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

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Abstract

The number of major Drug Trafficking Organizations (known as cartels) 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 violence and competition for market share among cartels. To measure cartel presence, a difficult to measure phenomenon, I construct a novel data set of cartel presence across Mexican municipalities by scraping Google News and using natural language processing. To study how market size and structure interact with violence, I exploit two empirical strategies using within municipality variation. First, I interact heroin prices with agro-climatic conditions to grow opium poppy, using exogenous variation in demand for heroin from the 2010 OxyContin reformulation. This reformulation made OxyContin harder to abuse and led some opioid abusers to switch to heroin. Second, I exploit variation in the timing of cartel entry in a municipality. Cartel presence increases substantially after 2010 in municipalities well-suited to grow opium poppy. As more cartels enter a market, homicide rates increase. These results suggest that substantial part of the increase in violence that Mexico experienced in the last fifteen years is due to criminal groups fighting for market share of heroin, not only due to changes in government enforcement.

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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]
-Mike 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 (know as cartels) are 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] The increase in the number of cartels 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.

Billions of dollars[5] are spent every year to reduce the presence of organized crime and the negative externalities associated with it. However, there is limited evidence on the underlying determinants of these externalities. This paper argues that the key to understanding the externalities is the relationship between market structure, institutional context, and violence.

In this paper, I seek to answer two questions. First, how do cartels react to an external demand shock for heroin. Second, what is the relationship between market structure and violence in the illegal drug market. I answer these question with three contributions. First, I create a novel data set on cartel presence across Mexican municipalities. Second, I use an external demand shock to the heroin market, the 2010 OxyContin reformulation, to estimate the effect of this market shift on cartel entry. Then, I estimate the relation-

[1] Ahmed (August 2015).
[2] Woody (November 2017).
[3] Counterfeiting is the most lucrative illegal activity with a yearly revenue of approximate $928 billion dollars 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."
[5] The US government spends around 15.8 billion dollars each year in law enforcement related to illegal drugs. https://www.drugwarfacts.org/chapter/economics

ship between cartel entry, exit, and violence. I find that the heroin market became less concentrated and that violence increases with cartel entry into a municipality.

The context for this analysis is the increase in demand and supply for legal opioids in the United States between 1996 and 2010. OxyContin became popular for recreational use and abuse because the drug offered more of the active ingredient, oxycodone. The pills were easily manipulated by crushing them so oxycode is released all at once instead of slowly. To reduce the misuse of legal opioids, 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 around 90% by 2016 (DEA 2018).

This shock allows me to use two different sources of exogenous variation, agro-climatic conditions to cultivate opium poppy[6] and the change of heroin prices in the United States. I use this variation to measure the effects of the demand shock on cartel presence and violence across Mexican municipalities. 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 use several machine learning techniques that allow me to approximate measures for illegal drug trafficking.

To the best of my knowledge, data detailing the presence of different cartels in different Mexican municipalities after 2010 is not available. Following Coscia and Rios (2017), I use web-content to obtain information of an otherwise difficult 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 media outlets contain regular, detailed, and systematic coverage of when and where criminal organizations are operating.

I use a web crawler, an automated script which methodically browses the web, to extract articles related to a municipality and cartel pair. Then, I use natural language processing to validate whether an article is actually discussing a cartel being active in that municipality. I use a semi-supervised[7] 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

[6] 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.

[7] Semi-supervised learning uses label and unlabeled data to gain more understanding of the population structure.

complex relationships between words in a sentence than a simple bag of words algorithm.[8] 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).[9] 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 looking into the articles and applying state-of-the-art natural language processing techniques to classify the articles. The data is also highly correlated with two data sets collected by hand from local newspapers (Sánchez Valdés 2015, 2017)[10] these data sets are snapshots for two different states in two different periods. The data is also highly correlated to State level data from the DEA.

Second, I build an opium suitability index for Mexican municipalities. A suitability index measures an area comparative advantage for crop cultivation base on geographic and climatic characteristics. 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 reducing a model dimensionality by generating zero-valued coefficients.[11]. The agro-climatic variables chosen through the optimal elastic net were then employed to build the suitability index for Mexican municipalities.[12] Across municipalities over time, the index is correlated with the occurrence of seizures and eradication of poppy crops by the Mexican Military. Time variation comes from the price of heroin in the United States. These two variables together define a municipality time specific shock which leads to differential exposure from the increased demand in the heroin market.

This paper provides four sets of results. First, I show that the increase in demand for heroin encouraged Drug Trafficking Organization to expand their operations into high-suitable municipalities. Estimates imply that when the price of heroin doubles a municipality in the 75 percentile of suitability will have an additional 5% probability of having more than one active cartels each year after the OxyContin reformulation compared to a municipality in the 25 percentile of suitability.[13] The result for the number of cartels is similar with the entry of 0.22 more cartels in a municipality in the 75 percentile of suitability compared with one in the 25 percentile. 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

[8] A full explanation of the algorithms and the techniques used can be found in Section 3 and Appendix A.2.

[9] These data set covers cartel presence between 1990 and 2010, the one built here is from 1990 to 2016.

[10] These two data sets can be find here: Sánchez Valdés (2015, 2017)

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

[12] The suitability index construct here is similar to the ones use in Bounadi (2018) and Gehring et al. (2018).

[13] Assuming that all the other characteristics of the municipalities are the same.

demand. These results are robust to different sets of controls and fixed effects.

Second, I find that the entry of a second, third, fourth, and fifth cartel increases the homicide rate per 100,000 inhabitants. For example, the entry of a second cartel in a municipality increases the murder rate by 34.3%, the pre-entry average is 15.38 homicides. The highest increase in the homicide rate is when the fifth cartel enters a municipality with a 94.8% increase in the homicide rate after the entry. The pre-entry homicide rate per 100,000 inhabitants is 17.31. 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 entry of the first cartel in a municipality does not increase violence. The exit of cartels from a location has a significant effect when a municipality goes from two cartels to one, this exit decreases the murder rate by 34%. These results suggests that it is not the presence of illegal activities that generates violence but the presence of more than one criminal organizations fighting for scare resources.

Third, I ask how the demand shock affected different socio-economic outcomes in the exposed municipalities. I find that the demand shock leads to a decrease in population and average years of education. 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 and the percentage of households with basic service: electricity, water and, sewage increases. 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, consistent with the value of opium going up as the relative value of marijuana decreases.

Finally, I identify which cartels expand to new markets and the fragmentation of existing cartels. 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[14] and the Knights Templar[15] and one contracting cartel, La Familia Michoacana. The two newly generated cartels splintered from existing organizations and immediately started fighting, with their parent organizations for highly suitable land to cultivate opium. Suggesting that market pressures could have influenced cartel fragmentation. These results are consistent with information from the Mexican Prosecutors Office and the DEA.

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

[14]Jalisco New Generation Cartel splinter from the Sinaloa Cartel.
[15]The Knights Templar splinter from La Familia Michoacana.

on violence and other outcomes. This paper speaks to four strands of 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 (Rios 2013; Dell 2015; Osorio 2015; Phillips 2015; Atuesta and Ponce 2017). This study provides evidence of an alternative channel, an increase in heroin demand, that might explain some of the increasing violence in Mexico. This paper is the first to try to casually isolate the effect of the OxyContin reformulation on drug cartel activity in Mexico.

This paper confirms the predictions of models where increasing value of territory leads to turf wars (Mesquita 2018; Castillo and Kronick 2019). It also confirms the result from Biderman et al. (2018) that estimates that a single gang having monopoly power in Brazil decreases violence.

These results also relate with the literature that study the effects of external demand and supply shocks to illegal markets. Millán-Quijano (2019) and Mejía and Restrepo (2013) use cocaine prices and link them to increased violence in Colombia, while Gehring et al. (2018) use heroin prices and their relationship to conflict in Afghanistan. My paper confirms the results from these literature in the Mexican context and ads the reaction on cartel competition. Furthermore, contributes to the literature on illegal markets and its effects on different outcomes (Dube et al. 2016; Sviatschi 2018; Dell et al. Forthcoming), by showing how the number of competing cartels affect socioeconomic outcomes across municipalities.

Finally this paper contributes to the increasing social science literature that uses text as data to measure otherwise hard to quantify phenomena. To the best of my knowledge this is the first paper in economics that uses a semi-supervised convolutional neural network. Previous papers using text as data, for example those surveyed by Gentzkow et al. (2017), use methods based on counting the number of times a word appears. The algorithm used here goes further by using the meaning of the word and the relative position of it on the sentence. The techniques presented here have the ability to help measure other difficult to quantify variables.

The rest of the paper is organized 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 section 7 concludes the paper.

2 Background

2.1 The Opioid Crises

From 1996 to 2010, consumption of legal opioids increased in the United States, leading to the opioid epidemic. One of the 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. Opioid abusers would crush the tablets to snort or inject them, undoing the time-release mechanism so that all the active ingredient is absorbed immediately by the body. In 2010 physician organizations pressured the government to make it harder to accumulate pills and to abuse them. As a result, the federal and state governments started to crack down on pill mills, and Purdue Pharma introduce 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 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).

2.2 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.[16] Heroin is an illegal highly addictive drug processed from opium. Mexican cartels exported some heroin but it was never their main activity.The heroin of Mexican origin seized by the DEA went from 22% before 2010, to 51% by 2011 and reached around 90% by 2016 (DEA 2018). 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.[17]

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 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.[18] 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.

[16] A brief history of the drug trade in Mexico and the war on drugs can be found in Appendix A.1.1 and Appendix A.1.2.

[17] A description of these nine cartels can be found in Appendix A.1.3.

[18] 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.

3.1 Cartel Presence

In order to measure cartel presence I need to construct a novel data set. These data set tracks for every Mexican municipality in each year in the 1990-2016 period whether or not each of the nine major Drug Trafficking Organizations were operating in that municipality. The algorithm I used to create this data set is the following one.

First, I use a web crawler[19] to scrape Google News Mexico. Google News is a news aggregator that watches more than 50,000 news sources worldwide. Google does not provide the number of sites it tracks for the Mexican version but through the scrape I was able to identified 770 local, 33 national, and 83 international media outlets that report in Spanish. This web crawler looked for any articles between 1990 and 2016 that contained a municipality-cartel pair.

The web crawler collected every article whose main body[20] mentions: i) a Mexican municipality and ii) the name of one of the nine major Drug Trafficking Organizations in Mexico. The number of articles found by the crawler are 1,201,483. I used a sentence extractor to keep the sentences from this articles that included a municipality-cartel pair.[21] 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 2,802,224.

Next, I manually classified $5,000$ sentences as either presence or not to train a semi-supervised CNN.[22] I use 80% of this sample as the training set and 20% as the test set. A CNN[23] 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 as follows. Sentences are first broken into words, then transformed into a word embedding matrix.[24] 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 classification accuracy of 0.86.[25]

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.

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

[20] Some media web pages include links to other articles in the side of the main content. If this side content includes the name of a cartel or the municipality sometimes the search engine will return this as a hit. Appendix A.2 includes examples of these type of media pages.

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

[22] Examples of this sentences can be found in Appendix A.2

[23] I also use a simple bag of words with logistic classifier the comparison between these two methods can be found in Appendix A.2

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

[25] A more technical explanation of the algorithm can be found in Appendix A.2

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. Coscia and Rios (2017) tracked the presence of the same nine DTOs at the municipal level between 1990 and 2010. They use a web crawler and then code a cartel as being present if the frequency of the hits for a particular municipality-cartel exceeds certain threshold. The correlation between their data and the one constructed here between 1990 and 2010 is 0.38.[26] 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 attributed to the difference in validation techniques, relative 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 0.71.

3.1.2 External validation:

The DEA has published a biannual map of cartel presence across Mexican states, 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 algorithm used here does not aim to classify dominance only presence.

The high correlation between my data set and the manually collected one provide evidence that the algorithm used here has a high performance compared to a human classification of 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.

The high correlation between the DEA data and my data set shows that using news articles as a source of illegal activity data might be as good as using data from the authorities. The advantage of using news is that they are reported 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. Figure 1a shows the mean average number of active cartels between 2004 and 2009 and Figure 1b shows the mean number of active cartels between 2010 and 2016. The maps show the increase

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

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.[27] Suitability indexes are built using agro-climatic characteristics and crop yields. Unfortunately, there does not exist historical data on opium production in Mexico.[28]

I built a suitability index using Afghanistan's output data. Afghanistan is the main world opium producer and the UN has been collecting data (through surveys and satellite images) on opium yields and hectares cultivated since the early 1990s.[29] I use yields by district between 2000 and 2018 plus 45 agro-climatic characteristics and all their interactions.[30] 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.3.

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.[31] This model is then used to predict log productivity of opium in Mexican municipalities given its agro-climatic characteristics.[32] 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.

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 in 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 there

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

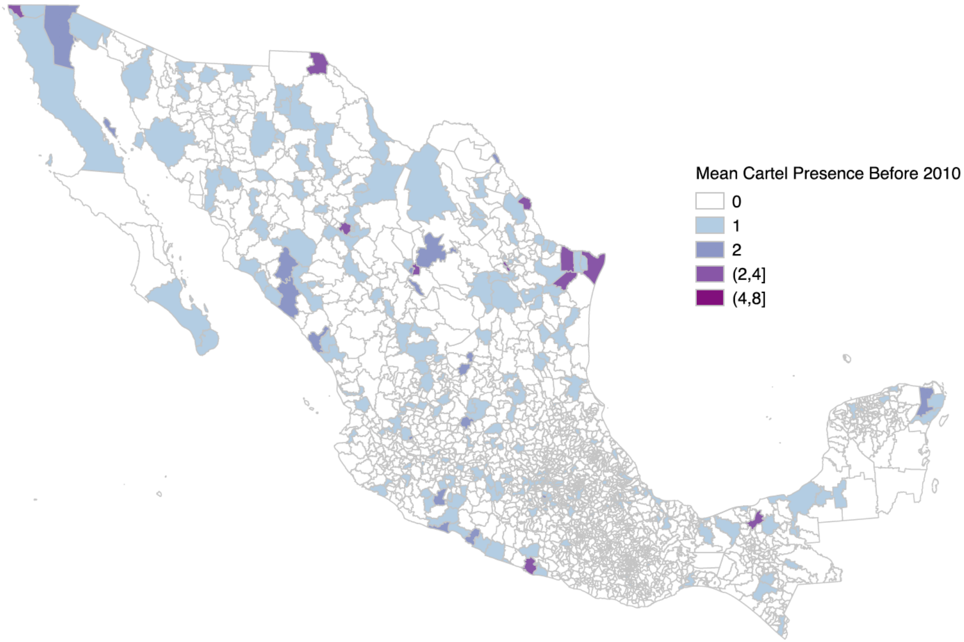
[28] UNDOC just started collecting these data in 2014 but they are still unable to provide accurate measures for opium yields at the municipality level.

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

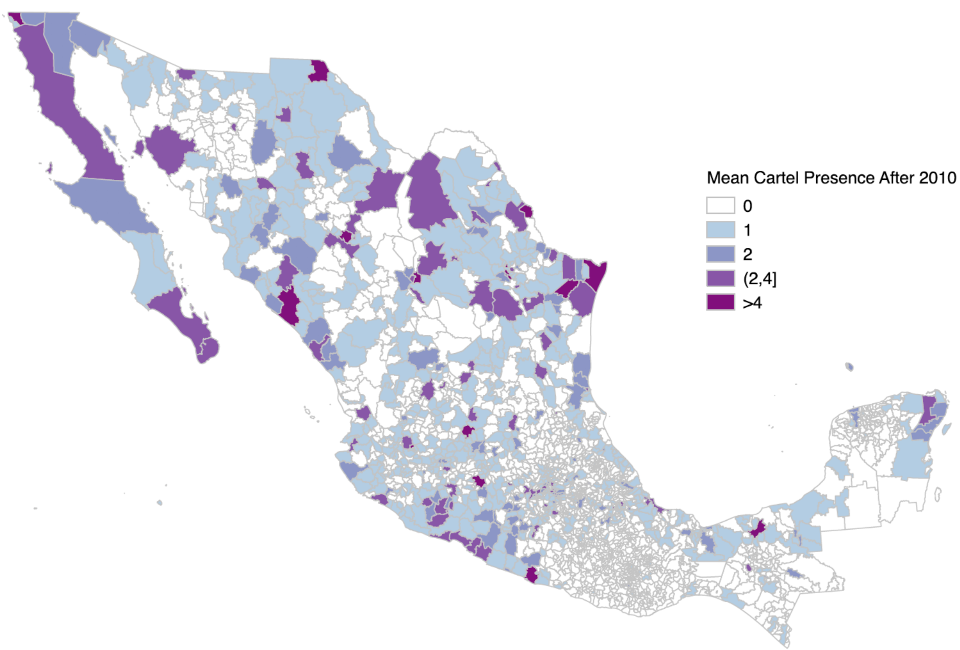
[30] The suitability index built here is similar to the ones used by Kienberger et al. (2017), Sonin et al. (2019), Bounadi (2018) and Gehring et al. (2018).

[31] 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.

[32] The shrinking and mixing parameters used can be found in Appendix A.3.



(a) Mean Cartel Presence 2004-2009



(b) Mean Cartel Presence 2010-2016

Figure 1: Cartel Presence

after 2010. The correlation between the index and opium poppy eradication data from the Mexican military between 2000 and 2005 is 0.45. The correlation between mean presence before 2010 and the suitability index 0.18 and the correlation after 2010 is 0.47.

Table 1 shows the relationship between the suitability index and mean hectares of opium poppy eradicated by the Mexican military. The coefficients show are the result of regressing the suitability index on the mean opium poppy eradication before and after 2010. The specification controls for police and 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)

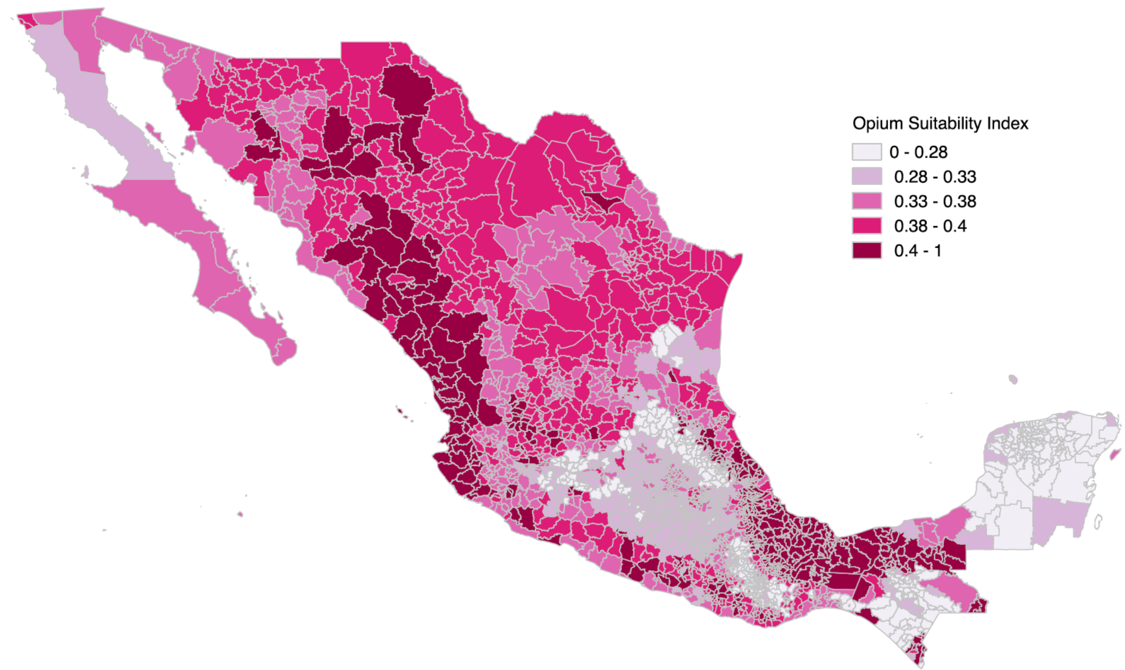
Notes: This table presents the results of a ordinary least square regression where the dependent variable is the mean eradication of opium poppy, measured in hectares. Controls for police, military presence and includes municipality fixed effects.$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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

Figure 2: Opium Poppy Suitability Index



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 a municipality is 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 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. Last, I address possible threats to my identification strategy.

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 of rents that each organization will win. To simplify the model, I assume that each municipality is an independent production site. I 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.[33] 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 $M = \sum_{i=1}^{N^*} M_i$, where N^* is the number of cartels that entered the municipality. The potential revenue of site j is given by R_j, this potential will depend on how suitable municipality j is.

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 active in that territory. 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 revenue that each cartel gets from

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

its investment. 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 municipality j is given by:

$$\pi_i = R_j s_i - M_i - F$$

where R_j is the exogenous total revenue from the production site j.

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.[34]

The Cournot symmetric NE in military expenditure in site j will be:

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

and the free entry condition is :

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

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 $R_j \to \infty$ so does $N \to \infty$. There are decreasing returns to military effort.
- If $\eta = 1$ then $N^* = \left(\frac{R_j}{F}\right)^{1/2}$ 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 $R_j \to \infty$ 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.

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_j, will have the following effects:*

1. *Total military expenditure M^* in the municipality will increase.*
2. *The number of active cartels N^* will also increase.*
3. *Violence will increase with them.*

[34] All the calculations can be found in Appendix A.4.

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, which 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.

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

$Suit_m$ is a measure of opium poppy suitability of municipality m, this measure is between 0 and 1, where 1 means perfectly suitable and 0 not suitable. $PriceHer_t$ is the retail price of a milligram of heroin in the US adjust by purity and inflation and normalized to 2002 dollars. The Y_{mt} are different measures of cartel presence: the probability of having more than one cartel present 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. Fixed effects controls for all individual municipality characteristics that are fixed over time. 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.[35] The only difference between this specification and an standard event study is that here the treatment is a continuous variable.[36]

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 $PostRef_{mt} = \mathbb{1}[t >= 2010]$. These dummies then are interacted with the suitability and heroin prices. Standard errors are clustered using Con-

[35] 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.

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

ley (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. The results using standard errors clustered at the municipality level can be found in Appendix A.6.1.

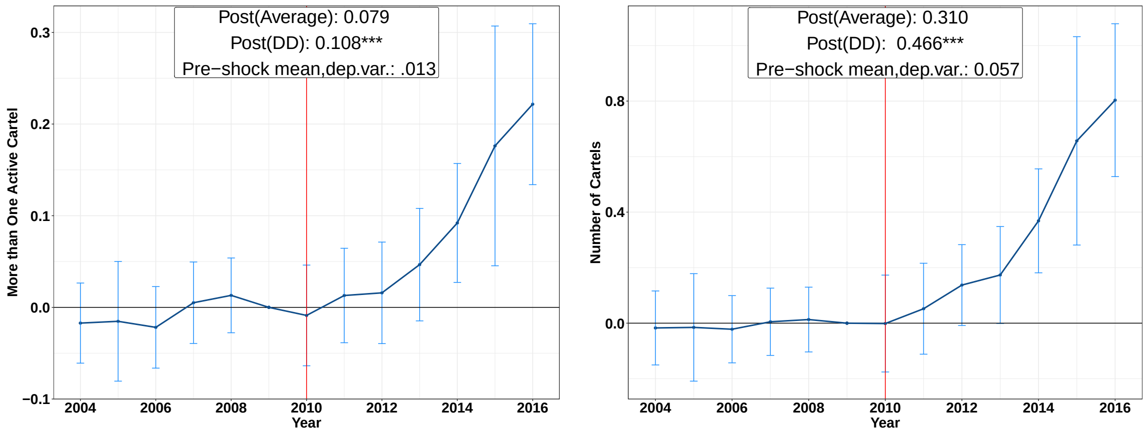
4.2.2 Results

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 3a shows the increase in the number of municipalities with more than one cartel active after 2010. The maps from Figure 1 and Figure 2 show a relationship between the suitability index and increase cartel presence, specially after 2010. To test the relationship between suitability and the increase in cartel presence I used specification (1). Figure 3a shows the event study 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 when the heroin price doubles in the United States. The probability of having more than one cartel present will be 5% higher in a municipality in the 75 percentile of suitability compared with one in the 25 percentile.

Figure 3b 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 0.05 cartels. To understand the magnitude of these coefficients, lets compare a municipality in the 75 percentile with one in the 25 percentile when the heroin price doubles. The number of active cartels will be 0.22 more cartels each year after the shock in the municipality in the 75 percentile compared with one in the 25 one.

Robustness Checks: Table 2 presents a series of robustness checks. 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



(a) More than one cartel active

(b) Number of active cartels

Figure 3: Event Study on cartel presence

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 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 months, 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.3.

Table 2: The effect of the reformulation on cartel activity

	Cartel Activity									
	More than one					Number of Cartels				
Average effect	0.108***	0.121***	0.064***	0.044***	0.049 ***	0.466***	0.537***	0.292***	0.227***	0.241***
post-2010	(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 $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.2.3 Threats to Identification

Here I address some potential concerns regarding the main identification strategy. First, I provide evidence that measuring cartel presence using news articles is not biased towards any particular cartel. Second, I 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 concern is measurement error in the cartel presence variable. 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.[37] Examples of these sentences can be found in Appendix A.2. From the 1,201,483 articles analyzed here that contained a cartel-municipality pair in the core of the article 44% of them do not have a byline. This means that the news outlet is the author of the article and not a particular journalist, this can also help journalists to avoid violence from the cartels.The data set that includes the location, date and media where these journalists either were killed or disappeared is public.[38]

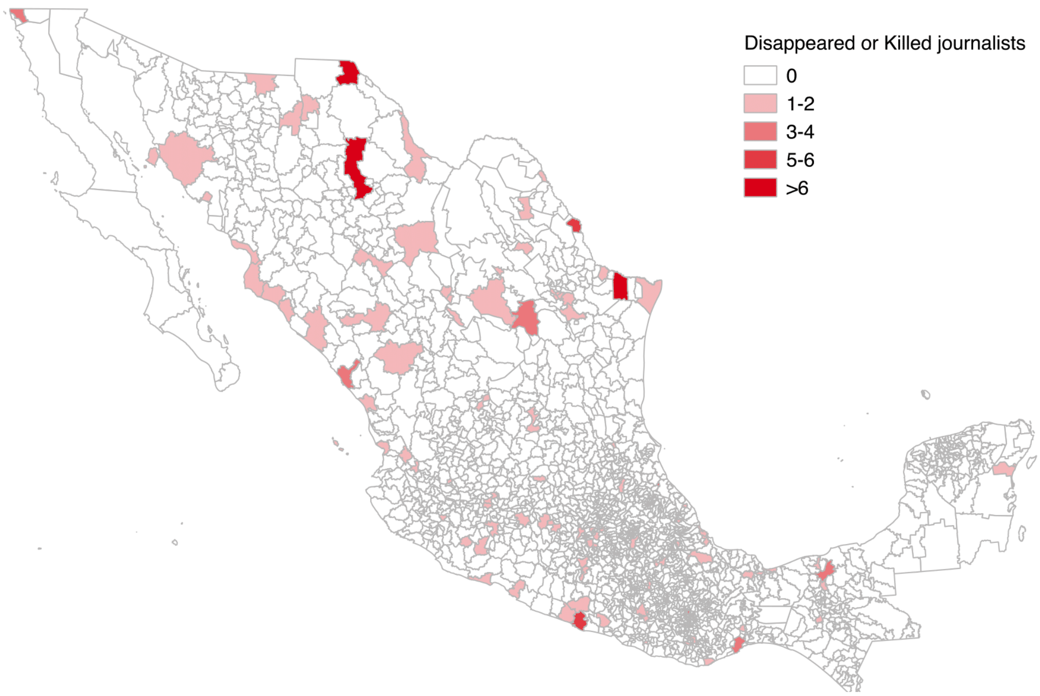
I use this data set to test if there is any particular bias towards journalist being killed by a particular cartel. In order to do this I regress the number of killed or disappeared journalists on each of the nine cartels presence. The coefficients from these regressions can be found in Appendix A.5. 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 0.17. These provides evidence that there does not seem to be any particular bias towards reporting or misreporting on a particular organization. Figure 4 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

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

[38]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.

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.

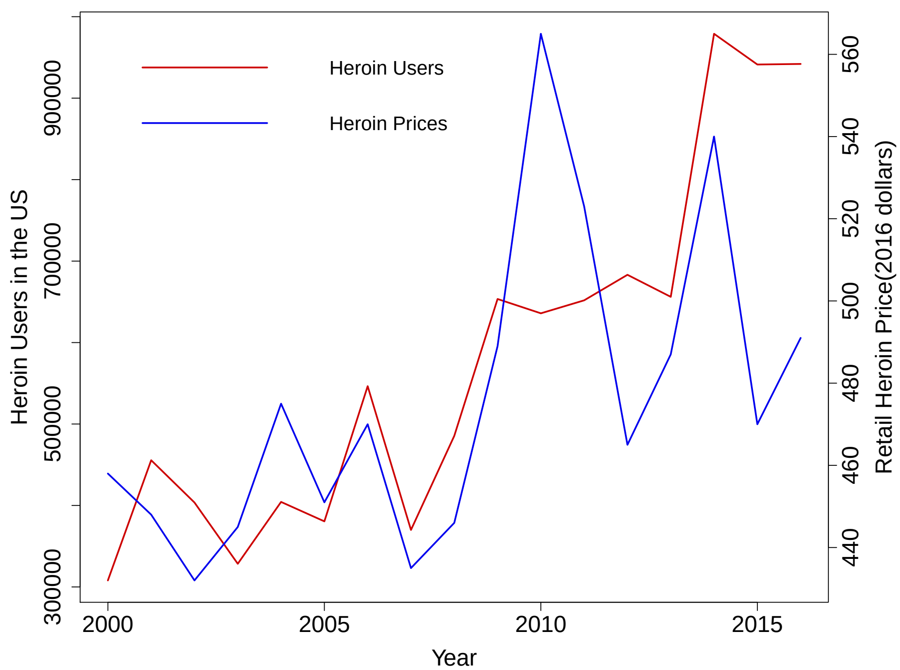
Figure 4: Disappeared or Killed Media Workers between 2004-2016



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 5 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 5: 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. Former Mexican President Felipe Calderón, in office between 2006-2012 from the conservative party PAN, declared war on drugs in 2006. The main government strategy was to behead criminal organizations by targeting high rank kingpings. This strategy generated a lot of instability inside the cartels which led to more violence (Jones 2013; Calderón et al. 2015; Phillips 2015; Signoret 2018). Despite this being true for the overall trend in violence, none of the strategies of the government will generate entry to suitable municipalities to grow opium poppy or a sharp shift in the heroin market around 2010. To address any possible concern regarding government enforcement 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 marijuana legalization across the United States. Even though, medicinal marijuana has been legal in some states since the mid-1990s, the legalization of recreational marijuana started in 2012. This does not seem to be a big problem and in any case 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.

5 Entry, Exit and Violence

5.1 Econometric Specification

This section provides evidence of the relationship between cartel entry, exit and the homicide rate. I use an event study specification that exploits heterogeneity on the time of entry and exit across municipalities. The relevant event of study is the entry or exit of the cartels. The relationship between the number of cartels and violence is not obvious. The presence of illegal activities does not necessarily breeds violence.Snyder and Duran-Martinez (2009) and Castillo and Kronick (2019) show that the ability to reach peaceful agreements to share profits between criminal organizations relies on how strong national institutions are. Mexico during this period of time lacked such conditions so I expect to see the criminal organizations fighting over potential profits. [39]

The main econometric specification used in this section is the following one:

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

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 β_{-1} to zero. I control for a vector of municipality

[39]Snyder and Duran-Martinez (2009) and Castillo and Kronick (2019) argue that the government plays a key element on how criminal organizations react to increasing profits. The none linearities between the number of active cartels and the homicide rate are probably related to government action. Incorporating these effects beyond political party and military and police presence are left for further research.

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 of 500Km.

5.2 Results

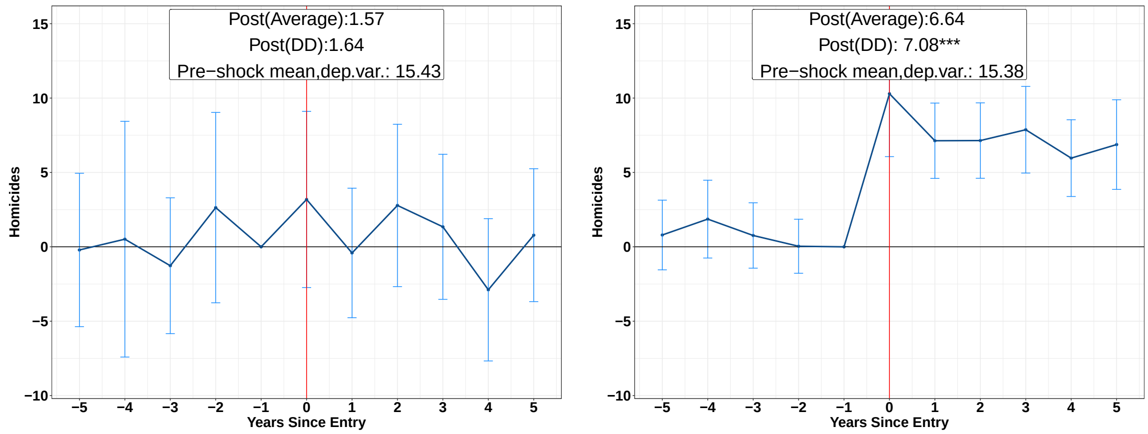
This section shows three main results. First, the presence of a single cartel does not increases violence. Second, there seems to be a non linear relationship between the number of cartels and the increase in the homicide rate. Last, the only significant effect from the exit is when a municipality goes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

Figure 6a 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 (Brazil) 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 6b shows that when a municipality goes from one to two cartels the homicide rate per 100,000 inhabitants increases by 7 homicides. The increase peaks at the year the second cartel enters and stays above pre-entry levels for the next five years. The entry of the third and fourth cartel increase the homicide rate by 13 homicides each one.

From Figure 7a there is an sharp increase the year the third cartel enters and the number of homicides remain high for the next five years. Figure 7b 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 8a shows that the biggest increase in the homicide rate occurs the year after the

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



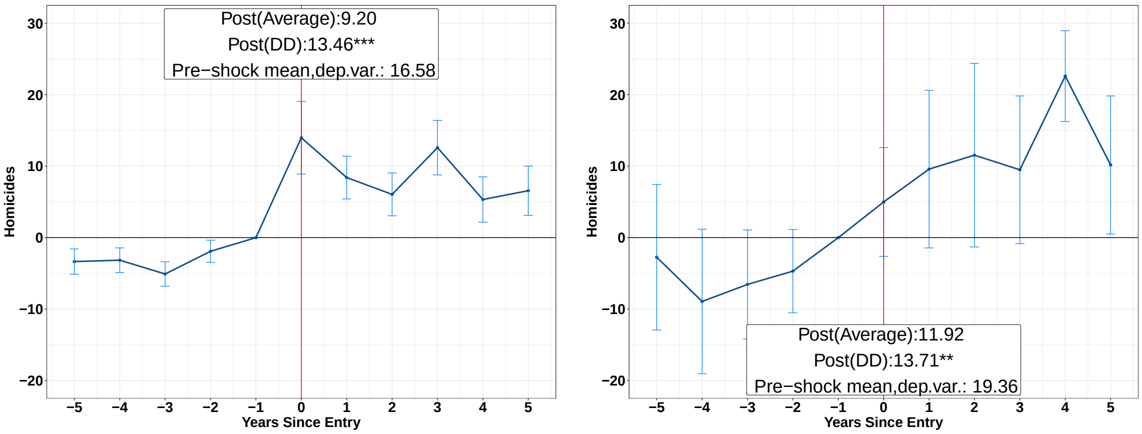
(a) First Cartel Entry

(b) Second Cartel Entry

Figure 6: Cartel Entry[40]

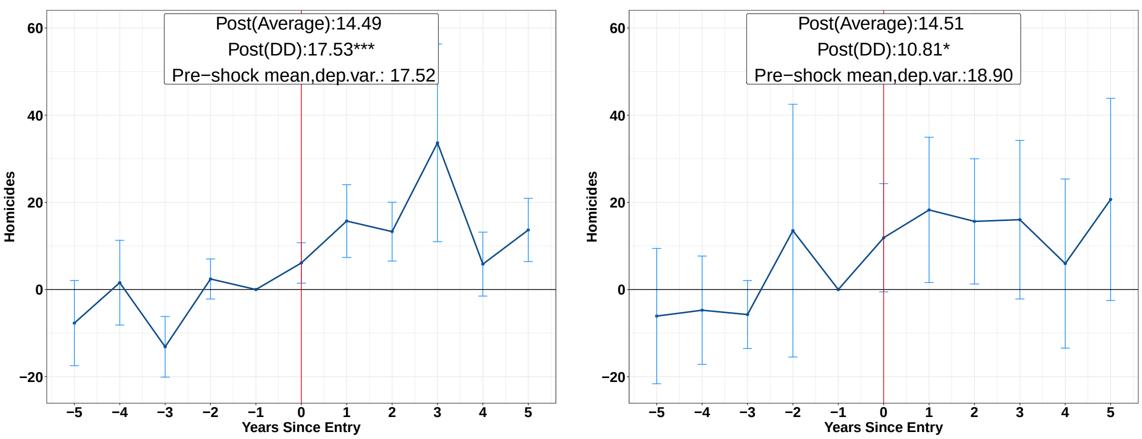
fifth cartel enters and not simultaneously with the entry. There is not as sharp an increase as there is for the entry of the second and third cartel. The coefficients are increasing and then get noisier. The entry of the sixth cartel increases the homicide rate by 10 extra homicides. There is not significant effect after the sixth cartel, but the number of municipalities with more than 6 cartels is only 14. These sets of results are robust to including controls for police presence, military presence, political party, baseline trends and state specific linear time trends. The tables that show the difference-in-difference coefficients from specification (2) can be found in the Appendix A.6.2.

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 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.



(a) Third Cartel Entry (b) Fourth Cartel Entry

Figure 7: Cartel Entry



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

Figure 8: Cartel Entry

Figure 9: Effect of one cartel exit in a municipality with two previously present cartels

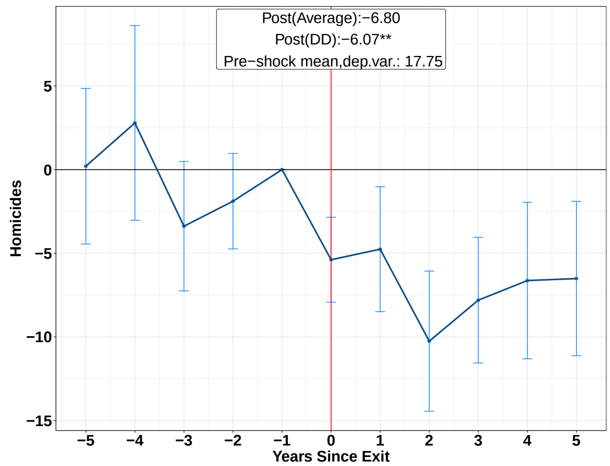
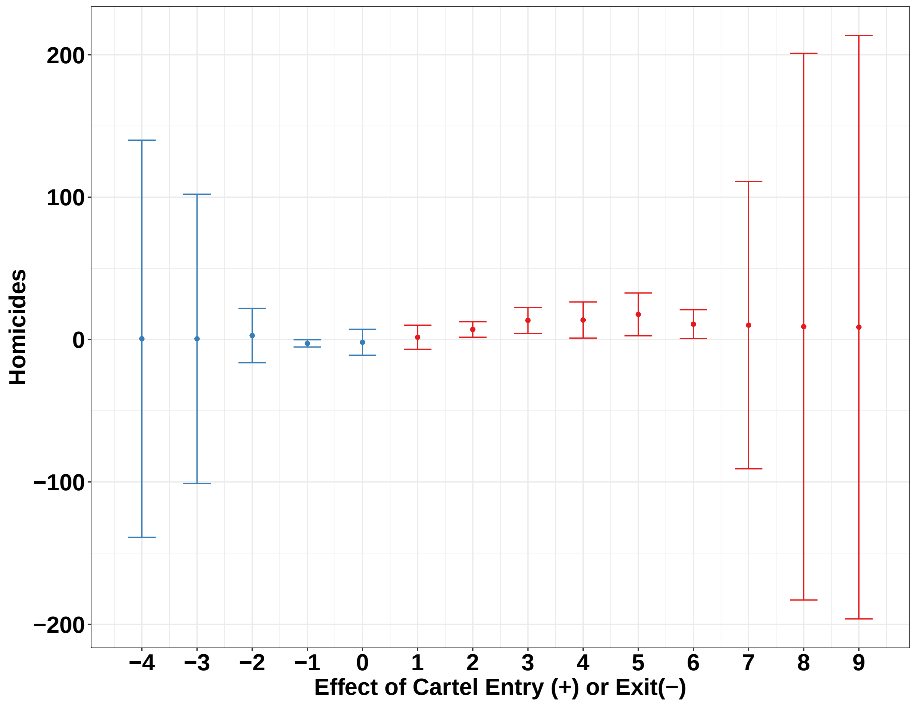


Figure 10 shows the difference-in-difference coefficients from equation (2) but with the event time year dummies replace by a dummy variable $PostEvent_{mt}$ using just municipality and calendar year fixed effects. The coefficients and error bars in red, show the effects of the entry of the first, second and so on up to the ninth cartel entry. 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 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.

Figure 10: Entry and Exit of Cartels

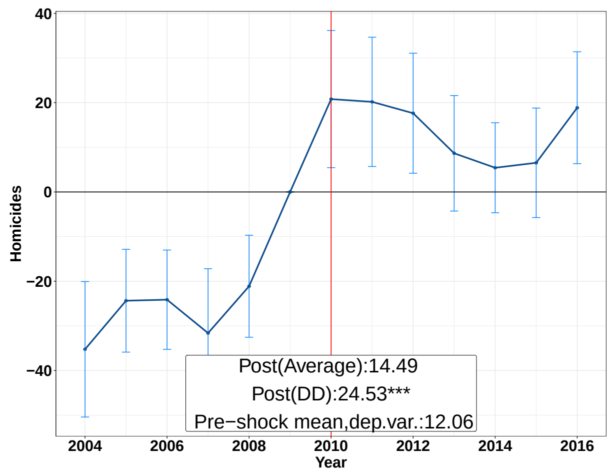


5.3 Effect of Demand Shock on Homicides, Migration, and Household Characteristics

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 100,000 inhabitants. A high-suitable municipality will have a homicide rate with 24 more homicides than a non-suitable municipality. Table 3 shows the results for the 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.

Figure 11: Homicides per 100,000 inhabitants



Change in Demographics: This section analyses the effect of the shock on different demographic outcomes. First, I estimate the effect of the shock on the population and households composition. The variables used are log of the population, mean years of education, and percentage of households with women as the head of the household.[41] The second set of variables 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 with access to basic services (water, electricity and sewer).[42] Figure 12a shows an steady decrease in the log of the population after 2010 and Figure 12b has a similar steady decrease in the average years of education. Figure 13, shows an increasing share of households with women as the head of the household. 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.6.3. To understand the magnitude of these coefficients I will compared a municipality in the 75 percentile with one in the 25 percentile of suitability, when heroin prices double in the United States. A municipality

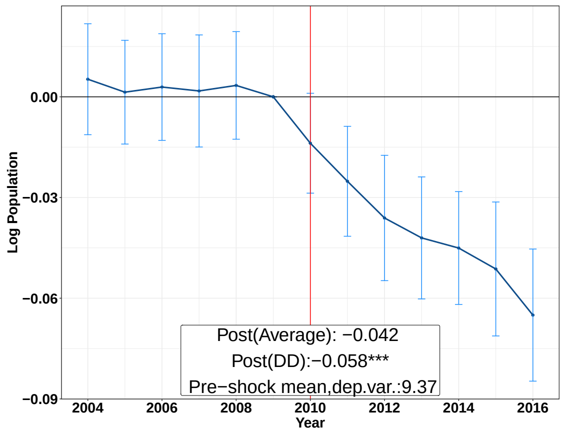
[41]The other variables analyzed are percentage of indigenous population, percentage of people with social security, adult illiteracy, and the mean number of occupants per dwelling. These four variables do not show significant changes during the time of the analysis.

[42]The other variables 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.

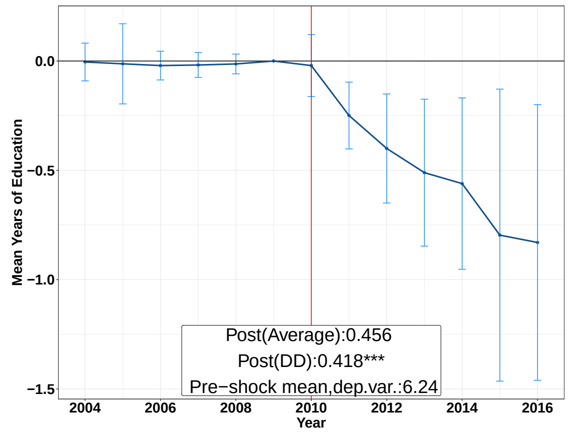
Table 3: Homicides per 100,000

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

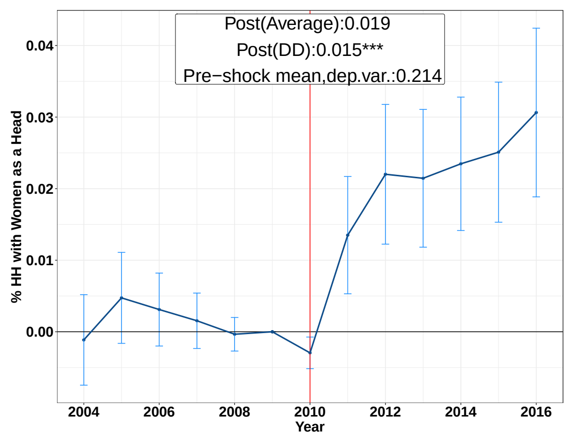


(a) Log of Population



(b) Mean Years of Education

Figure 12: Demographic outcomes

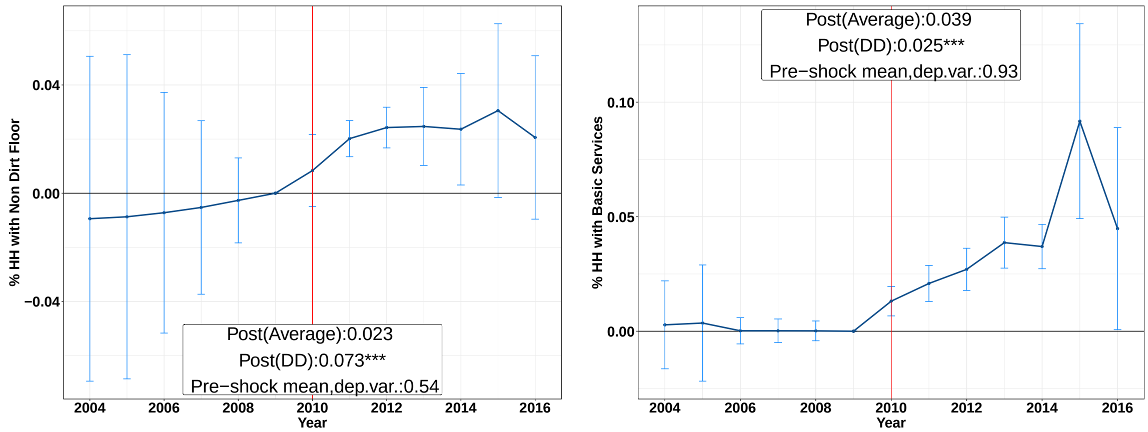


(a) Percentage of households with women as a head

Figure 13: Demographic outcomes

in the 75 percentile of suitability will have a 2.7% decrease in the log of population and a 19.58% decrease in the mean years of education compare to a municipality in the 25 percentile of suitability. The percentage of households with a women as a head will be 0.7% higher after the shock in the 75 municipality compare to one in the 15 percentile 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 14a there was an increase in the percentage of houses that had floors made of materials different from dirt. Figure 14b shows a steady



(a) Households with Non Dirt Floor

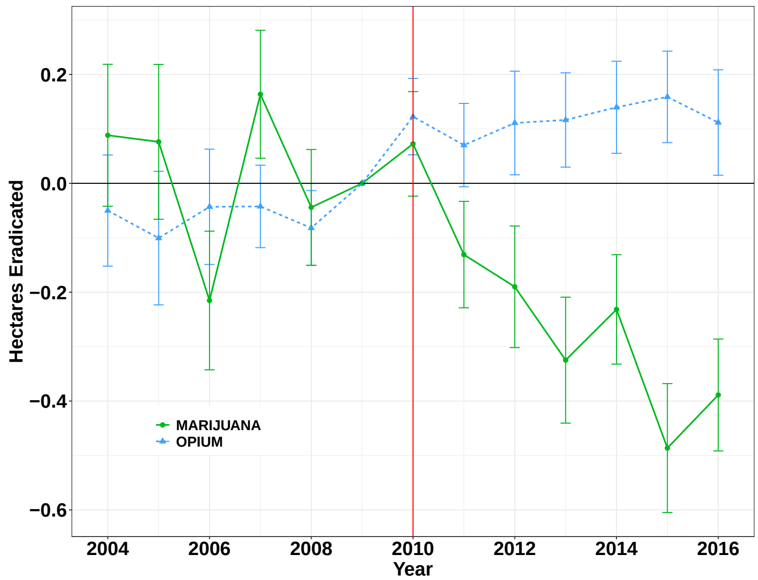
(b) Households with Basic Services (water/sewer/electricity)

Figure 14: Economic outcomes

increase in the percentage of households with basic services. 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 3.4% higher in a municipality in the 75 percentile compare with one in the 25 percentile of suitability when the prices of heroin in the United States double. The percentage of households with basic services will increase by 1.17% in a 75 percentile municipality compared to one in the 25 percentile one. The difference-in-difference coefficients for the different specifications can be found in Appendix A.6.3. These results suggest that there was an income boost from the increase in heroin prices and that it is probably increasing the quality of the houses of the poorest members of these communities. These results are in line with anecdotal 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 (2015).

Military Eradication: In this section I use the eradication data from the Mexican military to explore if the shock affected the amounts of opium and marijuana seized. 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.[43]

Figure 15: Log of Hectares eradicated



6 Cartel Competition and Concentration in the Heroin Market

In this section I provide evidence of the expansion of several cartels into the heroin market after the increase demand in the United States. In the background section I already mention that historically Mexico has produced opium and exported it to the United 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 by 2016. The graph also shows that the biggest drop 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

[43] Figures for seizures of cocaine and methampethamines can be found in the Appendix A.6.4.

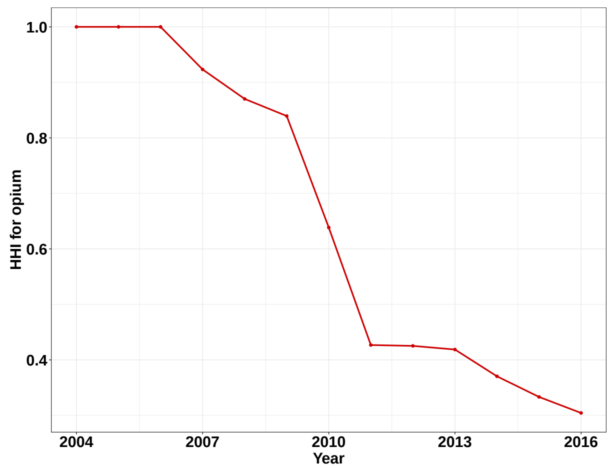
Table 4: Opium and Marijuana Eradication

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

their operations into this market.

Figure 16: HHI Opium



6.1 Identifying Expanding and Competitive Cartels

This paper considers nine main Drug Trafficking Organizations recognized by the Mexican Military and the DEA as the major actors. The interactions between these organizations are complex with them expanding, fragmenting, and disappearing. The last decade saw some of them fragmenting due to the government strategy of capturing kingpings. These strategies left power gaps that lead to internal disputes in these organizations Phillips (2015). Less explored is fragmentation due to market pressures. The increase in the market value of certain territories might incentivize drug traffickers to break from their main organizations or stop previously pacific agreements with former allies to capture higher market shares. Around the time of the shock the Jalisco New Generation Cartel split from the Sinaloa Cartel InSightCrime (2019) and took some of its former parent organization's territory suitable for growing opium poppy. The second fragmentation that happened was the Knights Templar 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.

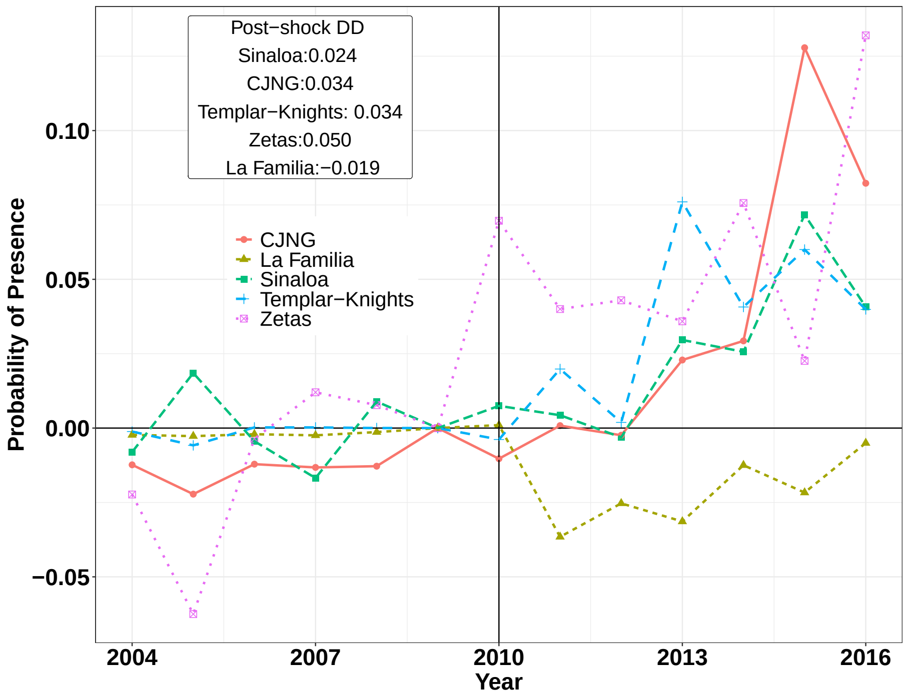
Econometric Specification:

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

where Y^c_{mt} is the probability of having the cartel c active in municipality m and time t. $Suit_m$ is the measure of suitability in the municipality m, $PriceHer_t$ is the retail price of heroin in the United States per milligram of heroin adjust by purity normalized to 2002 prices, 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 mayor 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 cartel c 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.6.5. 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 Organization 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 to this other four cartels and the coefficients can be found in Appendix A.6.5. These results suggests that market pressures can also lead criminal organizations to split and fight with previous allies to get control of valuable territory.

Figure 17: Effect of Demand Shock on Individual Cartel Entry



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 dimensions, 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 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 replicated 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.

More generally, this paper provides evidence of how the market structure of organized criminal activities determines the amount of violence, motivating future research on understanding their structure, competition practices, and relationships with the legal economy.

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A Appendix

A.1 Background

A.1.1 Drug Trade in Mexico

Mexico's location has made it a key country for 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.[44] 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 Ángel Félix

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

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 party PRI was in power. During the late 1980s the 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). Violence between several organizations escalated quickly to levels not seen before.

A.1.2 The War on Drugs

Former Mexican President Felipe Calderón, 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 Michoacán, 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; Phillips 2015; Signoret 2018). This strategy has led to cartel fragmentation, when the main kingpin is either detained or killed. This leaves 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 organizations.

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.[45] The War on Drugs led to a

[45] Feuer (December 2018)

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.

A.1.3 Mexican Cartels

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 García-Ábrego in 1996, the cartel kingpin, 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 to control 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 Félix Gallardo was arrested in 1989 he divided his former territory and gave it to former allies. His nephews the Arellano-Félix brothers got Tijuana. The cartel was in constant turf with the Sinaloa Cartel for the control of the border crossing in the city of Tijuana. By 2013, all the Arellano-Félix brothers were death or in prison. Enedina, the last Arellano-Félix 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 regain control of the city.

The Sinaloa Cartel: described as the largest and most powerful criminal organization in the Western Hemisphere. Joaquín, 'El Chapo' Guzman a former employee of the Gudalajara Cartel kept the Sinaloa territory after Félix 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's extradition the Sinaloa Cartel has remained one of Mexico's most powerful criminal organizations.

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 finances 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.

A.2 Using Google News and Natural Language Processing to Create a Dataset of 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.[46]

  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

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

(a) Example 1

(b) Example 2

Figure A.1: Web Pages Examples

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 A.1a 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 A.1b 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 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[47] 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 then use 4,000 as the training set and 1,000 as the test set. 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

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

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 classification accuracy of 0.86, 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.

- Alternative to using a CNN I could have used a bag of words algorithm to generate this data set. One main reason not to do this is because in the context of Drug Trafficking Organizations in Mexico context and meaning is key. There are several municipalities with the same name, drug dealers, politicians and military officers that share last name with the name of a municipality, and also DTOs, states, and municipalities that share the same name. To provide evidence that the CNN performs better than a bag of words algorithm I use the same train and test set as in the CNN to train a bag of words using a logistic classifier. The out of sample classification accuracy of this algorithm is 0.63 compare to the out of sample accuracy of the CNN 0.86. The accuracy goes down which was expected but in order to know how good it is at overall predicting cartel presence I compare this alternative data set with the same data sets used to validate the CNN one. The correlation between the bag of words data set and Coscia and Rios (2017) data goes down to 0.26, the correlation with the data sets created by Professor Victor Sanchez goes down to 0.41, and the correlation between this data and the DEA aggregate data at the state levels decreases to 0.14. This gives me confidence that the CNN and that including more complex mechanism of classifying sentences is a good idea specially in cases like this where context and meaning seem particularly relevant to correctly classify an article.

- Table A.1 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 A.2 shows the summary statistics for this data set between 2004 and 2016, the time period used for this paper. Active is a dummy that is one if there is at least one cartel active that year in the municipality. Competitive is another dummy that is one when there are at least two cartels active in a municipality.

Table A.1: 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 A.2: 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.3 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.[48]
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 $\lambda = 0.076$. Here α is the

[48] 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.4 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 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:

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

Symmetric equilibria will imply $M_i = M^*$ for all i so that equation (A.1) becomes:

$$\eta\left[\frac{N-1}{N}\right] = \frac{M^*}{R} \tag{A.2}$$

Two additional conditions most be satisfied at equilibrium. First, equation (A.1) 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:

$$\eta(N-1)[N(\eta-1)+2\eta] < 0 \tag{A.3}$$

Equation (A.3) 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 (A.2) the profits being positive can be rewritten as $N(\eta-1) - \eta \leq 0$. Rearranging this equation:

$$N \leq \frac{\eta}{\eta - 1} \tag{A.4}$$

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

A.5 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 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.

$$Y_{it} = \beta C_{it}^d + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_s t + \epsilon_{mt} \tag{A.5}$$

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 A.3 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 A.3: 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	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the results from regressiong the number of disappeared or killed media workers on the presence of the nine cartels. Significant at $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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 0.17. 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 0.13. This results and the map show in the threats to identification section provides evidence that despite the fact that is dangerous for the reporters to inform on drug cartels, there does not seem to be a particulae 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.6 Robustness checks

A.6.1 Cartel Activity

Table A.4 shows 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. Standard errors are clustered here at the municipality level. 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.

A.6.2 Cartel Entry and Exit

The next tables A.5, A.6, A.7, and A.8 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

Table A.4: The effect of the reformulation on cartel activity

	Cartel Activity									
	Competitive					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***
	(0.02)	(0.021)	(.018)	(.017)	(0.017)	(0.072)	(0.075)	(.058)	(0.057)	(0.061)
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					✓					✓

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) and (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered by municipality. Significant at $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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 A.5 to A.7 present the entry events and Table A.8 present the exit ones.

Table A.5: 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 A.6: 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

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 decreases with 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 a cartel when there are more than three organizations in a municipality.

Table A.7: 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 A.8: 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.6.3 The effect of the shock in socioeconomic outcomes

Tables A.9 to A.11 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 A.9, log of the population and mean years of education. Table A.10, percentage of households with a woman as the head. Finally, Table A.11 the percentage of households without dirt floor and the percentage of household with access to basic services (electricity, water, and sewage). Columns (1) and (6) present the results with municipality and year fixed effects. Columns (2) and (7) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (8) control for baseline characteristics interacted by year such as population, drug activity in 2000, and marginalization rate. Columns (4) and (9) add to the baseline trends, the set of controls from Column (2) and (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The results for all the other outcomes that did not change significantly during this period are available upon request. The results in the main part of the paper are robust to all the controls and fixed effects added in here.

Table A.9: Population and Education

	Demographics:									
	log(population)					Years of Education				
Post2010	-0.058^{***}	-0.014^{***}	-0.069^{***}	-0.026^{**}	-0.040^{***}	-0.418^{***}	-0.815^{***}	-0.085^{*}	-0.111^{**}	-0.366^{***}
	(0.0001)	(0.004)	(0.013)	(0.012)	(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

A.6.4 Military Seizures

Throughout the whole paper I argue that is the expansion of the demand for heroin led to cartel entry and subsequence violence. In order to rule out other drugs expanding at the same time or in the same municipalities as opium poppy I use specification (1) for the amount of kilograms of cocaine and methampethamines seized by the Mexican military. There does not seem to be any increase in the seizures of any of these two drugs in suitable municipalities to grow opium poppy and there is also not an effect after 2010. Figure A.2 shows the coefficients from the event study specification, the quantity of cocaine and

Table A.10: Women as Head of Household

	Demographics:				
	% Women Head of Households				
Post2010	0.015***	0.011*	0.011*	0.010**	0.021***
	(0.002)	(0.005)	(0.005)	(0.005)	(0.006)
Observations	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
Municipalities FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Covariates		✓		✓	✓
Baseline trends			✓	✓	✓
State trends					✓

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

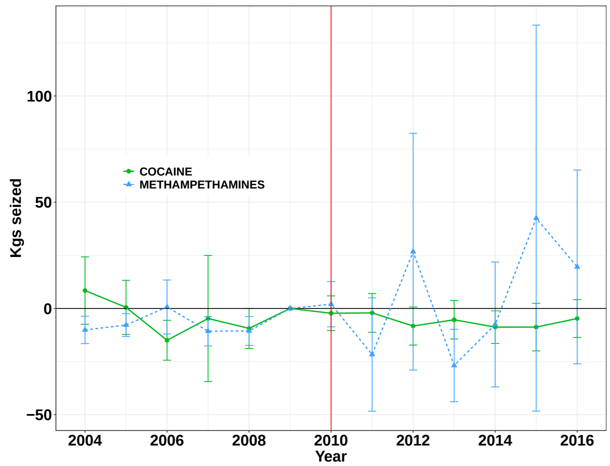
Table A.11: No-Dirt Floor and No-Basic Services

	Economic outcomes:									
	% without Dirt Floor					% of Households with basic Services				
Post2010	0.073***	0.038*	0.081***	0.081***	0.056***	0.025***	0.014*	0.021**	0.013**	0.015***
	(0.009)	(0.017)	(0.013)	(0.013)	(0.016)	(0.000)	(0.008)	(0.008)	(0.002)	(0.001)
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	0.93	0.93	0.93	0.93	0.93
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓	✓		✓		✓	✓
Baseline trends			✓	✓	✓			✓	✓	✓
State trends					✓					✓

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

methampethamines is constant and not affected by how suitable a municipality is. This provides evidence that the increase in cartel entry into high-suitable municipalities after 2010 is entirely related to the shift in the heroin market and not to any other drug market.

Figure A.2: Kilograms seized by the Mexican military



A.6.5 Cartel Competition

The next tables A.12 to A.16 show the coefficients for equation (1) but with the event time year dummies replaced by a dummy variable $PostShock_{mt}$ interacted with the suitability index and the heroin price in the United States. The relevant event is again the 2010 OxyContin reformulation. Each table presents the difference-in-difference model for two dependent variables. The dependent variables are dummies for cartel presence of each of the nine major organizations. Columns (1) and (6) present the results with municipality and year fixed effects.Columns (2) and (7) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (8) control for baseline characteristics interacted by year such as population, drug activity in 2000 and marginalization rate. Columns (4) and (9) add to the baseline trends, the set of controls from Column (2) and (7). Columns (5) and (10) add state specific time trends. Standard errors are clustered using a 500 Km radius. Significant at $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The results for the cartels expanding, entering and shrinking are robust to all the controls and fixed effects. The coefficients for the other four cartels are not significant for all the specifications, but all the coefficients are positive across specifications. These results and analysis of entry patterns of the cartels suggest that all of them except for La Familia expanded into territory well-suited to cultivate opium poppy. Maps of the evolution of each cartel are available upon request.

Table A.12: 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 A.13: Templar-Knights and La Familia Michoacana

	Cartel Activity by Cartel									
	Knights Templar 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 A.14: 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 A.15: 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 A.16: Tijuana and Gulf Cartels

	Cartel Activity by Cartel									
	Tijuana Cartel					Gulf 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