://ecocrop.fao.org/ecocrop/srv/en/dataSheet?id=8296

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

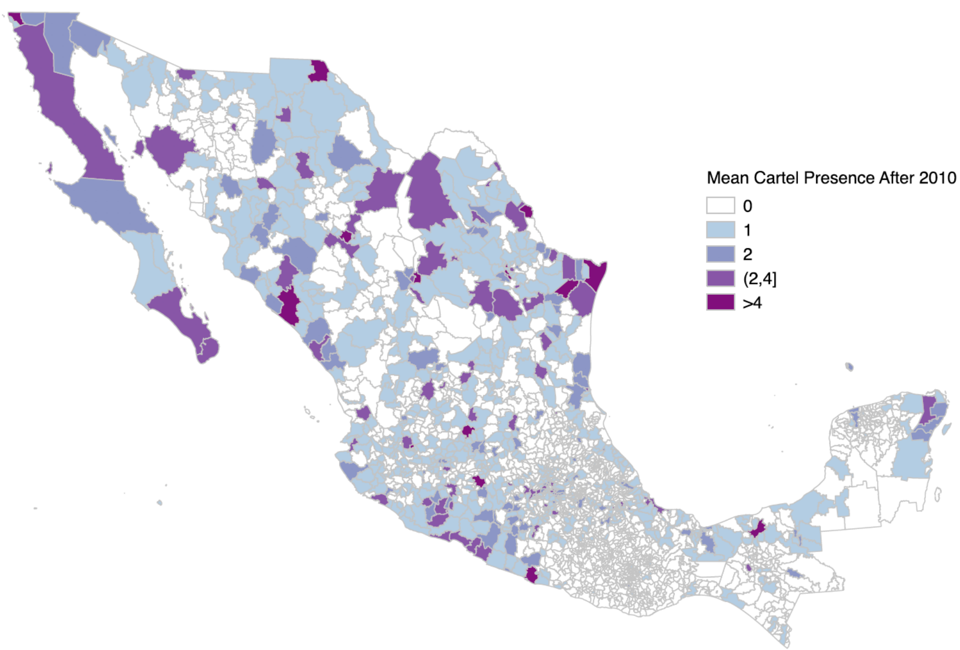
24 https://www.unodc.org/unodc/en/crop-monitoring/index.html?tag=Afghanistan

25 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)

26 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.



(a) Mean Cartel Presence 2004-2009



(b) Mean Cartel Presence 2010-2016

Figure 1: Cartel Presence

characteristics.[27] This measure is then standardized and its range set between 0 and 1 for interpretation purposes, 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 together with the maps Figure 1. Imply that cartel presence is related to opium suitability particularly after 2010. Mostly all the states in the Pacific coast; Sinaloa, Nayarit, Jalisco, Colima, Michoacán and Guerrero, are highly suitable to grow opium and the number of active cartels increased after 2010. The correlation between mean presence before 2010 and the suitability index 0.186 and the correlation after 2010 is 0.469.

Table 1 shows the relationship between the suitability index and mean hectares of opium poppy eradicated by the Mexican military. The coefficients show there are the results of regressing the suitability index on the mean opium poppy eradication before and after 2010. The specification controls by police, military presence and includes municipality fixed effects. Highly suitable municipalities have eradications which imply that some opium is being produce there.

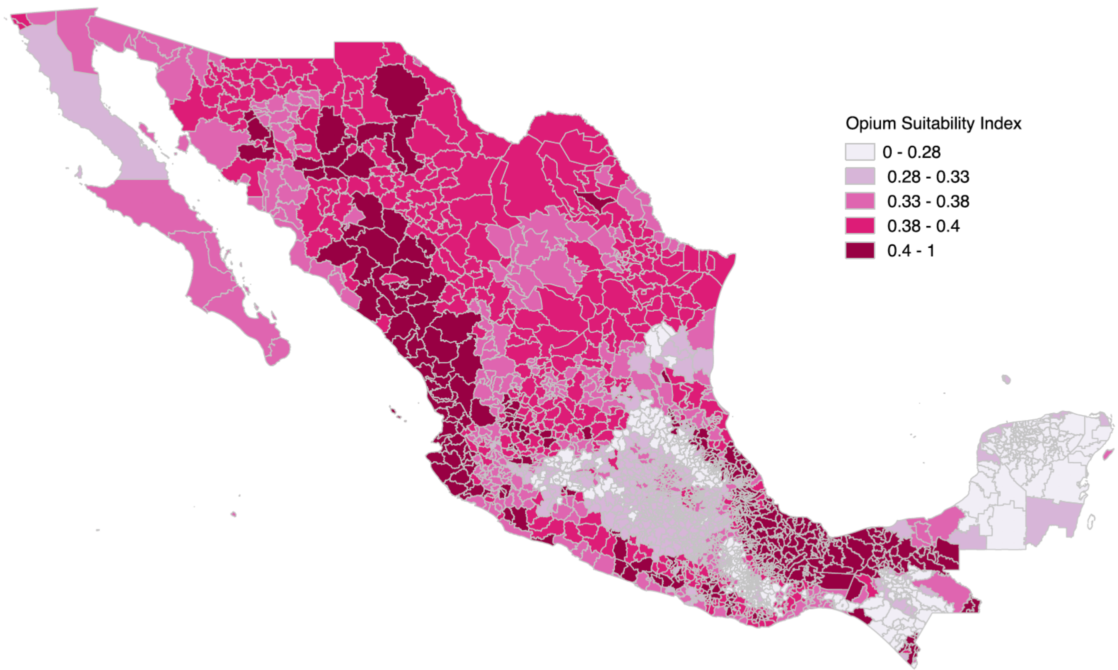
Table 1: Suitability Index and Eradication

	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 regression where the dependent variable is the mean eradication of opium poppy, measured in hectares. Controls for police, military presence and includes municipality fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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

Figure 2: Opium Poppy Suitability Index



3.3 Homicide and Demographic 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 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, 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. I also use the CONEVAL data set that reports an index of how marginalize is a municipality and data on the affiliated political parties of mayors and governors are drawn from CIDAC and INAFED.

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.[28] 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, this potential will depend on how suitable a municipality is. Military capacity has no dynamic effect.

In the first stage, cartels decide whether to enter or not a site and pay fixed cost F. Cartels need to make sure the site is productive and also know who else is in that territory.

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

In the second stage, they decide how much to invest in military capacity.

The following success function will determine the market share each cartel will have as a function of its own investment and the investment of all the other competitors:

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

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 the production site.
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 is zero if military capacity is zero and that it increases with total expenditure.
As long as $\eta \leq 2$ there will be well-behaved symmetric Nash equilibria in M_i with non-negative profits.[29]
The Cournot symmetric NE in military expenditure will be:

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

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 $N^* = \left(\frac{R}{F}\right)^{1/2}$ In this case 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 cases.

29 All the calculations can be found in Appendix A.

These three results are summarized in Proposition 1:

Proposition 1. *Suppose that the return to military efforts is $\eta \leq 2$. Then a positive shock to the total revenue from a production site, R, will have the following effects:*

1. *Total military expenditure M^* in the cite will increase.*
2. *The number of active cartels N^* will also increase.*
3. *As these two increase violence will increase with them.*

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 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, this was followed by an increase in heroin overdose deaths and a spike in heroin prices in the United States. This seems like a plausible exogenous shock to the heroin market that might affected entry decisions into new territories of Drug Trafficking Organizations. 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.

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

$Suit_m$ 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 dollars. 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.[30]

[30] 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.

The only difference between this specification and an standard event study is that here the treatment is a continuous variable.[31]

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 that violence and cartel activity might be completely driven by the war on drugs and not by market pressures.

The main threat to identification is using news articles to build the cartel presence data set. I already showed in the data section that this data set is highly correlated with other data sets built through news articles. The data set is also highly correlated with aggregate data from the DEA. Despite this, it could be that the 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 and 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.[32] Examples of these sentences can be found in Appendix A.1. The data set that includes the location, date and media where these journalists either were killed or disappeared is public.[33]

I use this data set to test if there is any particular bias towards journalist being killed by a particular cartel. In order to do this I regress the number of killed or disappeared journalists on each of the nine cartels presence. The coefficients from these regressions

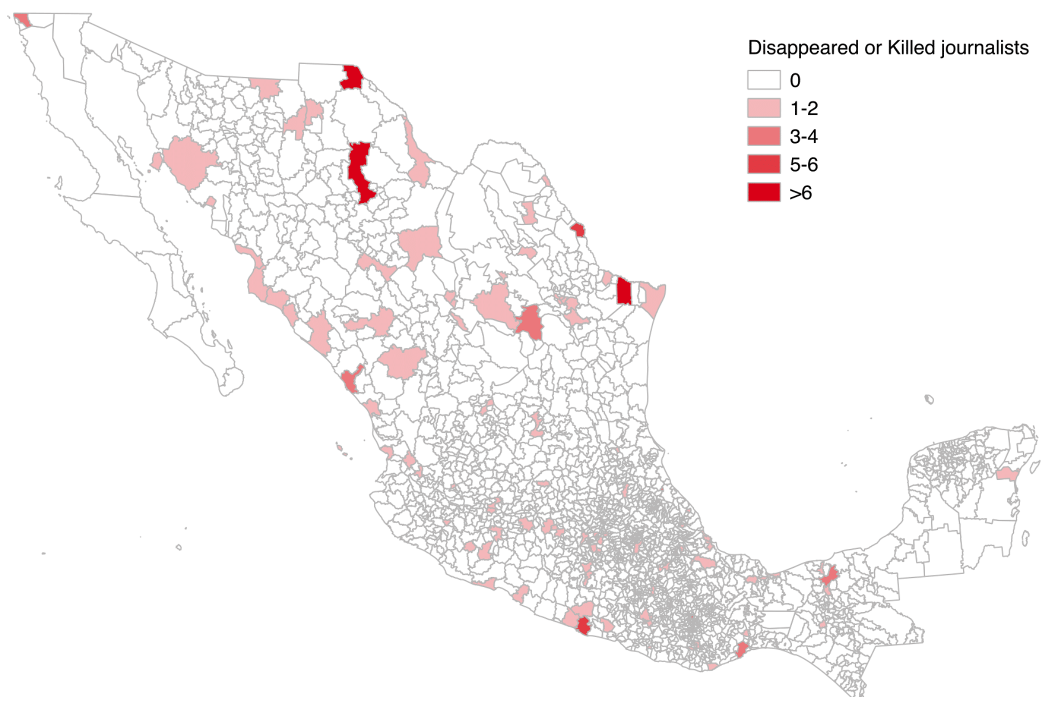
[31] Strategy commonly use to estimate the effect of commodity shocks Dube and Vargas (2013)

[32] Police reports are not public so they cannot be use to create a cartel presence data set.

[33] 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

can be found in Appendix A.4 The specifications controls for police and military presence, political party at the municipality and state level and they also include municipality and year fixed effects and state specific time trends. Standard errors are clustered at the municipality level. None of these coefficients are significant and all of them are near zero. Correlations between the journalist data set and each cartel presence are low. The highest one is for Los Zetas and is .17 These provides evidence that there does not seem to be any particular bias towards reporting or misreporting on a particular organization. Figure 3 shows the map of where media workers have either disappeared or being killed between 2004 and 2016. There is not a particular area where they are concentrated. The correlation between this map and the mean number of active cartels during this period is 0.45. This confirms that all the journalists where attacked in a municipality with at least one cartel active but that there does not seem to be a particular cartel perpetuating all the attacks against the press.

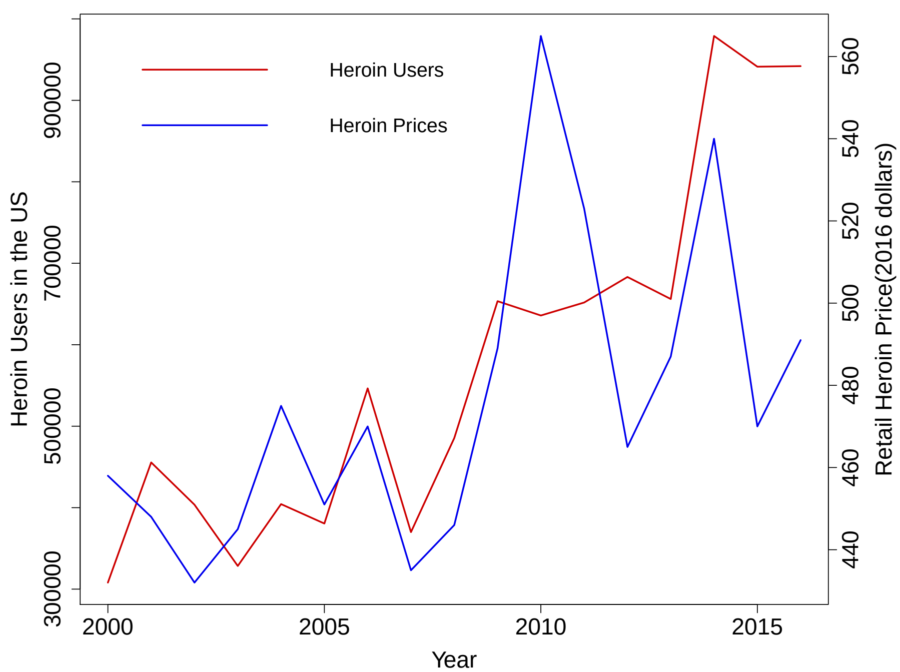
Figure 3: Disappeared or Killed Media Workers between 2004-2016



Despite this, the dataset I built might underestimate actual cartel presence. Journalists and police reports are made when something actually happens in a municipality related to a particular organization. Therefor, I am probably just observing when there is a violent event, an arrest or an interdiction. This implies that when a cartel is active but the police or the military do not know about it this data set would not observe it either. Then all the results were the dependent variable is cartel presence will not be biased by this measurement error. The results when the independent variable is cartel activity will be biased towards zero. Thus all the results from this paper can be considered as a lower bound of the effect that cartels have on violence.

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 86% 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 4 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.

Figure 4: 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.

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 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.

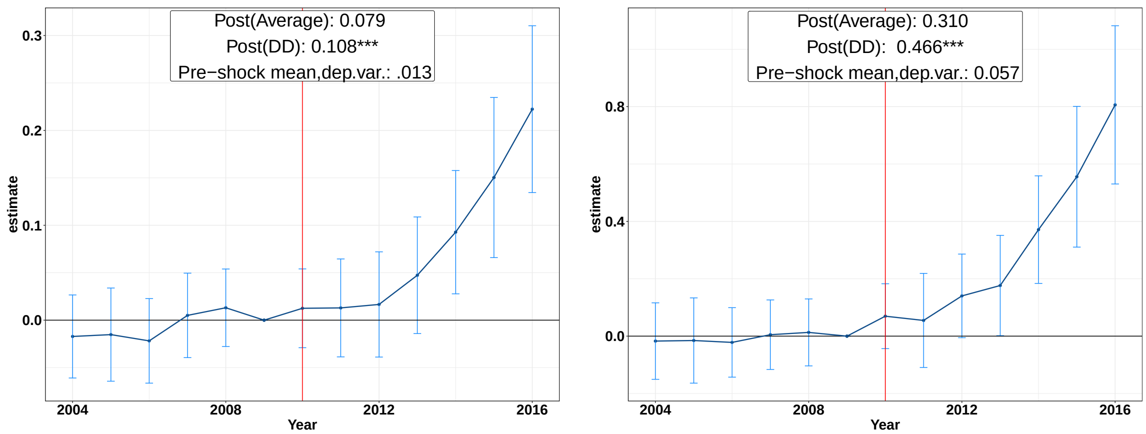
4.2.3 Results

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 changed after the shock. 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.

Cartel Activity: Figure 1 shows the increase in the number of municipalities with more than one cartel after 2010. Figure 2 shows the suitability index for each municipality. These three maps I observe a relationship between suitability and increased cartel presence, specially after 2010. To test the relationship between suitability and the increase in cartel presence I used specification (1). Figure 5 shows the event study coefficients, panel (a) shows these coefficients when the dependent variable is one if the municipality has more than one cartel and zero otherwise. The graph shows that the pre-shock probability of having more than one cartel present is 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 present will be 14% higher in a perfectly-suitable municipality compare to a non-suitable municipality.[34]

Figure 4 panel (b) shows the coefficients from specification (1), where Y_{mt} is the number of active cartels in municipality m at year 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 increasing after 2010. The average post-shock event study coefficient is 0.310, the difference-in-difference coefficient is 0.466, and the pre-shock average number of cartels is

[34] Perfectly-suitable means the suitability index is 1 and non-suitable means the suitability index is 0.



(a) More than one cartel active

(b) Number of active cartels

Figure 5: Event Study on cartel presence

0.05 cartels. To understand the magnitude of these coefficients, lets compare the perfectly-suitable municipality with the non-suitable one when heroin prices increase by 30%. The number of active cartels will be 0.6 more cartels each year after the shock in a perfectly-suitable municipality compare to a non-suitable one.

Robustness Checks: Table 2 addresses some concerns presented in section 4.2.2. The first column uses the specification in equation 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, 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 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.

In sum, patterns of cartel entry are consistent with Proposition 1. The increase in the value of some production sites encourage more cartel entry. When the prices of the final product is high more Drug Trafficking Organizations will try to enter the more suitable

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 $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

production sites. 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.

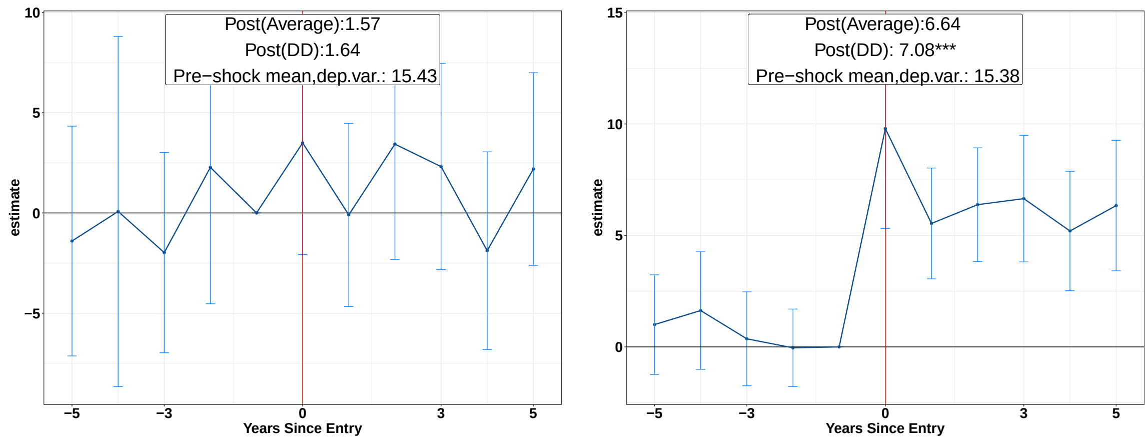
5 Entry, Exit and Violence:

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*b*) 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:

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

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 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



(a) First Cartel Entry

(b) Second Cartel Entry

Figure 6: Cartel Entry[35]

of 500Km.

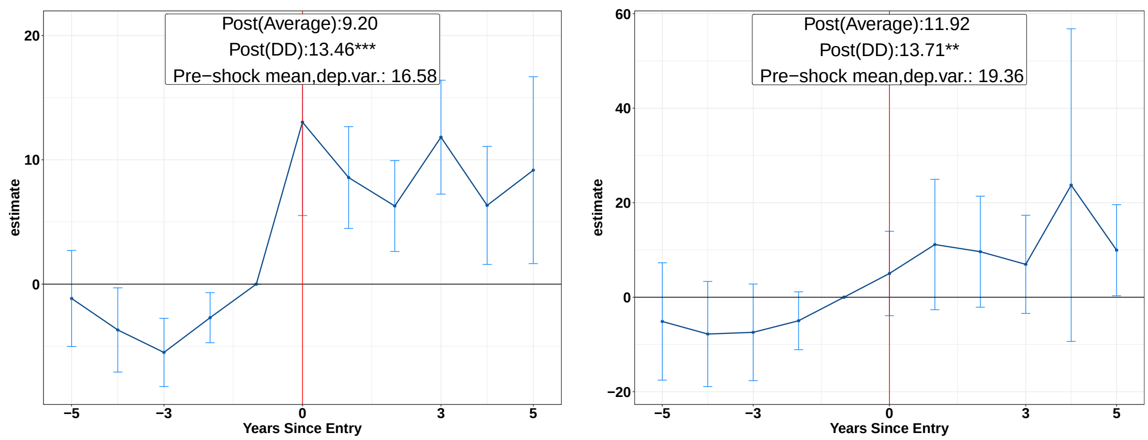
5.1 Results

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.

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 one to two cartels

35 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



(a) Third Cartel Entry

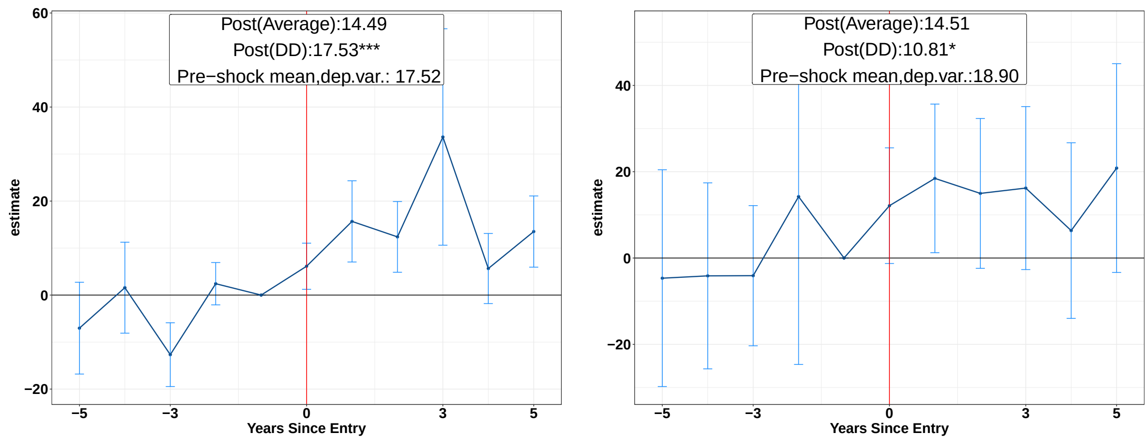
(b) Fourth Cartel Entry

Figure 7: Cartel Entry

the homicide rate per 100,000 inhabitants increases by 7 homicides. The increase peaks at the year the second cartel enters and stays high for the next five years. The entry of the third and fourth cartel increase the homicide rate by 13 homicide each one. From Figure 7, panel (a) there is an sharp increase the year the third cartel enters and the number of homicides remain high for the next five years. Figure 6, panel (b) shows the effect from the entry of the fourth cartel. This graph shows a pre-trend before the event, a peak a year after the fourth cartel enters, and a slightly decline after the second year. The entry of the fifth cartel increases the homicide rate by 17 homicides. This is the biggest increase and Figure 8, panel (a) 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. 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.5.1

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 9 shows the coefficients from

radius.



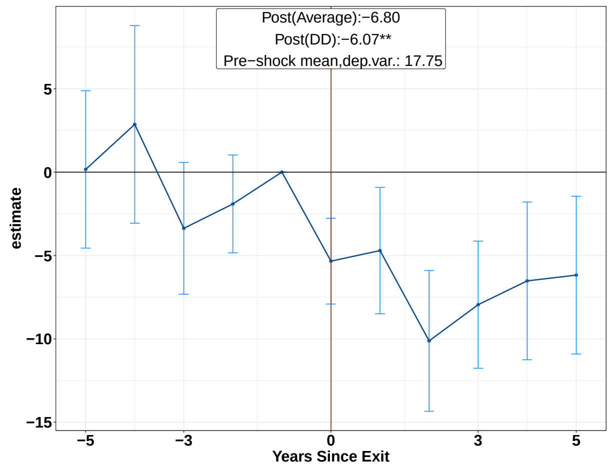
(a) Fifth Cartel Entry (b) Sixth Cartel Entry

Figure 8: Cartel Entry

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 results from this section suggest that when a single organization has monopoly power over 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 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 a non-linear relationship between the entry of the cartels and the homicide rate per 100,000 inhabitants. The standard errors of these estimates are bigger as the number of active cartels increases in a municipality. This is because there are not as 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

Figure 9: Going from two to one active cartel



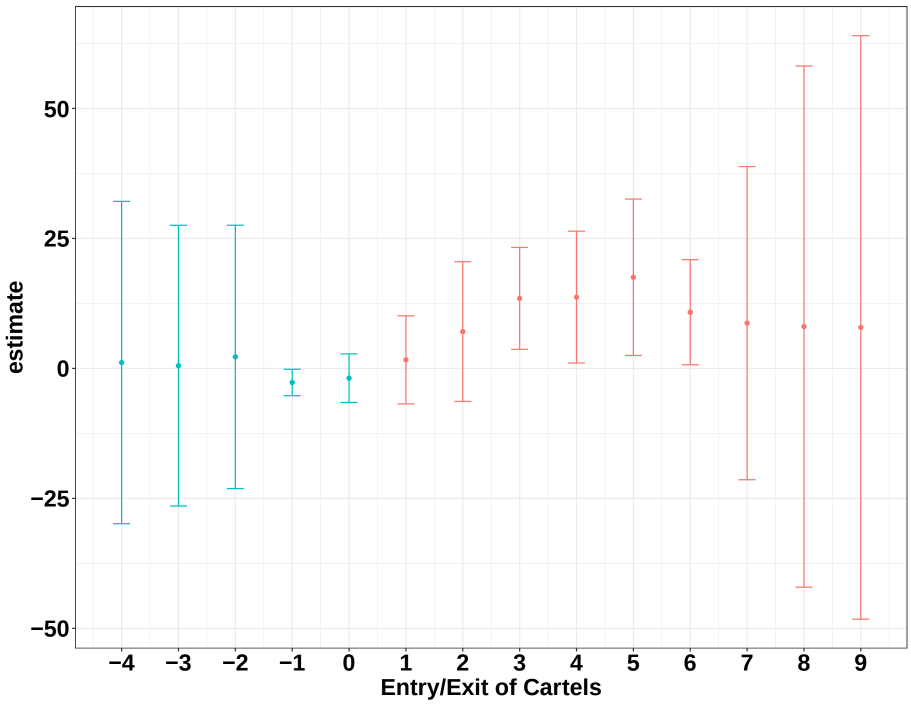
of them, -2. The effect of a municipality that goes from four to three cartels, -3, and the first bar shows the coefficient and standard errors from municipalities that had five cartels and experience the exit of one of them. This figure summarizes the relationship between cartel entry, exit and the homicide rate. The significant effects occur when a municipality goes from one to two or two to one. This confirms that when there is a single criminal organization in one place homicides should not increase. 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 appears 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 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 11 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 per a 100,000 inhabitants. A high-suitable municipality will have a homicide rate with 24 more homicides than a non-suitable

Figure 10: Entry and Exit of Cartels



municipality. 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 education, percentage of households with women as the head of the household and mean number of occupants per dwelling.[36] 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).[37] Figure 12, panel

[36] 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.

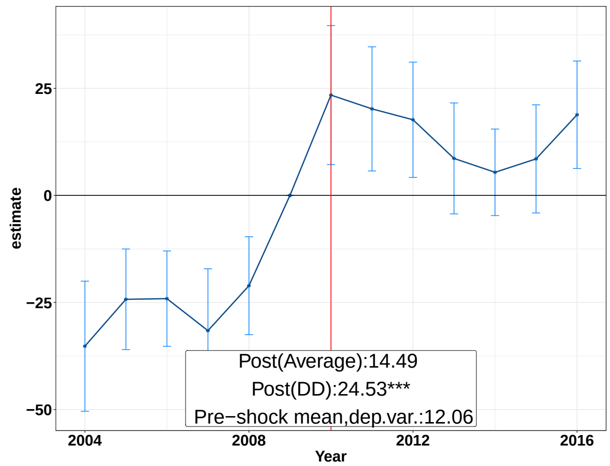
[37] The other variables that I analyzed were percentage of households that own a TV, refrigerator, washer, car, phone, and/or a computer. These variables have an increasing trend during the whole sample or are completely flat during the period analyzed.

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					✓

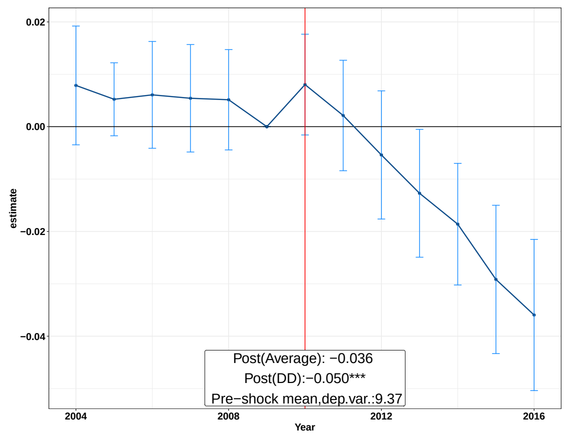
Notes: This table presents the results of the difference-in-difference model for the dependent variables: homicide per 100,000 inhabitants. This results are estimated using the the same specification as Equation 1, but with the event dummy years replace by a post shock dummy interacted with suitability 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 11: Homicides per 100,000 inhabitants

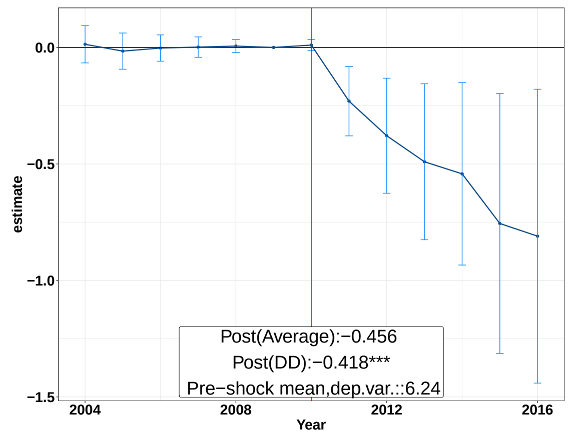


(a) shows an steady decrease in the log of the population after 2010 and Figure 11, panel (b) has a similar steady decrease in the average years of education. Figure 12, panels (a) and (b) show an increasing share of households with women as the head of the household and an increasing number of occupants 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.5.2. To understand the magnitude of these coefficients I will compare a high-suitable(suitability of one) municipality with a low-suitable(suitability of zero) 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 a non-suitable one.

Economic Outcomes: The next set of results suggest that the shock might have had a positive impact in some socio-economic outcomes. Figure 14 shows the coefficients from the event study specification (1). From Figure 14, panel (a) there was an increase in the percentage of houses that had floors made of materials different from dirt. Figure 14, 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.5.2. These results suggest that there was an income boost from the increase in heroin prices and that it is

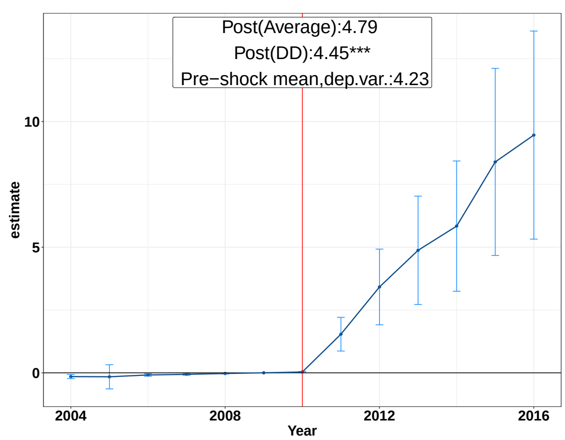


(a) Log of Population

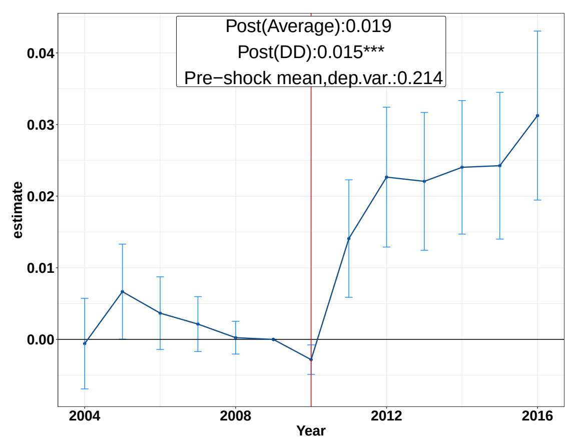


(b) Mean Years of Education

Figure 12: Demographic outcomes

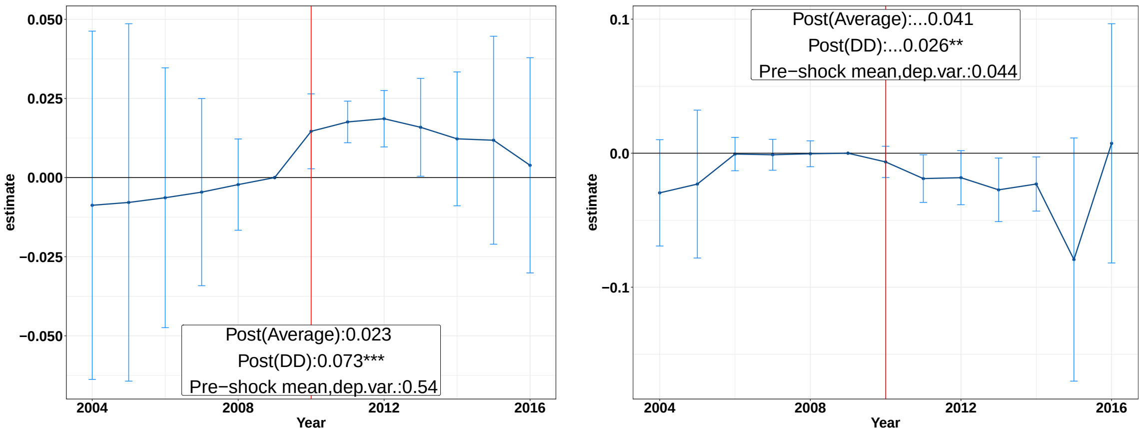


(a) Occupants per dwelling



(b) Percentage of households with women as a head

Figure 13: Demographic outcomes



(a) Households with Non Dirt Floor

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

Figure 14: Economic outcomes

probably increasing the quality of the houses of the poorest members of these communities. These results are in line with anecdotical evidence from opium poppy farmers that saw an increase in the amount pay by the cartels during this period of time. A kilogram of raw opium could be sell at around 275 dollars in 2011 and went up to 900 by 2014 Stevenson (October 2015).

Military eradication In this section I use the eradication data from the Mexican military to explore 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 15 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 a 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 increases relative to the value of marijuana, which lead to the farmers to switch crops.

6 Cartel Competition and concentration in the heroin market

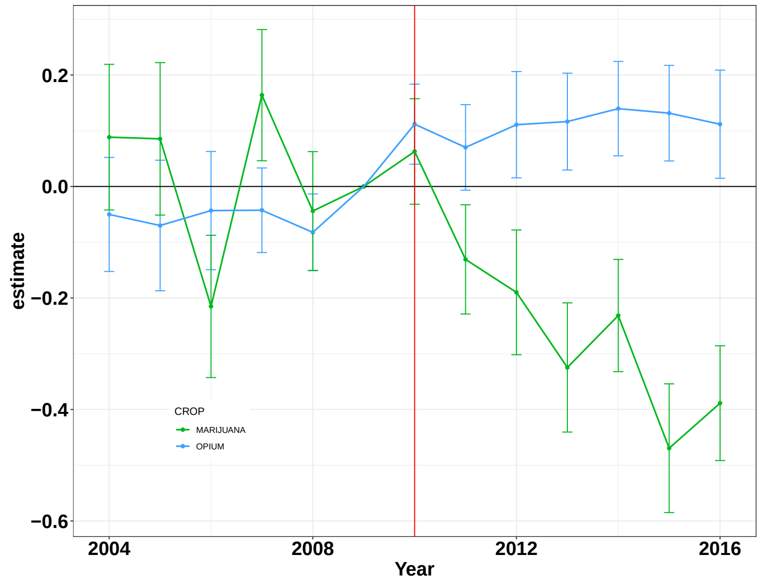
In this section I provide evidence of the expansion of several cartels into the heroin market after the increase demand in the United States. In the background section I already mention that historically Mexico has produced opium and exported it to the United

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 $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 15: Log of Hectares eradicated

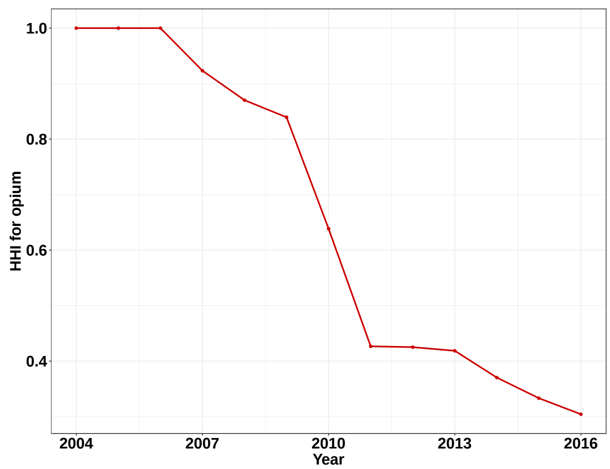


States but it was never their main activity. Until 2006, there was just one cartel, the Sinaloa Cartel; in areas where opium poppy was eradicated by the Mexican government. By 2016, the nine main organizations can be found in municipalities where opium poppy was eradicated by the military. Figure 16 shows the Herfindahl–Hirschman Index for the raw opium market. The index was calculated 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 that when the demand for heroin increased in the United States the cartels decided to enter or expand their operations into this market.

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

Figure 16: HH1 Opium



(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. 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 was the Templar-Knights Cartel splitting from La Familia Michoacana. The group that started as a self-defense against criminal organizations rapidly became a drug cartel. 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:

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

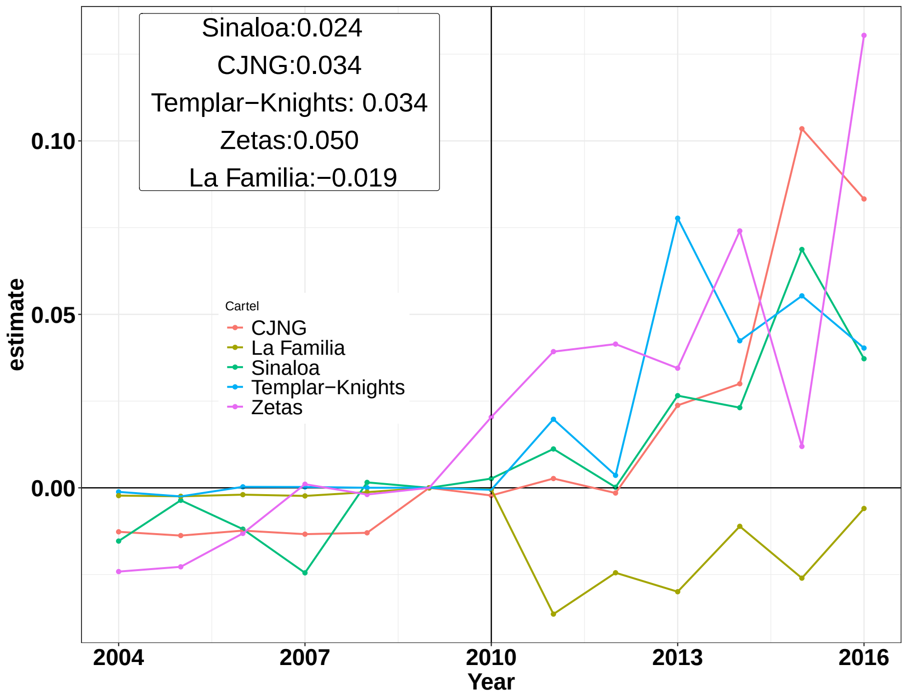
where Y_{mt}^{c} is the probability of having the cartel c active in municipality m and time t. $Suit_m$ is the measure of suitability in the municipality m, $PriceHer_t$ is the retail price of heroin in the United States per milligram of heroin adjust by purity in 2016 dollars, X_{mt} is a set of controls 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 17 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 graph presents the results for the five main cartels that have activity in the heroin market. There are two cartels expanding, 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.5.3. 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.

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. 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 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. 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

Figure 17: Cartel Presence by Cartel



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.

This paper also provides two novel data sets that can be used to answer other questions related to how Mexican Drug Trafficking Organizations operate and react to different policies. I also provide a set of techniques that can be replicate elsewhere to generate new data sets. The use of online content and deep learning should become a more common practice that would allow us to measure otherwise difficult to quantify phenomena.

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.

Esquivel, J. (March 2016), ‘La heroína mexicana a la conquista del mercado estadunidense’, Proceso.
URL: *https://www.proceso.com.mx/434801/tanto-la-heroina-mexicana-a-la-conquista-del-mercado-estadunidense*

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.

Kim, Y. (2014), 'Convolutional neural networks for sentence classification'.

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*a*), 'Does illegality breed violence? Drug trafficking and state-sponsored protection rackets', *Crime Law Soc Change* .

Snyder, R. and Duran-Martinez, A. (2009*b*), '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* .

Stevenson, M. (October 2015), 'Narco Mexicano produce más opio', Dallas News en Español.
URL: *https://www.dallasnews.com/espanol/al-dia/mexico/2015/10/05/narco-mexicano-produce-mas-opio/*

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 I used to generate the cartel presence data set is described here:

- Web scraping: I used the nine cartels that the DEA and the Mexican persecutor's office recognize as major Drug Trafficking Organizations. With these organizations and all the Mexican municipalities I created a unique set of key words that were used to search in the Google News interface. To reduce ambiguities regarding municipalities and cartel names I followed the same rules as Coscia and Rios (2017). These unique words combinations were passed to the crawler that looked for any information source containing the municipality-cartel pair between 1990 and 2016. The algorithm found 2'249,561 news articles.[38]
  The next step consists on dropping all the articles that are not talking about a municipality-cartel pair. The search engine will sometimes give back links that does not contained the query in the main article. It may give back as a valid hit of a particular query a news article that talks about one cartel in the core and mentions in the side of the article a municipality. Figure 18 panel (a) shows an example of this. The main article talks about the Sinaloa Cartel being present in the city of La Paz but one of the side articles talks about the municipality of Los Cabos. The search engine will gave a valid hit on this article for the pairs La Paz-Sinaloa Cartel and Los Cabos-Sinaloa Cartel, when the main article is just talking about presence in the first case. The other kind of invalid hits that this step eliminates is the ones where the name of a city or municipality is part of the newspaper name. Figure 18 panel (b) shows an example of this. The main article describes a police operation in Coyoacán in Mexico City were they capture several members of the Beltran-Leyva organization. The problem is that the newspaper name is "El Siglo de Torreón" and Torreón is a municipality. Then the web crawler will return this article as the pair Coyoacán-Beltran Leyva and Torreón-Beltran Leyva but just the first pair describes presence of the organization in that municipality.

- Natural Language Processing: in order to only keep the articles that talk about a municipality-cartel pair I first used several python libraries that extract the main core from the whole html. Keeping just the articles with the municipality-cartel pair will prevent the kind of errors described above. The number of remaining articles after this process was 1'201,483. I used a sentence extraction algorithm to keep each sentence of the articles that mention any municipality-cartel pair. This process found 2'802,224 of these 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, these sentences

[38] I restricted the search for articles in Spanish and appearing in Google News Mexico interface.

(a) Example 1

(b) Example 2

Figure 18: Web Pages Examples

confirms that journalist are still reporting on Drug Trafficking Organizations but mostly after the police has made a report.

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 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).*

To classify each of the sentences as the cartel c being in municipality m I used a semi-supervised convolutional neural network Young et al. (2017). The input that the CNN uses are the sentences. First, I used a pre-trained word embedding in Spanish, trained using Wikipedia articles to transformed each of the words in the sentence into a vector. A word embedding maps meaning into a geometric space, transforming each sentence into a matrix. Let $w_i \in R^d$ be the word embedding for the ith word in a sentence, the particular embedding has $d = 100$. A sentence with n words is then represented as a matrix $W \in R^{nxd}$. The convolution will be apply to this matrix. The convolution involves a filter $k \in R^{hd}$ which is applied to a window of h words to produce a new feature. A number of different filters is then applied to the embedding matrix with different windows sizes that slide over the entire word embedding matrix. Each of them extracts a particular pattern from the n-gram. The

particular CNN used here is a one dimensional convolution with a window size of five, 128 filters, and with a rectifier[39] activation function. Each convolution layer is followed by a max-pooling operation that will map the results of each filter into a fixed dimensionality output. The neural network has 10 hidden layers that used the rectifier activation function and there is a final layer that uses the sigmoid function to classify each sentence as a 1, cartel presence or a 0 non cartel presence. All the parameters for this CNN where chosen by a grid-search of 100 points in each dimension and these combination of parameters gave the higher out of sample predictability.
To train this model I manually classified 5,000 sentences and the use 4,000 as the training set and 1,000 as the test sets. The CNN used here is semi-supervised because it uses unlabeled data to understand the general population data. This method is useful when, like in these case you have a small label subset and a large unlabeled data. The algorithm works as follows, after using the small train data and getting a good prediction, use the unlabeled data to generate predictions (pseudo-labels). Concatenate the labels and the features of the training and test set. Then, train the model again using this new training data. The objective of this kind of training is that the network is able to learn more of the general structure of the data.
The chosen CNN has an out of sample accuracy of 0.8644, this means in the 1,000 sentences that where never include in neither the original data set nor the semi supervised training. Once each sentence is classify as a 1, presence or a 0 no presence. I identify the municipality-cartel pair in each sentence and assigned to that pair. The years are extracted from the whole article, if there is a year in or near the sentence then the presence is assigned to that year. If there is not year in the article I used the publication date as the year.

- Table 5 shows when and where each cartel appears for the first time in the data set created by the algorithm above. The first Column shows the year the cartels first appeared in the data set, some of this cartels are older but the algorithm did not search before 1990. The second Column shows the first municipality where each cartel appears in the data set and the next four columns show in how many municipalities each cartel was active in 1990, 2000, 2010 and 2016. Table 6 shows the summary statistics for this data set between 2004 and 2016. The data set the time period used in this paper. Active measures municipalities with at least one cartel active in a particular year and competitive is one if there are two or more cartels in a municipality and zero otherwise.

[39] An activation function defined as the positive part of its argument.

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

Table 6: Cartel Presence Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Beltran-Leyva	41,752	0.017	0.128	0	0	0	1
Gulf	41,752	0.011	0.103	0	0	0	1
CJNG	41,752	0.014	0.117	0	0	0	1
Juarez	41,752	0.014	0.119	0	0	0	1
Sinaloa	41,752	0.023	0.148	0	0	0	1
Knights-Templar	41,752	0.012	0.107	0	0	0	1
Tijuana	41,752	0.007	0.083	0	0	0	1
La Familia	41,752	0.011	0.106	0	0	0	1
Zetas	41,752	0.033	0.178	0	0	0	1
Number of Cartels	41,752	0.140	0.628	0	0	0	9
Active	41,752	0.072	0.259	0	0	0	1
Competitive	41,752	0.034	0.180	0	0	0	1

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.[40]
The variables used 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)
- 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. I choose the best model using a 10 fold validation. The best model has parameters $\alpha = .4$ and $\lambda = 0.07557243$. Here α is the

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

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.
Variables selected by the elastic net:
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 Theoretical Framework:

Under Cournot competition a vector $[M_1^*, ..., M_N^*]$ will be an equilibrium if M_i^* maximizes π_i with the strategies of all the other cartels treated as fixed $\bar{M}_{-i}^*$. Symmetric equilibria will be such that $M_i^* = M^*$ for $i = 1, ..., N$. In this section I present conditions that ensure the existence of these kind of equilibria.

A cartel i will choose the its military capacity in order to maximize its profits $\pi_i = Rs_i - M_i - F$ taking as given all the other cartels military capacity.
The first order condition will be given by:

$$\frac{R\eta M_i^{\eta-1}}{\sum_{j=1}^{N} M_j^{\eta}} - \frac{ReM_i^{2\eta-1}}{(\sum_{j=1}^{N} M_j^{\eta})^2} - 1 = 0 \tag{4}$$

Symmetric equilibria will imply $M_i = M^*$ for all i so that equation (4) becomes:

$$\eta\left[\frac{N-1}{N}\right] = \frac{M^*}{R} \tag{5}$$

Two additional conditions most be satisfied at equilibrium. First, equation (4) must indicate a local maximum for the profit function. It is sufficient to have $\frac{\partial^2 \pi_i}{\partial M_i^2} < 0$. This second derivative when the military capacity is the same for all cartels become:

$$\eta(N-1)[N(\eta-1)+2\eta] < 0 \tag{6}$$

Equation (6) implies that $N \geq 2$ in order for $\eta > 0$.

Second, π_i at the equilibrium need to be non-negative, otherwise the cartels will be better off staying out of the market. Profits need to be such that $\pi_i = Rs_i - M - F > 0$. From equation (5) the profits being positive can be rewritten as $N(\eta-1) - \eta \leq 0$. Rearranging this equation:

$$N \leq \frac{\eta}{\eta-1} \tag{7}$$

Like $n \geq 2$ this implies that there will exist symmetric equilibria as long as $0 \leq \eta \leq 2$.

A.4 Disappeared and killed journalists data

Mexico is one of the most dangerous countries to be a journalist. Official sources report 207 disappeared or killed media workers since 2000. Most of these crimes remained unsolved, improperly investigated, and with few perpetrators arrested and convicted. The victims are spread across 23 states and 109 different municipalities. The type of media they worked includes freelancers, government, international, local, and national newspaper reporters, and also TV, and radio presenters.

In order to test if there is any particular bias towards misreporting a particular cartel I regress the number of killed or disappeared journalists on each of the nine cartels presence.

$$Y_{it} = \beta C_{it}^d + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_s t + \epsilon_{mt} \tag{8}$$

Y_{it} is the number of disappeared or killed journalists in municipality m in year t. C_{it}^d is a dummy variable that indicates whether the cartel d is present in municipality m and year t. 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 municipalities and states that might made them more dangerous for journalists. X_{mt} is a set of controls that includes; police, and military presence, a dummy if the mayor is from the conservative party PAN and a dummy if both the mayor an the state governor are from the conservative party PAN. Standard errors are clustered at the municipal level.

Table 6 shows the results of this regression for each cartel. All the coefficients are near zero and none of them are significant. This confirms that there does not seem to be a

Table 7: Relationship between death and disappeared journalist and cartel presence

	Killed or disappeared media workers								
	killed								
Sinaloa	0.016								
	(0.009)								
Beltran-Leyva		0.008							
		(0.009)							
Gulf			−0.013						
			(0.009)						
CJNG				0.019					
				(0.012)					
Juarez					−0.007				
					(0.012)				
Knights-Templar						−0.015			
						(0.012)			
Tijuana							−0.007		
							(0.028)		
La Familia								−0.004	
								(0.011)	
Los Zetas									0.012
									(0.009)
Observations	32,012	32,012	32,012	32,012	32,012	32,012	32,012	32,012	32,012
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓
State trends	✓	✓	✓	✓	✓	✓	✓	✓	✓

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

particular cartel more lethal to media workers. The correlation between the journalists data set and the presence of each cartel is also low. The highest correlation is with Los Zetas and it is .17. There does not seem to be a high correlation between the total number of cartels active in a municipality and the number of disappeared or killed journalists either. This correlation is .13. This results and the map show in the threats to identification section provides evidence that despite the fact how dangerous is for reporters to inform on drug cartels, there does not seem to be a particular cartel that is more dangerous than the other ones. This implies that using news articles to measure cartel presence is a good and is probably close to data that local authorities have.

A.5 Robustness checks

A.5.1 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.

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 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.

Table 8: 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

Table 9: 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 10: 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 11: 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

A.5.2 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.

A.5.3 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

Table 12: 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 13: 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 14: 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

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 15: 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 16: 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 17: 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 18: 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 19: 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