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ESSAYS IN COMPETITION IN THE MEXICAN ECONOMY: FROM TELECOMMUNICATIONS TO HEROIN

Sobrino Macias, Maria Fernanda

Princeton, NJ : Princeton University

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ESSAYS IN COMPETITION IN THE MEXICAN ECONOMY: FROM TELECOMMUNICATIONS TO HEROIN

Maria Fernanda Sobrino Macias

A DISSERTATION

PRESENTED TO THE FACULTY

OF PRINCETON UNIVERSITY

IN CANDIDACY FOR THE DEGREE

OF DOCTOR OF PHILOSOPHY

RECOMMENDED FOR ACCEPTANCE

BY THE DEPARTMENT OF ECONOMICS

ADVISOR: Thomas Fujiwara

SEPTEMBER 2020

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Abstract:

This collection of essays used different policy shocks to investigate their effects on the Mexican economy. The first chapter evaluates the regional impact of an increase in the availability of telecommunications infrastructure. The government made available part of its public network to new entrants to increase competition in the highly concentrated telecommunications sector. The economy is characterized as a model with regional and sectoral linkages. Differently from existing models, it has an oligopolistic sector to match the telecommunications sector in the Mexican economy. I used the model to determine the effect of the shock in employment, gross domestic product, productivity, and the number of entrants in each region. The base economy was calibrated before the actual policy change using different data sets. This calibration allows me to shock the economy with different policy changes. Overall the exercise in this chapter shows the relationship between a policy change and the regional effects from it.

Chapters two and three examine the relationship between violence and competition for market shares among Drug Trafficking Organizations (known as cartels). The context for these two chapters is the last two decades in Mexico and the United States. Mexico saw an increase in the number of major drug cartels from four to nine, which was accompanied by an increase in drug-related violence. Meanwhile, in the U.S., the demand and supply of legal opioids increased, leading to some people to abuse them. In 2010 the FDA approved the reformulation of one of the most abused opioids, which led some abusers to switch to its illegal counterpart, heroin. I exploit different empirical strategies using within municipality variation. The results from the last two chapters suggest that substantial part of the increase in violence that Mexico experienced in the last fifteen years was due to criminal organizations fighting for market shares of heroin, not only due to changes in government enforcement strategies.

Acknowledgments:

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

For my parents

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Chapter 1

Market structure regional effects: The telecommunications sector in Mexico

1.1 Introduction

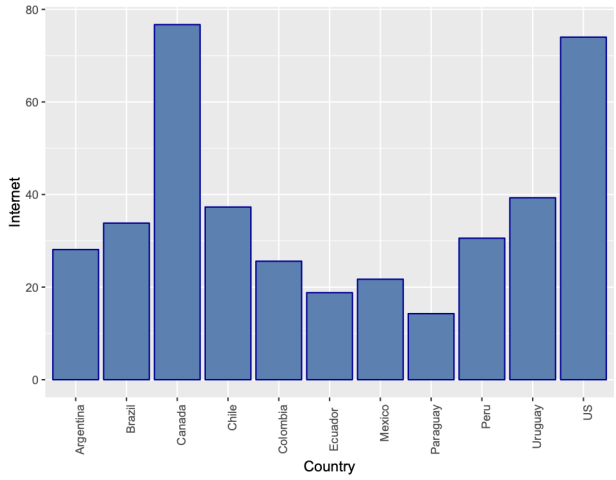
Telecommunications infrastructure is a significant driver for research, innovation, and growth. Greenstein and Spiller (1996) find empirical evidence that information infrastructure[1] yields high economic returns. Meanwhile, Roller and Waverman (2001) provide evidence that there is a positive and significant link between telecommunications infrastructure and economic development. Telecommunication infrastructure generates spillovers and positive externalities across sectors. The importance of quality and availability of information technology grows every day, with more and more sectors needing this kind of service. Therefore, the relevance of these technologies for the economy.

The global telecommunications revenue as a percentage of global GDP has been growing since 2000; it went from around 1.89% in 2000 to 4% of global GDP by 2012.[2]

[1] I will use telecommunications infrastructure and information infrastructure as interchangeable in this chapter.

[2] Data from The World Bank.

Figure 1.1: Internet Penetration in America 2008



The fast growth of the sector, plus the existence of high entry fixed costs has driven governments to intervene in the market. These interventions aim to make the sector more efficient and competitive. In most counties, there have been movements toward the liberalization and privatization of the sector. Mostly big, inefficient incumbents unwilling to reduce fixed costs motivated these reforms.

Mexico exhibits an exciting telecommunications sector to be studied. The sector was originally a public monopoly until the government sold it to a private company that was warrantee to be the single provider. The OECD (2010) describes the telecommunications sector in Mexico as inefficient and uncompetitive. The inefficiency comes from the lack of competition, which leads to high prices, low market penetration, and insufficient infrastructure. Figure 1.1 shows internet penetration in the region in 2008; Mexico was one of the lowest.

The Mexican government decided in 2009 to auction part of their optic fiber network. This auction would allow possible entrants to the telecommunication sectors to pay lower access costs increasing competition in the sector. The network auction by the government consisted of 20,148 Km of black fiber in three different routes that covered 50% of the population. Before the availability of this fiber, an entrant willing to access the market had two options to enter the market. Either, building

a new network and doubling the existing infrastructure, or renting everything from the incumbent. The incumbent had the only national network, which led to a lack of competition in the sector. The consequences of a monopolistic provider of backbone resulted in a low entry, low broadband penetration, and low quality and high prices to the consumers.

To study how this heterogeneous shock affected the different regions in the country, I built on Caliendo et al. (2017) regional model. The only difference between the model presented here and the original one is the telecommunication sector. In order to capture the market structure observed in the sector, this industry will be an oligopoly competing in quantities. I used available data from the Mexican government to calibrate the model and built a base model. Then, I ran two different counterfactuals from alternative policy changes.

The first shock is the auction of the dark fiber. This shock is heterogeneous because the three different fiber routes did not cover the whole country. The percentage of the population exposed to the new networks was different across states. How much each region is affected by the new infrastructure will depend on its particular sectoral composition. Input-output relationships, local factors, migration, and trade will determine the impact of the shock in the regional equilibrium. The model does a good job at matching the number of new entrants that each state will have both before and after the shock. After the shock, the most exposed regions in terms of their population and the states with low competition will see bigger increases in their GDP and TFP. The states that were not at all exposed to the new infrastructure see outmigration and lower productivity and gross product.

The second shock is a homogeneous one across all the regions. This shock simulates what would have happened if all the regions had access to the same infrastructure. In the particular case of the telecommunications sector, this means a decrease in entry costs in every state. The effects of this shock are different from the effects of

the heterogeneous one. The increases in welfare, GDP, and productivity are bigger for the second shock. The states that see the increase also differ from the ones in the first shock. States with big shares of land and structures and with concentrated markets before the shock will see the biggest increase in all their outcomes. Poor and already competitive states will experience outmigration and a decrease in their GDP and TFP.

The rest of the paper is organized as follows. The next subsection is a short explanation of the telecommunications sector in Mexico. The second section describes the quantitative model. The third section describes in detail the data used to calibrate the model and how well the base model describes the base year 2008. Section fourth presents the actual policy change and fictional policy intervention where the government decides to auction the whole network. Section 5 concludes.

1.1.1 The telecommunication sector in Mexico

The telecommunications sector in Mexico was a public monopoly until 1989. In 1990 the government sold Telmex to a private agent with the license to operate, build and exploit the public network for 50 years. The government and the new firm signed a contract that established that the government would not give any license to operate in the sector for the first six years. This contract imposed asymmetric conditions for any potential entrant to the sector. The initial conditions set by this first contract left Telmex with a considerable advantage over any potential entrant.

In 1993 Mexico signed NAFTA; this agreement included a section on the telecommunications sector. The agreement explicitly binds the parties to increase competition in the telecommunications sector. The Mexican government slowly complied with this agreement through the Federal Law of Telecommunications(LFT). This law established the liberalization of the fixed-line telephony, both for local and long-distance calls. The LFT opened the sector to competition; interconnection between

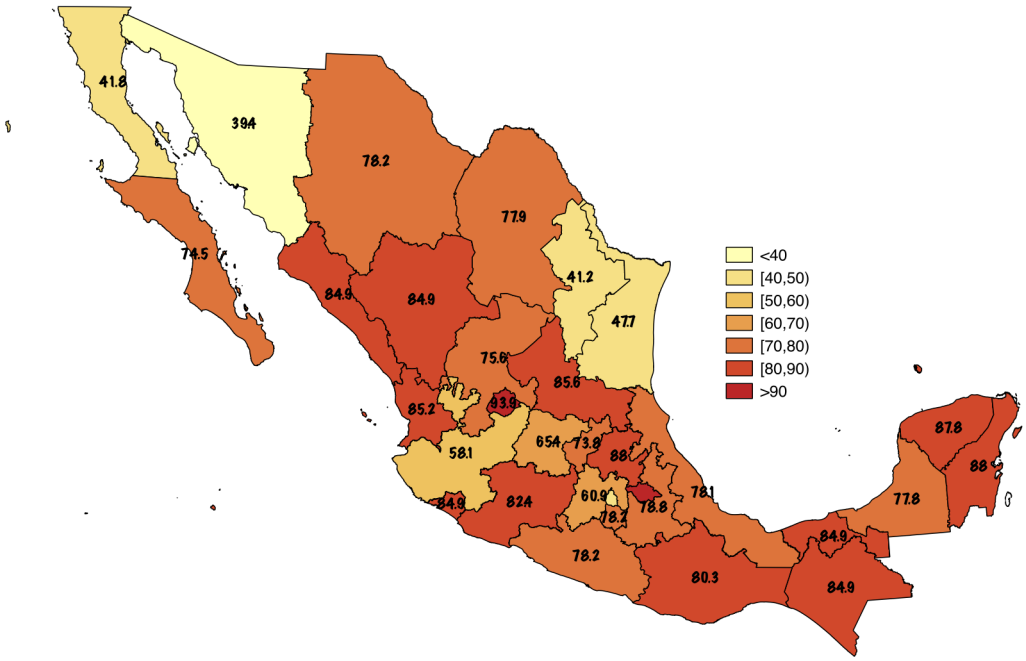
different operators became compulsory, and the government regulated network rates for companies with substantial market power for the first time.

Despite the government efforts to increase competition, the law was not very effective at achieving this. Telmex first-mover advantage was too hard to overcome by possible entrants. Firms willing to enter the market needed to decide whether they build an entirely new network or rented the existing infrastructure from the incumbent. The incumbent was legally bound to participate in bargains with possible entrants but had the option of never closing a deal. The Mexican government had a second problem in enforcing competition laws. The Mexican system of law gives the option to the incumbent to postpone for years the enforcement of regulations that do not favor it by filling appeals of review and amparo proceedings.

Until 2006 only the government and Telmex owned backbone legally capable of providing telephone and internet services. Cable companies which infrastructure is similar and can be modified to provide fixed telecommunications services were left outside the market by law. In 2006 an agreement was signed that allowed cable companies to rent their infrastructure to possible entrants and to offer bidirectional data services such as internet and fixed telephony. Telmex faced for the first time some competition. The effect was not as significant as the government expected; cable companies did not have a national backbone. They only owned pieces of infrastructure in large cities, so prices were just affected in these metropolitan areas, leaving high prices in all the other parts of the country. Fixed telephony, internet access, and service conditions were still uneven across regions, and even in large cities, prices were high for international standards.

Figure 1.2 shows the incumbent percentage of the market in each state in 2008. As shown in the map, Telmex had at least 40% of market shares across all states. With 14 states with more than 80% of the market owned by Telmex.

Figure 1.2: Market share of Telmex by region



In 2009, the government decided to provide a cheaper way to access the market. The National Commission of Electricity (CFE) owns a national network of dark backbone fiber[3] capable of providing any telecommunication service. The government decided to auction 3 segments of this network, 20,148 km of dark fiber that cover 50.8% of the population. Grupo Televisa (Movistar, Televisa, and Megacable) won the auction and allowed other small providers to rent the infrastructure from them instead than renting to the incumbent. According to the authorities at CFE this auction reduced the cost of entry to the telecommunications market for new firms by 50%. The network did not cover every state, and the percentage of the population of each state that it covers was different across states. This auction is the policy change evaluated below.

[3]Dark backbone fiber is unused optical fiber capable of providing electricity and telecommunications services

1.2 A Spatial Equilibrium Model with one Oligopolistic Sector

The main objective of this chapter is to explain the effect of a policy change in an oligopolistic sector in all the other sectors of the economy. The model also explains the effects across regions. As such, the model follows the one built by Caliendo et al. (2017). The main difference between their model and the one presented here is the addition of an oligopolistic sector.

The model is a two factor static model with N regions and J sectors. A particular region is denoted by $n \in \{1, ..., N\}$ and a particular sector by $j \in \{1, ..., J\}$. The first $J-1$ sectors operate under perfect competition while the last one J is an oligopolistic sector.

The economy has two factors of production; labor and a composite factor that includes land and structures. Workers can freely move across regions. Land and Structures H_n are a fixed endowment of a particular region n and can be use by any sector in the economy. Total population is L and each region has a population of L_n. There are two different kinds of goods in the economy; tradable and non-tradable. The tradable goods can be traded across regions. The model abstracts to any international trade or migration.

1.2.1 Consumers

Consumers in each region n have Cobb-Douglas preference over final goods, the representative consumer in region n solves

$$max \prod_j (c_n^j)^{\alpha_j} \quad s.t \quad \sum_{j=1}^{J} P_n^j c_n^j \leq I_n \tag{1.1}$$

where α^j are the shares of final domestic consumption and P_n^j are the prices of the final goods in region n and sector j. The free mobility condition of the agents implies that in equilibrium they are indifferent to regions. Which means that total utility will be given by

$$U = \frac{I_n}{P_n} \quad \forall n \in \{1, ..., N\} \tag{1.2}$$

I_n, is the income in region n and $P_n = \prod_{j=1}^{J} \frac{P_n^j}{\alpha^j}^{\alpha^j}$ is the price index in region n.

1.2.2 Income

Income for an agent that lives in region n is the sum of returns to land and structures, returns to labor, and the shares of the oligopoly profits. Each region gets the whole returns to its own land and structures. The oligopoly profits are added up and then evenly split across the population. Then, the per-capita income in region n can be expressed as follows:

$$I_n = \frac{r_n H_n}{L_n} + \omega_n + \Lambda \tag{1.3}$$

Where ω_n is the wage and r_n is the rental rate of land and structures, and $\frac{r_n H_n}{L_n}$ is the per capita income from renting land and structures to firms in region n. The term Λ represents the share oligopolistic profits assigned to each agent in the economy. In particular, $\Lambda = \frac{\sum_{n=1}^{N} \Pi_n}{\sum_{n=1}^{N} L_i}$ represents the total per capita profit from the oligopoly. Π_n is the profit of the oligopoly in region n and is given by $\Pi_n = \pi_n^I + \sum_{j=1}^{M} \pi_n^{ej}$. Where I denoted the incumbent firm in the region and M are the successful entrants.

The value for an agent that locates in region n is

$$v_n = \frac{r_n H_n / L_n + \omega_n + \Lambda}{P_n} \tag{1.4}$$

where P_n is region n price index described above. Agents can freely move across regions. Hence, $U = v_n$, $\forall n$

1.2.3 Technology

The technology setting follows Eaton and Kortum (2002). Final goods, including the oligopolistic one, are used for consumption and as inputs for producing intermediate goods. Each sector j produces final goods using a continuum of variates of intermediate goods.

Intermediate Goods

Representative firms, in each region n and in each sector $i \in \{1, ..., J-1\}$, the ones operating under perfect competition, produce a continuum of varieties of intermediate goods. Each sector and region has an idiosyncratic productivity z_n^j. This productivity level is a random draw from a Fréchet distribution with shape parameter θ^j and location parameter 1. Draws are independent across goods, sectors, and regions and θ^j just varies across sectors but not regions. The productivity by sector and region is also determined by a fundamental productivity parameter T_n^j specific by sector and region. Each sector $J-1$ is going to produce the continuum of intermediate goods using, labor, land and structures, and final goods as inputs. The production function for a variety associated with idiosyncratic productivity z_n^j in region n and sector j is going to be

$$q_n^j(z_n^j) = z_n^j \left[T_n^j (h_n^j(z_n^j)_n^\beta (l_n^j(z_n^j)^{1-\beta_n}\right]^{\gamma_n^j} \prod_{k=1}^{J} \left[M_n^{jk}(z_n^j)\right]^{\gamma_n^{jk}} \tag{1.5}$$

where h_n^j and l_n^j are the demand for structures and labor in region n and sector j, M_n^{jk} is the demand of final goods by firms in sector j from firms in sector k. $\gamma_n^{jk} \geq 0$ is the share of sector j goods spend on material from sector k and $\gamma_n^j = 1 - \sum_{k=1}^{J} \gamma_n^{jk}$ is the share of value added in gross output. This assumes that the production function has constant returns to scale.

The minimization problem for an intermediate goods firm will imply that the input cost in region n and sector j can be expressed as

$$x_n^j = A_n^j \left[r_n^{\beta_n} w_n^{1-\beta_n}\right]^{\gamma_n^j} \prod_{k=1}^{J} \left[P_n^k\right]^{\gamma_n^{jk}} \tag{1.6}$$

where $A_n^j = \left[\gamma_n^j (1-\beta_n)^{1-\beta_n} \beta_n^{\beta_n}\right]^{-\gamma_n^{jk}} \prod_{k=1}^{J} [\gamma_n^{jk}]^{-\gamma_n^{jk}}$. The unit cost for a firm in region n and sector j with idiosyncratic shock z_n^j.

$$cost_n^j(z_n^j) = \frac{x_n^j}{z_n^j [T_n^j]^{\gamma_n^j}} \tag{1.7}$$

Then, firms in region n will decide to produce the variety given by the productivity draw z_n^j as long as its price is greater or equal to $cost_n^j(z_n^j)$. Given that the intermediate goods market is competitive, then firms that produce a given variety will price it equal to its $cost_n^j(z_n^j)$.

Final Competitive Goods

Final goods in region n and sector $j \in \{1, ..., N-1\}$ are produced by combining intermediate goods from each competitive sector. The quantity of final goods in region n and sector j will be Q_n^j and the quantity demanded of an intermediate good of a particular variety is $\tilde{q}_n^j(z^j)$. Here $z^j = (z_1^j, ..., z_N^j)$ is the particular vector of productivities for sector j across all regions.

The demand for a given variety will be given by

$$Q_n^j = \left[\int \tilde{q}_n^j(z^j)^{1-\frac{1}{\eta_n^j}} \phi^j(z^j) dz^j\right]^{\frac{\eta_n^j}{\eta_n^j - 1}} \tag{1.8}$$

where the joint density of the idiosyncratic shocks ,z^j, is $\phi^j(z^j) = exp\{-\sum_{n=1}^{N} (z_n^j)^{-\theta^j}\}$, with marginal densities given by $\phi_n^j(z_n^j) = exp\{-(z_n^j)^{-\theta^j}\}$ and the integral is over all

the positive real numbers of dimension N. The non-tradable goods only care about the density $\phi_n^j(z_n^j)$ since they can only used locally produced goods. For each of these sectors, $j \in \{1, ..., N\}$ there is a free entry condition that implies that profits are zero.

Demand for each variety is going to be

$$\tilde{q}_n^j = \left[\frac{p_n^j(z^j)}{P_n^j}\right]^{-\gamma_n^j} Q_n^j \tag{1.9}$$

and the price index for sector j in region n can be expressed as follows

$$P_n = \left[\int p_n^j(z^j)^{1-\eta_n^j} \phi^j(z^j) dz^j\right]^{\frac{1}{1-\eta_n^j}} \tag{1.10}$$

Oligopolistic Sector

There is going to be an oligopolistic sector that produces a final good. In particular, the telecommunications sector will be described as one operating under an oligopoly. In each region n there will be an incumbent and N_n possible entrants to this sector.

The players in this sector are going to decide whether to enter the sector or not and then how much they need to produce. In the first stage, the possible entrants decide whether to enter or not. If they decide to enter a particular region n, they need to pay a fixed cost a_n to the incumbent. A firm willing to enter the telecommunications market can do it though three channels. First, build its own infrastructure which implies a big sunk cost and duplication of structures. The second and third are by renting the incumbent infrastructure. The difference between these two types of entry is that the entrant can decide to rent just the network and build its own modems and switches or rent the whole infrastructure Laffont and Tirole (2001).

The game describe here will consider one type of entry: the entrants rent part of the infrastructure from the incumbent and build the remaining infrastructure. The possibility of entrants to duplicate the infrastructure is left out given the Mexican

context between 2006 and 2010. There is not any evidence of any entrant building a new backbone across the country or in any particular region.

The access cost that an entrant to region n will pay is $r_n a_n$, note that this is pay in structures units. I will consider the access fee as a sunk cost rather than a per unit of bandwidth, the different marginal costs will account for the different per bandwidth costs.

In the second stage, after an entrant decided to enter and already pay the access fee they will draw a marginal cost $c_n^i$from a uniform distribution. The only assumption about these marginal costs is that $c_n^i > c_n^I$, where c_n^I is the marginal cost of the incumbent. After M, entrants decide to enter they maximize their profits by choosing the amount of broadband services that they will offer. This will be described as Cournot competition.

The sector as a whole will be price and demand taker. The telecommunication sector is not big enough to affect neither the price index, nor the wages or rents. In the particular case of Mexico, the telecommunications sector represents 3% of the total GDP.

Total demand in region n for the telecommunications sector (T) is going to be

$$\begin{aligned} Q_n^T &= L_n C_n^T + \sum_j \int_0^\infty M_n^{T_j}(z)\phi_n^k(z)dz \\ &= \alpha^T \frac{L_n I_n}{P_n^T} + \sum_j \int_0^\infty \frac{\gamma_n^{jT} p_n^j(z^j) q_n^j(z^j)}{P_n^T} dz \\ &= \frac{1}{P_n^T}\left(\alpha^T L_n I_n + \sum_j \int_0^\infty \gamma_n^{jT} p_n^j(z) q_n^j(z)\right) \\ &\implies Q_n^T = \frac{1}{P_n^T} C_n = q_I + \sum_k q_e^k \end{aligned} \tag{1.11}$$

Where $C_n = \alpha^T L_n I_n + \sum_j \int_0^\infty \gamma_n^{jT} p_n^j(z) q_n^j(z)$ is going to be a constant in equilibrium that only depends on the equilibrium income in region n.

The incumbent maximizes its profits taking as given the demand for telecommuni-

cation services, the number of active entrants, and the quantity supply by each of them. The active entrants also take the demand as given and the incumbent supplied quantity.

The production function for the telecommunications final good has constant returns to scale and uses as inputs labor and land and structures.[4]

$$y_n^T = A_n^{Tt}(h_n^{Tt})_n^{\beta}(l_n^{Tt})^{1-\beta_n} \tag{1.12}$$

where t denotes any active firm in the telecommunications sector in region n. The marginal cost for a particular firm t can be express as

$$c_n^{Tt} = \frac{w_n^{1-\beta_n} r_n^{\beta_n}}{A_n^{Tt}} f(\beta_n) \tag{1.13}$$

with $f(\beta_n) = \left(\frac{1-\beta_n}{\beta_n}\right)^{\beta_n} + \left(\frac{\beta_n}{1-\beta_n}\right)^{1-\beta_n}$.

Firms t in the telecommunications sector solve a two stage game. In the first stage the entrants decide whether to enter or not and then draw their marginal cost.[5] In the second stage, firms choose the quantity they will produce to maximize their profits. Using backwards inductions, the incumbent problem is

$$max \quad P_n^T q_n^i - c_n^I q_n^I + mr_n a_n \equiv max \quad \frac{1}{q_n^I + \sum_k q_n^{ek}} C - c_n^I q_n^i + mr_n a_n$$

The incumbent best response is given by

$$C \sum_k q_n^{ek} = c_n^I \left(q_n^I + \sum_k q_n^{ek} \right)^2 \tag{1.14}$$

[4]The oligopolistic sector would not use any intermediate goods for producing the final good. The telecommunications sector usually just need infrastructure and labor to work and it also facilitates the algebra in the whole chapter.

[5]In this specification picking the marginal cost or the productivity are equivalent because prices are given.

the sum in the last equations is over all the active entrants, denoted by k.

The entrants problem is similar to the incumbent one and can be expressed by

$$max \quad p_n^T q_n^{ek} - c_n^{ek} q_n^{ek} - r_n a_n$$

Then, the best response for every active entrant is

$$C q_n^I + C \sum_{i \neq k} q_n^{ei} = c_n^{ek} \Big(q_n^I + q_n^{ek} + \sum_{i \neq k} q_n^{ei} \Big)^2 \tag{1.15}$$

Each entrant will decide between the profits given by the quantity derived from equation (1.15) and zero.

In the first stage, entrants decide whether to enter or not. Using backward induction the necessary condition for entry is

$$q_n^{ek} \geq \frac{r_n a_n}{P_n^T - c_n^{Tk}} \tag{1.16}$$

As long as an entrant satisfies equation (1.16), entrant k enters the market and produces quantity q_n^{ek}. There is a potential pool of N_n entrants and in equilibrium m of them will enter the market. The set of equations above describe the subgame perfect equilibrium.

The total per capita profit from the oligopoly $\Lambda = \frac{\lambda}{L}$ is described below

$$\lambda = \sum_{n=1}^{N} \Pi_n = \sum_{n=1}^{N} \Big(\pi_n + \sum_{i=1}^{k_n} \pi_n^i \Big) = \sum_{n=1}^{N} \Big(P_n^T Q_n^T - c_n^I q_n^I - \sum_{j=1}^{k_n} c_n^{ej} q_n^{ej} \Big) \tag{1.17}$$

where k_n is the number of active entrants in equilibrium in region n. The access fees cancel out by construction, they are just a transfer between the incumbent and the entrants.

1.2.4 Prices and Regional Trade

All the competitive sectors follow Eaton and Kortum (2002). Final goods are not tradable. The only tradable goods are the intermediate goods in tradable sectors. The trade of these goods is costly. The cost of trading one unit of intermediate tradable good in sector j between region i and n is $\kappa_{ni}^j \geq 1$. Then, the price paid for a particular variety whose productivity is z^j, $p_n^j(z^j)$ is going to be the minimum of the unit costs across locations, adjusted by the transport costs κ_{ni}^j. The price of a variety in region n is expressed by

$$p_n^j(z^j) = \min_i \left\{ \frac{\kappa_{ni}^j x_i^j}{z_i^j [T_i^j]^{\gamma_i^j}} \right\}$$

These assumptions allows me to solve for the price distribution. Then, the price of final good j in region n, when sector j is tradable is given by

$$P_n^j = \Gamma(\xi_n^j)^{\frac{1}{1-\eta_n^j}} \left[\sum_{i=1}^{N} (x_i^j \kappa_{ni}^j)^{-\theta^j} [T_i^j]^{\theta^j \gamma_i^j} \right]^{-\frac{1}{\theta^j}} \tag{1.18}$$

Meanwhile the prices in non-tradable sectors are

$$P_n^j = \Gamma(\xi_n^j)^{\frac{1}{1-\eta_n^j}} x_n^j [T_n]^{-\gamma_n^j} \tag{1.19}$$

where $\Gamma(\xi_n^j)$ is a Gamma function evaluated at $\xi_n^j = 1 + (1 - \eta_n^j)/\eta^j$. The only missing price is the one in the telecommunications sector. This price is determined by the subgame perfect equilibrium described in the previous section.

Total expenditure on final goods in region n is $X_n^j = P_n^j Q_n^j$. The zero profit condition, except for the telecommunications sector, implies that total expenditures on intermediate goods in a given sector exhaust total revenue from final goods.

$$\int p_n^j(z^j) \tilde{q}_n^j(z^j) \phi^j(z^j) dz^j = P_n^j Q_n^j \quad \forall j = 1, ..., J-1 \tag{1.20}$$

Let π_{ni}^{j} be the share of regions n's total expenditure on sector j's intermediate goods purchased from region i. Following Eaton and Kortum (2002), using the properties of the Fréchet distribution. The expenditure shares are given by

$$\pi_{ni}^{j} = \frac{X_{ni}^{j}}{X_{n}^{j}} = \frac{[x_{i}^{j}\kappa_{ni}^{j}]^{-\theta^{j}}(T_{i}^{j})^{\theta^{j}\gamma_{i}^{j}}}{\sum_{m=1}^{N}[x_{m}^{j}\kappa_{nm}^{j}]^{-\theta^{j}}(T_{m}^{j})^{\theta^{j}\gamma_{m}^{j}}} \tag{1.21}$$

For non-tradable sectors $\kappa_{ni}^{j} = \infty$ then $\pi_{nn}^{j} = 1$.

1.2.5 Market Clearing and Labor Mobility

In regional equilibrium labor markets most clear, which implies

$$\sum_{j=1}^{J} L_{n}^{j} = \sum_{j=1}^{J-1} \int l_{n}^{j}(z)\phi_{n}^{j}(z)dz + \sum_{i=1}^{KT} l_{n}^{iT} \tag{1.22}$$

where the first part of the equation represents the labor market for all the competitive sectors and the second part corresponds to the telecommunications sector. KT is the number of active firms in region n for this sector.

National market clearing condition is

$$\sum_{n=1}^{N} L_{n} = L \tag{1.23}$$

In regional equilibrium, land and structures must satisfy a similar restriction

$$\sum_{j=1}^{J} H_{n}^{j} = \sum_{j=1}^{J-1} \int h_{n}^{j}(z)\phi_{n}^{j}(z)dz + \sum_{i=1}^{KT} h_{n}^{iT} \tag{1.24}$$

where KT is the number of active firms in the telecommunications sector in region n. The access cost for the entrants is pay in structures so the term H_{n}^{T} includes the fixed cost payed by each entrant to the incumbent.

National market clearing condition is

$$\sum_{n=1}^{N} H_n = H \tag{1.25}$$

The final competitive goods, must satisfy

$$\alpha^j L_n I_N + \sum_{k=1}^{J} \gamma_n^{kj} \sum_{i=1}^{N} (\pi_{in}^k X_i^k) = X_n^j \tag{1.26}$$

The condition for the telecommunications sector is the same, the only difference is that the profits from this sector follow a different definition. In particular, $X_n^j = P_n^j Q_n^j = P_n^j(q^I + \sum_{i=1}^{KT} q_e^i)$. This condition is given by

$$L_n c_n^T + \sum_{k=1}^{J} M_n^{kT} = L_n c_n^T + \sum_{k=1}^{J} \int M_n^{kT}(z)\phi_n^k(z)dz = q^I + \sum_{i=1}^{KT} q_e^i \tag{1.27}$$

where, q^I denotes the incumbent quantity and q_e the entrants quantity supply in the telecommunications sector.

In equilibrium total expenditure by a given region n on intermediates purchased from all other regions is equal to the total revenue from selling intermediates to all the other regions. This just mean that there is trade balance across regions. The trade balance condition is given by

$$\sum_{j=1}^{J-1} \sum_{i=1}^{N} \pi_{ni}^j X_n^j = \sum_{j=1}^{j-1} \sum_{i=1}^{N} \pi_{in}^j X_i^j \tag{1.28}$$

Agents move freely across regions, then the free mobility condition is given by

$$U = \frac{I_n}{P_n} = \Big(\frac{w_n}{1-\beta_n} + \Lambda\Big)\frac{1}{P_n} \tag{1.29}$$

Definition 1. *Given factors supplies for labor L and land and structures* $\{H_n\}_{n=1}^N$ *an equilibrium in this economy is a set of prices* r_n, ω_n, P_n^k, *and* P_n^T, *a set of structures, labor, and final goods allocations* H_n^k, L_n^k, *and* M_n^{jk}. *Trade shares* π_{in}^k, *quantities produced by each player in the oligopoly* q_n^{Te}, *the number of active firms in this sector m, the per capita profits from the oligopoly* Λ, *and an utility level U, such that the optimization of conditions for consumers; equations (1.2) and (1.4), conditions for intermediate goods hold; equations (1.6) and (1.7) hold, conditions for the competitive final goods; equations (1.9) and (1.10) hold, conditions for the subgame perfect equilibrium of the oligopoly sector; equations (1.14), (1.15), and (1.16) hold. Aggregate trade is balanced; equation (1.28) holds, all markets clear; equations (1.22), (1.23), (1.24), (1.25), (1.26), and (1.27) hold, and utility is equalized across regions; equation (1.29) holds.*

1.3 Data and Calibration

The ultimate goal of the model describe in the previous section is to quantitatively compare different scenarios. In particular, how different policies in the telecommunication sector affect different regions and sectors. To be able to do this comparisons the model from the previous section needs to be calibrated. In particular I need the parameters, $\{\theta^j, \alpha^j, \beta_n, \gamma_n^j, \gamma_n^{jk}, a_n^T, c_n^I, c_n^{ei}\}_{n=1,j=1,k=1,i=1}^{N,J,J,M_n}$, exogenous variables $\{\kappa_{in}^j, T_n^j\}_{i=1,n=1,j=1}^{N,N,J}$ and variables $\{I_n, L_n^k\}_{n=1,k=1}^{N,J}$.

Now I briefly describe how I obtain the parameters. The main data sources are the National Economic Census and the National Accounting data from the Mexican government.

1.3.1 Calibration

Transport Costs

There does not exist data on regional trade flows for Mexico, so this cannot be used to calibrate the transport costs to match the trade flows. Instead, I followed Donaldson (2010) and Fernando and Sandoval Hernandez (2015). I used the complete national network data set from INEGI. This data set includes all the highways, freeways, and rural roads. The data also includes some maritime routes[6], unfortunately there is not available data on railroads and air travel. The North American Transportation Statistics(NATS) estimates that 90% of the goods transport inside Mexico are move either by road or boat. Therefore, it seems plausible to get a good estimation of transport cost using just the available data on roads and maritime roads.

The transport cost were estimated using the Dijstrka Algorithm. This algorithm calculated the shortest path between the 2456 municipality capitals, in the 32 states. The INEGI roads data set includes average speed in each type of road which allowed me to calculate the average speed in the shortest path from one municipality to another one. These calculations generated a symmetric nXn matrix with zeros in the diagonal. Where n is the number of municipalities in the country. This chapter unit of observation will be the states. Then, I needed to calculate a average time and distance between each state. The average distance and time between any two states was calculated as a weighted average using the municipalities populations and sizes.

The result from these calculations is a symmetric matrix with zeros in the diagonal, where each element is the average time to get from state i to state j. The matrix elements are denoted by $\delta(i, j)$. As in Donaldson (2010) and Fernando and

[6]The data set just consider three maritime routes in the Pacific ocean that connect Baja California Sur with the rest of the country. I constructed a set of other maritime routes that connect the main ports of the country. The final maritime network and details on how it was built can be found in the Appendix 1.B.1.

Sandoval Hernandez (2015) transport costs are given by

$$TC(i,j) = \begin{cases} e^{\lambda\delta(i,j)} & i \neq j \\ 1 & i = j \end{cases}$$

where λ captures the effect of time in the transportation cost. The calibration of parameter λ follows Donaldson (2010). This implies that transport costs are given by

$$lnTC(i,j) = lnp(i,j) - lnp(i,i)$$

Hence, the best way to estimate the total transport cost between two regions is with data on a particular product that is sold across all the states. I used avocado prices from January first 2010 to December 31 2013, this data comes from the Mexican Ministry of Economy. This data set includes the state of origin and destination of 19 different presentations of first class Hass avocado and the final price at the state of destination. The avocado market is concentrated with 85% of the production coming from the state of Michoacán.

The specification used to estimated the log of the prices is a fixed effects regression that can be expressed as follows.

$$lnp_{kodt} = \lambda\delta(o,d) + \beta + \beta_{ot} + \beta_k + \beta_d + \epsilon_{kodt} \tag{1.30}$$

Where o is the origin state, t is the date, d the destination state and k is a categorical variable for each type of avocado presentation. Table 1.1 shows the results from this regression.

The λ I used in this chapter is the forth one, the one with all the possible fixed effects. Type probably has an effect in the transport costs, the size of the box might affect the mode of transportation. The destination market and the combination of ori-

Table 1.1: Estimation

Variable				
Time	0.0097	.0092	.0025	.0088
	(.0007)	(.0009)	(.0002)	(.0008)
Intercept	6.094	6.120	6.294	6.115
	(.0153)	(.0163)	(.0113)	(.0156)
R^2	.8462	.8496	.8348	.8504
Fixed Effects				
Type	No	No	Yes	Yes
Destination	No	Yes	No	Yes
Origin/Date	Yes	Yes	Yes	Yes

gin and date may also affect transport cost. Destination and origin fixed effects control by things like non physical barriers or pre-existing relationships between states.[7]

Oligopoly Parameters

Solving for the equilibrium of the model requires identifying marginal costs and access costs for the oligopolistic sector. I used data from the IFT(Mexican Institute of Telecommunications), this data set includes the number of firms, the year they become active, any merge between firms, and the market share of every firm by state in 2008. Using the structure of the oligopoly entry game, I estimated marginal costs for entrants and the incumbent.

Marginal costs for entrants were calculated and then used to construct an interval from which possible entrants will draw their marginal cost. The access cost came from the non-negative profits entry condition.[8]

Other parameters

The model matches some features of the 32 states in Mexico and 24 sectors. There are 12 tradable sectors and 12 non-tradable ones, including the telecommunications one. This calibration follows Caliendo et al. (2017) but using data from Mexico during

[7]The main problem with this estimation is that λ will be the same for any good transported. The cost for transporting avocados is not representative of other goods such as computers or machinery.

[8]See appendix 1.B.2 for a more detail explanation on how these parameters were obtained.

2008. All the data come from INEGI different data sets. The two main data sources are the National Accounting and the 2009 National Economic Census.

These two data sets include data on total production, intermediate inputs, value added, number of workers, and total payments to workers by state and by sector. The main problem with this data is that they do not match the National Accounting data. The National Accounting includes an estimation of informal workers by sectors. I scaled up the Economic Census data to match the National Accounting one. This is important because according to INEGI 25% of the GDP in 2008 came from the informal sector. The scale up was done by sector and region.

After scaling up I observe the following variables in this data set L_n^k, L_n and L. The total number of workers in the Mexican economy in 2008 was 93,751,000. Income per state is given by $I_n = \frac{VA_n}{L_n}$, where VA_n is value added by region and it is observe in the data.

Value added shares are calculated as follows $\gamma_n^j = \frac{VA_n^j}{Y_n^j}$ where Y_n^j is gross output in the region sector pair (n, j) which is observed in the data set described above. The shares of intermediate goods from sector k in total payments to sector j is given by $\tilde{\gamma}^{jk}$. These shares come from the input-output matrix published by INEGI in 2008, these matrix is by sector but not by region. Then, $\gamma_n^{jk} = (1 - \gamma_n^j)\tilde{\gamma}^{jk}$.

The share of income spent in goods from sector j α^j is given by the following observables

$$\alpha^j = \frac{Y^j + M^j - E^j - \sum_k \gamma^{kj}(1-\gamma^k)Y^k}{\sum_j (Y^j + M^j - E^j - \sum_k \gamma^{kj}(1-\gamma^k)Y^k)}$$

where Y^j is gross output in sector j, M^j total imports from sector j, E^j total exports from sector j.

The share of labor use in each region $1 - \beta_n^j$ is calculated as follows. The data set describe above has compensation data for all the region sector pairs (n, j) then just divide this by value added. This is going to be the calibration for the parameters $\bar{\beta}_n^j$. Following Caliendo et al. (2017) I adjust this parameter as $\beta_n = \frac{\beta_n - 0.17}{0.83}$.

Productivity levels T_n^j were calibrated using data on total factor productivity from INEGI. INEGI uses the KLEMS model to measure productivity. The deterministic productivity levels are going to be $TFP_n^j = (T_n^j)^{\gamma_n^j}$ were TFP_n^j is the measure of total factor productivity from the data.

The sectoral dispersion productivities θ^j came from Caliendo and Parro (2014). They calculated this parameter for 20 different sectors that were match with the 12 tradable sectors used in here. The values used can be found in Appendix 1.B.3.

The elasticities of substitution between varieties in each sector came from Blanke-nau and Cassou (2011), these elasticities are constant across regions η^j. The elas-ticities from the paper are at a more aggregated level than the sectors used here, then some aggregation of sectors is needed in order to use these parameters. The aggregation and the parameters can be found in Appendix 1.B.2.

1.3.2 Base Model

After calibrating the model with the available industry and trade data I inverted the model to have a base scenario to compare different policy changes. The inverted model generates the land and structures distribution across regions, GDP, TFP, trade shares, and the agents welfare.

Figure 1.3 shows the percentage that each state owns from the total national structures. The missing value in the map is Mexico City which share of land and structures is 13.38%. The map shows that Mexico City and Campeche are the states that own more of the national land and structures. The next big states in ownership of land and structures are Nuevo Leon, Jalisco, and the State of Mexico. The ownership of land and structures predicted by the model follows closely the states GDP and the calibrated income by state I_n.

Figure 1.4 shows two graphs that compare the data with the model for the GDP. The model does a good job in almost all sectors and regions. The only underestimation

Figure 1.3: Ownership by state of land and structures

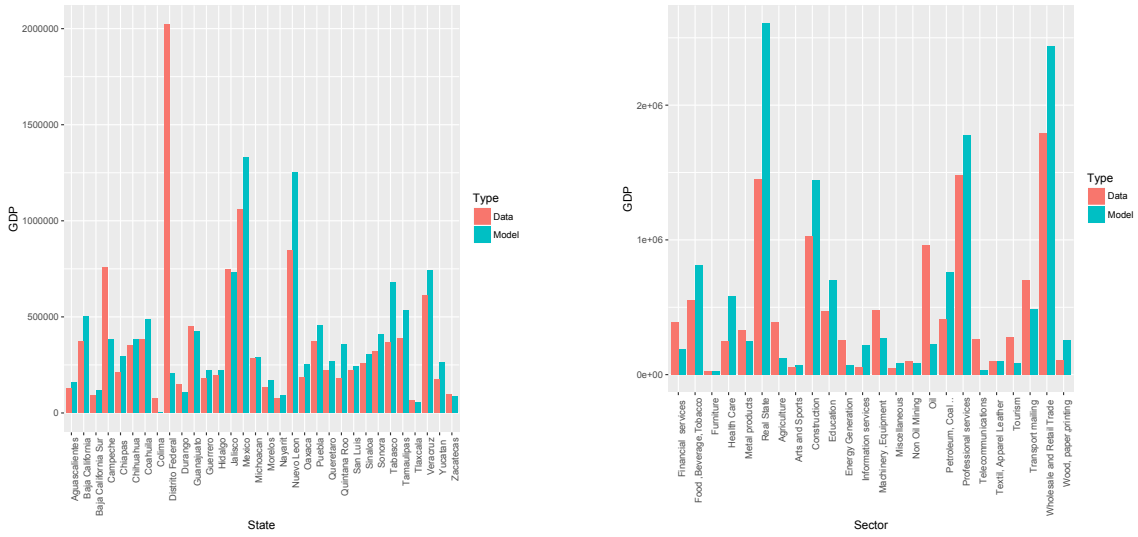


is for Mexico City. Overall the model is overestimating in most states and sectors. This can be explain by the parameters that were not calibrated for the Mexican economy.[9]

1.3.3 TFP, GDP and Welfare

This section describes how to arrive to measures of total factor productivity, GDP, and welfare. The calculations are done used available data for the Mexican economy. These measures are later used to compare the base model to different policy changes scenarios.

[9]These parameters are the elasticities of substitution between varieties and the sectoral dispersion productivities



(a) States (b) Sectors

Figure 1.4: Model and Data total GDP by region and sector

Measured TFP

Total factor productivity for a region-sector pair (n, j) for all $j \in \{1, ..., J-1\}$ is given by

$$A_n^j = \frac{x_n^j}{P_n^j} \tag{1.31}$$

While total factor productivity for the telecommunications sector is given by

$$A_n^{tT} = \frac{\omega_n^{1-\beta_n} r_n^{\beta_n}}{c_n^j} f(\beta) n \tag{1.32}$$

where t is any of the active telecommunications firms in region n. The sector Total Factor Productivity for the telecommunication sector is a weighted average of the market share of all the active firms $A_n^T = \sum_{i=1}^{M} \frac{q_n^i}{Q_n^T} A_n^i$. Then, sector TFP A^j can be written as follows $A^j = \sum_{n=1}^{N} A_n^j$ and regional TFP by $A_n = \sum_{j=1}^{J} A_n^j$.

The aggregate TFP for the whole economy is $A = \sum_{j=1}^{J} \sum_{n=1}^{N} A_n^j$.

GDP

Real GDP for each sector and region pair can be expressed as

$$GDP_n^j = \frac{\omega_n L_n^j}{(1-\beta_n)P_n^j} \tag{1.33}$$

For the telecommunication sector GDP is just gross production by the whole sector $GDP_n^T = P_n^T Q_n^T$. Sector GDP is the sum across regions $GDP^j = \sum_{i=1}^{N} GDP_n^j$ and regional GDP is the sum across sectors $GDP_n = \sum_{j=1}^{J} GDP_n^j$.

Welfare

Welfate for an agent living in region n is given by

$$U = \frac{I_n}{P_n} = \Big(\frac{\omega_n}{1-\beta)n} + \Lambda\Big)\frac{1}{P_n}$$

All the results from the policy changes are shown in maps that measure the percentage changes in these three variables.

1.4 Policy Changes

After calibrating the model against available industry and trade data, I study the effect of two different policy changes in the telecommunication sector. The first policy change is the one that happened in 2009. The second one, is a counterfactual policy change that allows me to see what would have happened if the shock to the telecommunications sector was homogeneous across regions. To facilitate comparisons across states all the results are presented as perceptual changes in employment, GDP, TFP, and the number of entrants[10] to the telecommunications sector.

[10]The quantities for the number of entrants are not round numbers. This is because they are the result from the average number of firms from one million draws in each region.

1.4.1 Auction of part of the backbone

In 2009 the government auction part of their dark fiber network. The auction included three different fiber routes with different number of filaments 6, 12, 18, 24, and 36. Filaments usually determine the capacity of the network. The three routes comprise of a total of 20,148 Km of dark fiber. This auction included the following pieces:

- Pacific: goes from Baja California to Oaxaca plus a small not connected piece in Baja California Sur 8,120 Km.
- Center: from Chihuahua to Chiapas 5,789 Km.
- Gulf of Mexico: around the Yucatán Peninsula 5,560 Km.

These three networks cover 138 cities across Mexico and around 50.6% of the population. Figure 1.5 shows them.

Figure 1.5: Backbone Network



I built the heterogeneous regional shock as follows. Using data from the Federal Electricity Commission on every city that was benefit from the network. I calculate the share of the total population by state that live in parts if the state with the new available network. The total share of the state population was calculated using 2008 data. From the 32 states in Mexico there were just two non-affected states by the shock, Colima and Morelos. The other 30 states saw an increase in their network availability after 2008 compared with previous years.

According to a press releases from the Electricity Commission, the auction led to a decrease in costs of around 50% for new entrants in the telecommunication sector. Then, I used data from Telmex, the incumbent, and entrants to disaggregate the 50% cost reduction between access and marginal costs. The entrants sign an agreement with the incumbent to be able to use their infrastructure. The access cost in these agreements include: access and use of share passive infrastructure and access and use of towers and physical space. These costs are pay yearly to the incumbent and are defined as fixed costs here. The marginal cost that each entrant pays to the incumbent is the amount of capacity and traffic used by each entrants. The access costs account for 73.23% of the total costs pay to the incumbent by a new entrant.

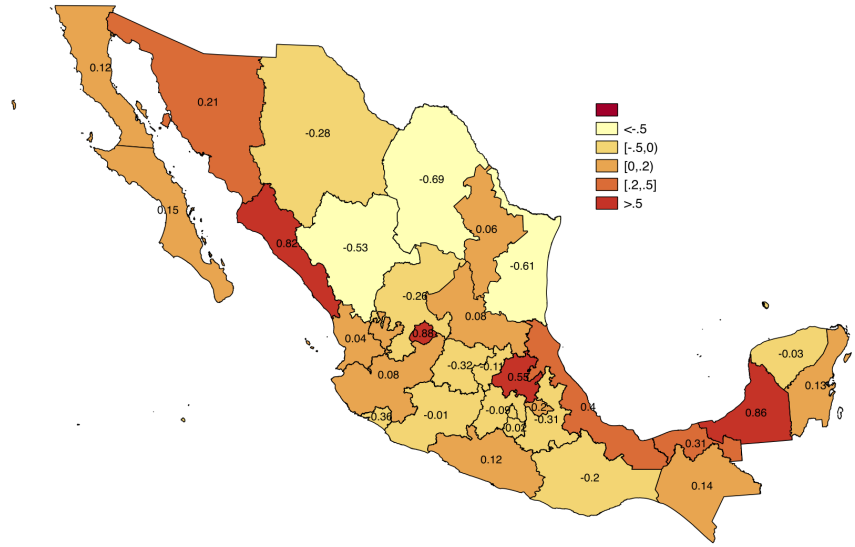
I calculated the shock for each region using the percentage describe above. For example, a region where 100% of its population was exposed to the shock experience a 50% decrease in total cost for any potential entrant. This cost is divided by a 36.6% decrease in access costs and a 13.4% decrease in the marginal costs. Using the base model calibration described in the section above, I applied the shock. An algorithm that describes how the shock was incorporated into the model and how to calculate the new equilibrium is described in the Appendix 1.C. The solution from the policy shock is a new equilibrium allocation of labor, GDP, TFP, trade shares[11], and welfare.

[11]Trade shares in the new equilibrium does not add up to one. This is happening due to the converging criteria in the numerical exercise. The algorithm solves a non-linear system with 541,696 variables. The tolerance parameter was set such that the algorithm converges in a reasonable amount

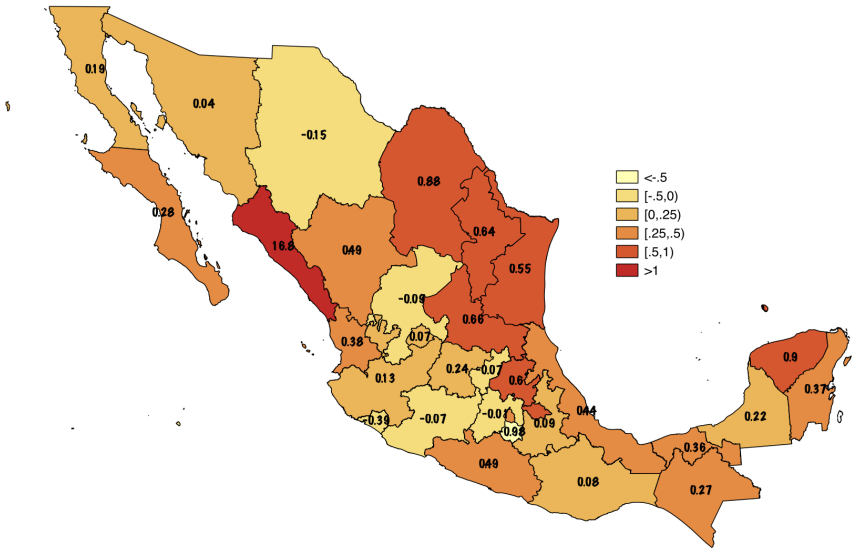
Overall the heterogeneous shock to the telecommunications sector increased welfare by 0.13 percent. Figures in 1.6 shows the effect of the heterogeneous shock in the regional labor market and in the GDP. The numbers show in the maps are percentage changes deviating from the base case. The darker the tone in this maps the higher change in that variable. The change in regional employment shows four states that see a considerable increase in the number of workers moving there. These states are Sinaloa, Campeche, Hidalgo, and Aguascalientes. Three of these states; Sinaloa, Campeche, and Aguascalientes, are the ones that the new network covers all their population. This implies that after the backbone became available it is not surprising that they are the states that benefit the most from the new network. The total population of Hidalgo was not affected by the shock; just around 35% of the population was affected but the telecommunications industry was highly concentrated in this state. The incumbent had the most market share in this state. All the changes in the labor market are bounded between a decrease of 5% and an increase of 5%. The effect on the regional GDP follows a similar pattern as the changes in labor. States that were exposed to the new infrastructure see a percentage increase in their GDP while states that were not exposed to it see a percentage decrease in the GDP. In particular, the two states that did not see an increase in their network Morelos and Colima saw the biggest decreases in GDP after the shock. States that were least affected by the shock also observe a decrease in their GDP, this is the case for Michoacán, Chihuahua, and the State of Mexico. Map 1.6b shows that the change in the GDP for almost all the states was small, the only state with a significant change in its GDP is Sinaloa. Again, this follows from the state being particularly exposed to the shock.

Changes in TFP follow a similar patter as the changes in GDP, expect for the Baja California Peninsula that saw an increase in TFP but not a big increase in GDP. The TFP growth in the peninsula can be explain as follows. The shock made available new

of time. The results from changing this tolerance parameter remain almost the same, trade shares get closer to one but the time the algorithm takes to converge increases exponentially.



(a) Regional Change in Employment



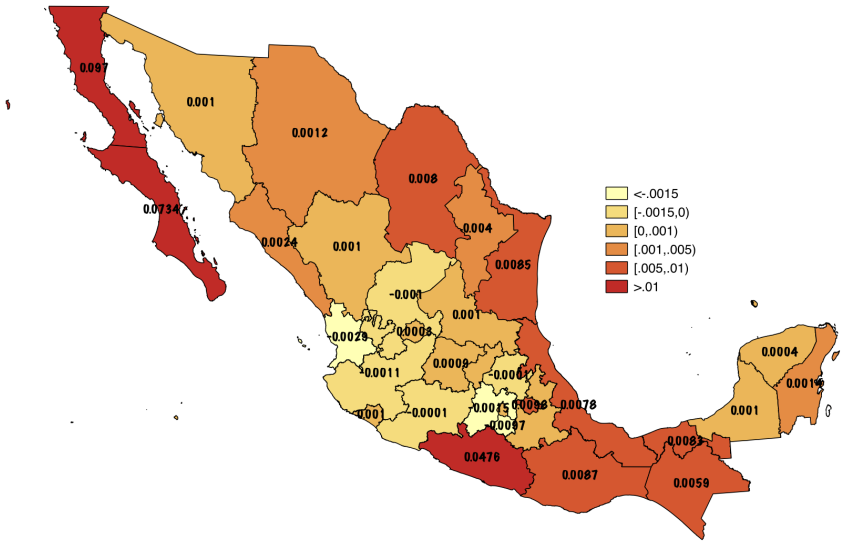
(b) Regional Change in GDP

Figure 1.6: Regional Effect from the Heterogeneous Shock

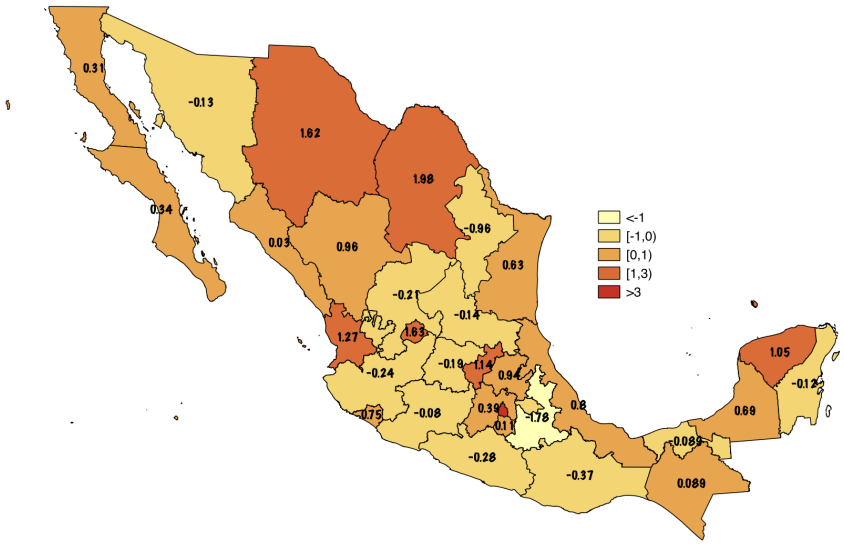
infrastructure that was previously scare. The new network availability reduced access prices which lead to more entry and a consequential decrease in the overall price of telecommunication services. The reduce price in one sector reduces the cost of every sector that uses this particular service, the more intensive a sector is in the use of telecommunication the more cost reduction. The change of cost will drive workers to move and changes in the overall productivity and GDP across regions. Figure 1.7a shows the percentage changes in total factor productivity across regions.

All the changes on labor, GDP, and TFP are driven by the new infrastructure available in the telecommunications sector. As explain in the paragraph above, the new backbone availability drives cost of access to new firms in the sector down. I will expect to see an important increase in the number of entrants in regions with high market share of the incumbent before the shock and that were particularly affected by the shock. Figure 1.7b shows the percentage change in the number of entrants after the shock. The map shows that big markets like Mexico City can support higher competition. Places that had concentrated markets before the shock like the Yucatan peninsula also see an increase in the number of entrants, independently of the markets being relatively small. Finally, small poor markets in the south of Mexico do not see an increase in entry after the shock regardless of the new availability of infrastructure. This provides some evidence that in some markets a cheap access to basic infrastructure is not enough to make the market competitive. Sunk cost might still be too high for entrants in these locations.

All the maps shown here are not big enough to show values for Mexico City which are; employment -0.58%, GDP 0.17%, TFP 0.004%, and 2 new entrants after the shock.



(a) Regional Change in TFP



(b) Entrants by State

Figure 1.7: Regional Effect from the Heterogeneous Shock

1.4.2 Homogeneous Shock

The actual policy did not cover the whole population, the government auction just a small part of their available network. In this counterfactual I ask what would have happened if the government made available its infrastructure to the whole country. Lets assume that every single state receives the same access to infrastructure and that this new available network allows entrants to pay reduced costs. The access cost reduction will be 36.6% and the marginal cost reduction 13.4% for every single state. The exercise is solve as in the previous section, where I compare the base-line equilibrium with the new equilibrium after the shock.

After an homogeneous shock across regions to the telecommunications sector, welfare will increase by 0.35% for all agents, this increase is higher than the one experience by the heterogeneous shock. The welfare increase is expected to be higher because the homogeneous shock is higher than the heterogeneous one presented above.

Figures 1.8 and 1.9 show the changes in employment, GDP, TFP, and the number of entrants after the homogeneous shock. All the results show in the maps are percentage changes with respect to the base model. The employment map 1.8a shows workers moving into states that use to have a high concentration in the telecommunications sector. In particular they move to the states of Sinaloa, Jalisco, Tamaulipas, and Campeche. Campeche is the state with a higher immigration because is one of the states with a high share of ownership of land and structures. The state has this high ownership due to being the state were most of the oil is produced in the country. The shock will encourage workers to move to this relative rich state.

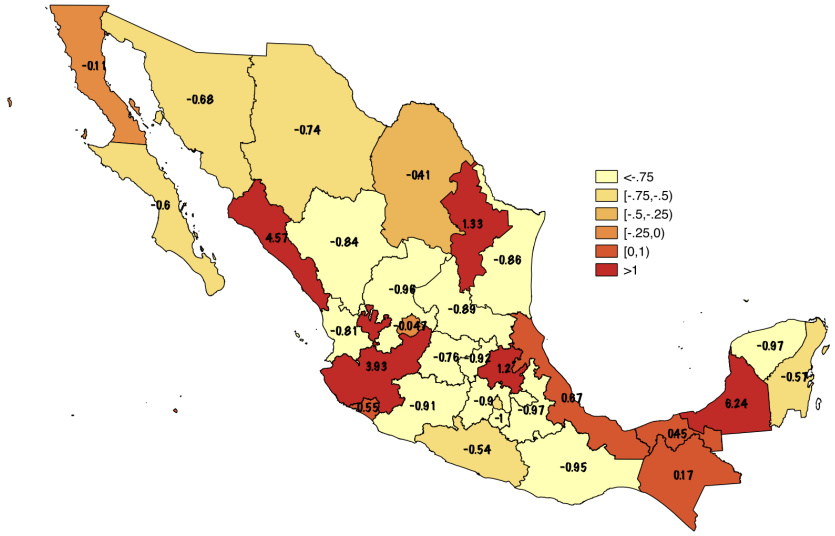
Figure 1.8b shows the changes in GDP. These changes follow the same pattern as the employment changes. The shock leads to all states to increase their GDP compared to the base case. The states that increase their GDP more are the relative big in population or land and structures states with initial high market concentration in the telecommunications sector.

Figure 1.9a describes the changes in TFP after the shock. Despite the changes following a similar pattern as the ones experience by the labor market and the total GDP, the change in TFP is a little bit different. Three big states in the share of land and structures are winning the most, Sinaloa, Jalisco, and Campeche. While, relative small states that had a concentrated telecommunications market before the shock do not show a significant increase in the total factor productivity.

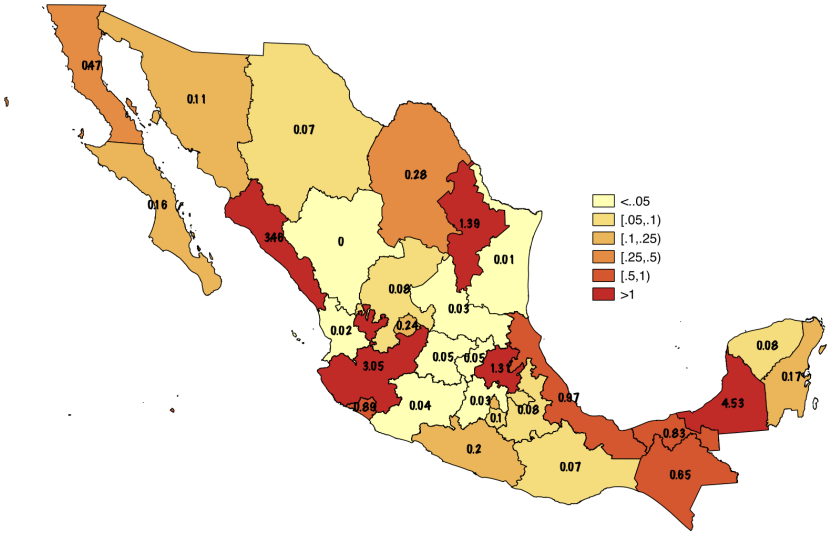
Finally, figure 1.9b shows the number of entrants in each state after the shock. The map shows two states; Jalisco and Coahuila with extraordinary entry after the shock. These two states had a high concentration before the shock and are relatively big in terms of population and share of land and structures. These two characteristics make them ideal for new firms to be able to enter to the market. The other interesting case is the states that saw an increase of almost zero or a decrease in the number of entrants. These states; Chiapas, Puebla, Mexico City, and Guanajuato, share some characteristics that make them less attractive after the shock. They either already have a competitive market in the telecommunications sector; Mexico City and Guanajuato, or are relatively poor in the share of land and structures; Puebla and Chiapas. Either of these will make these markets less attractive to new entrants despite the fact of the lower access and marginal costs.

1.5 Conclusion

This chapter analyzes the regional effects from a policy change in the telecommunications sector. The particular policy analyzed was the auction of part of the government dark fiber. The Mexican government decided to do this in order to increase competition in the sector that eventually could translate in mayor internet access across the country. The policy reduced the entry cost for potential firms. The policy decision was modeled as an heterogeneous shock across regions to the telecommunications sec-

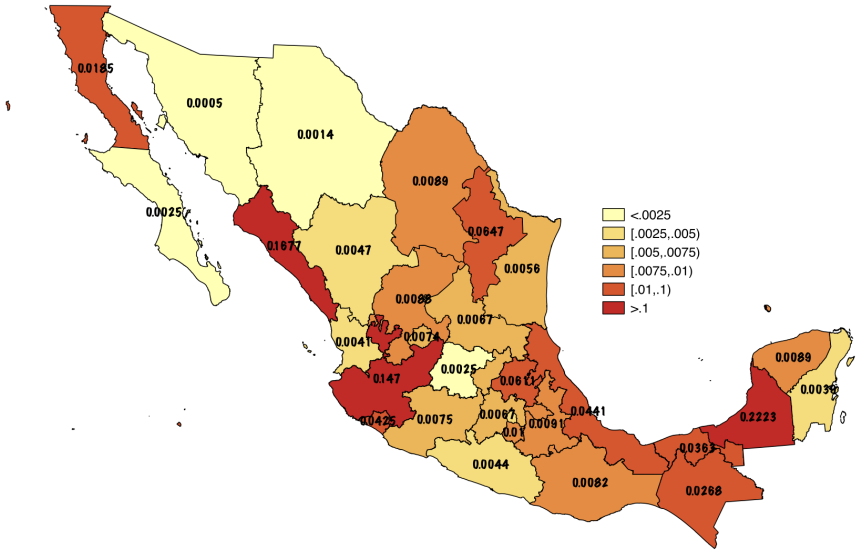


(a) Regional Change in Employment

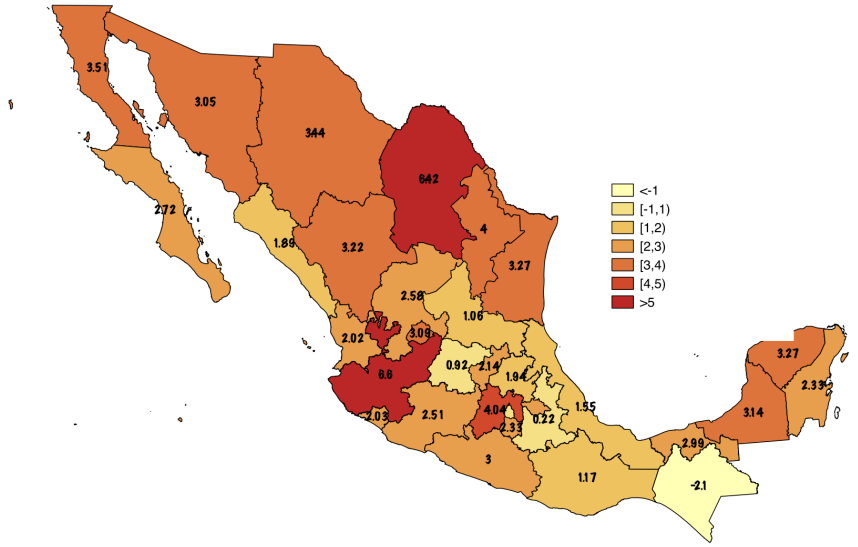


(b) Regional Change in GDP

Figure 1.8: Regional Effect from the Homogeneous Shock



(a) Regional Change in TFP



(b) New Entrants

Figure 1.9: Regional Effect from the Homogeneous Shock

tor. Each state was affected differently by the shock because the network provided by the government did not cover the whole country.

I characterized the Mexican economy in a model with regional and sectoral interactions. The model considered multiple regions, transport costs, labor mobility across regions, and fixed land and structures. Differently from existing models I add an oligopolistic sector in order to match the telecommunications sector in the Mexican economy. I calibrated the model to match labor by region and sector from the Mexican economy. I used several data sets in order to calibrate the parameters of the model. The calibration allowed me to have a base economy to be able to shock it with different counterfactuals.

The main shock that I applied to the economy was the actual policy change in Mexico; the auction of part of the government infrastructure. The second shock is an homogeneous decrease in the entry cost to the telecommunications sector across regions. These two shocks affect the economy differently, it does not matter if two states were shocked similarly the regional and general equilibria were different. After the first shock, states were most of their population was exposed to the shock had high levels of employment flowing into them. These states also experienced an increase in their total factor productivity and their GDP. The states that benefited more in terms of productivity from the shock are the ones more exposed to the new network. Meanwhile, the states that benefit more in terms of GDP and employment were big states in the share of structures that they own and that had a high concentrated market in the telecommunications market before the shock. The number of new entrants to the telecommunications sector was also higher in these states.

The results from the homogeneous shock were different that the ones from the heterogeneous one. Workers move to relative big states by the share of structures they owned with small competition. States that had competitive markets before the shock saw outmigration and a relative low entry after the homogeneous shock. The

change in GDP and TFP look similar in both counterfactuals. Relative poor states with concentrated markets before the shock did not win that much from the policy change. This is driven by the structure of the model and the industry composition of the poor states. Overall the exercise in this chapter shows the relationship between a policy change and the regional effects it will have.

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Appendix

1.A First Order Conditions

Consumers:

Consumers in each location n are going to choose consumption bundles in order to maximize their utility. The utility function is a Cobb Douglas with α^j shares of each sector good.

The representative consumer is going to maximize:

$$\max \quad \prod_j (c_n^j)^{\alpha_j} \quad s.t \quad \sum_{j=1}^{J} P_n^j c_n^j \leq I_n$$

$$\Rightarrow \quad c_n^j = \frac{\alpha^j I_n}{P_n^j} \quad \forall j \tag{1.34}$$

Where the income of the representative consumer is going to be:

$$I_n = r_n \frac{H_n}{L_n} + w_n + \Lambda$$

this implies that the consumer supply one unit of labor, the return to land and structures is evenly distributed in each region and $\Lambda = \frac{\Pi}{L}$. Here Π is the sum over all the regions profits from the monopoly.

Then plug-in in equation 1 back in the utility function:

$$U = \prod_j (c_n^j)^{\alpha_j} = \prod_j \left(\frac{\alpha^j I_n}{P_n}\right)^{\alpha^j} = \left(\frac{I_n}{P_n}\right) \prod_j (\alpha^j)^{\alpha^j} = \frac{I_n}{P_n}$$

Intermediate goods:

Intermediate representative firms are going to produce varieties that differ in their idiosyncratic productivity level z_n^j. This firms are going to solve:

$$\min \quad w_n l_n^j(z_n^j) + r_n h_n^j(z_n^j) + \sum_{k=1}^{J} P_n^k M_n^{jk}(z_n^j) \quad s.t \quad z_n^j [T_n^j [h_n^j(z_n^j)]^{\beta_n} [l_n^j(z_n^j)]^{1-\beta_n}]^{\gamma_n^j} \prod_{k=1}^{J} [M_n^{jk}(z_n^j)]^{\gamma_n^{jk}} = 1$$

the first order conditions from this optimization are:

$$w_n = \lambda \gamma_n^j (1-\beta_n) z_n^j (T_n^j (h_n^j)^{\beta_n})^{\gamma_n^j} (l_n^j)^{(1-\beta_n)\gamma_n^j - 1} \prod_{k=1}^{J} (M_n^{jk})^{\gamma_n^{jk}}$$

$$r_n = \lambda \gamma_n^j \beta_n z_n^j (T_n^j (l_n^j)^{1-\beta_n})^{\gamma_n^j} (h_n^j)^{\beta_n \gamma_n^j - 1} \prod_{k=1}^{J} (M_n^{jk})^{\gamma_n^{jk}}$$

$$P_n^k = \lambda \gamma_n^{jk} (M_n^{jk})^{\gamma_n^{jk}-1} \prod_{i \neq k} (M_n^{ji})^{\gamma_n^{ji}} z_n^j [T_n^j (l_n^j)^{\beta_n} (h_n^j)^{1-\beta_n}]^{\gamma_n^j}$$

Combining all the first order conditions, the cost of an input basket in region n and sector j is going to be:

$$x_n^j = [(1-\beta_n)^{(\beta_n - 1)(\beta_n)^{-\beta_n}}]^{\gamma_n^j} \Big[\prod_{k=1}^{J} (\gamma_n^{jk})^{-\gamma_n^{jk}} \Big] (\gamma_n^j)^{-\gamma_n^j} [r_n^{\beta_n} w_n^{1-\beta_n}]^{\gamma_n^j} \prod_{k=1}^{J} (P_n^k)^{\gamma_n^{jk}}$$

Unit cost is then given by $\frac{x_n^j}{z_n^j (T_n^j)^{\gamma_n^j}}$ From the producer maximization problem there are going to be relationships between labor, land and structures and final goods demands

$$h_n^j(z_n^j) = \frac{\gamma_n^j \beta_n}{r_n} p_n^j(z^j) q_n^j(z_n^j)$$

$$l_n^j(z_n^j) = \frac{\gamma_n^j (1-\beta_n)}{w_n} p_n^j(z^j) q_n^j(z_n^j)$$

$$M_n^{jk}(z_n^j) = \frac{\gamma_n^{jk}}{P_n^k} p_n^j(z^j) q_n^j(z_n^j)$$

From the two first equations above:

$$r_n h_n^j(z_n^j) = w_n \frac{\beta_n}{1-\beta_n} l_n^j(z_n^j)$$

Final goods: Final good representative firm is going to solve:

$$\max P_n^j Q_n^j - \int p_n^j(z^j) \widetilde{q}_n^j(z^j) \phi^j(z^j) dz^j$$

where $Q_n^j = \Big[\int \widetilde{q}_n^j(z^j)^{1-1/\eta_n^j} \phi^j(z^j) dz^j \Big]^{\eta_n^j/(\eta_n^j-1)}$

Demand function and price indexed are going to be:

$$\widetilde{q}_n^j(z^j) = \Big(\frac{p_n^j(z^j)}{P_n^j} \Big)^{-\eta_n^j} Q_n^j$$

$$P_n^j = \Big[\int p_n^j(z^j)^{1-\eta_n^j} \phi^j(z^j) dz^j \Big]^{1/(1-\eta_n^j)}$$

1.B Data and Calibration

1.B.1 Maritime Network

The official data from INEGI include three maritime routes that connect Baja California Sur with the rest of the country. I used the 16 largest ports of the country, largest in the amount of goods that are move across them. The ports are: Guaymas, Topolobambo, Mazatlán, Puerto Vallarta, Manzanillo, Lázaro Cárdenas, Acapulco, Salina Cruz, Huatulco, Puerto Chiapas, Progreso, Dos Bocas, Veracruz, Tuxpán, Tampico, and Altamira.

The artificial maritime network was built using GIS software to generate artificial arc between all viable ports. This alternative network is particularly dense in the

Gulf of Mexico. The average speed I assigned to each of the routes is 30km/h, this is the average speed reported in the INEGI dataset for all the maritime routes. Figure 1.10 shows the network used to calculate all the transport cost in this chapter.

Figure 1.10: Transport Network



1.B.2 Oligopoly Parameters

After getting the marginal and access costs from the model. I ran the game one million times in each region. The average number of firms from the draws and the actual number of firms are close enough. The calibration does a good job predicting the average number of active firms in each region.

Table 1.2 shows the actual active firms and the predicted firms from the entry game. On average the model underestimates the number of entrants by 0.05 entrants by state, with an standard deviation of 0.14. These predicted values give me confidence that the model is doing a good job at estimating the number of entrants.

Table 1.2: Predicted Firms

State	Data	Predicted firms	State	Data	Predicted firms
Aguascalientes	5	5.08	Morelos	5	4.97
Baja California	10	10.13	Nayarit	3	2.93
Baja California Sur	4	4.14	Nuevo Leon	8	7.93
Campeche	5	5.38	Oaxaca	3	2.8
Coahuila	9	8.89	Puebla	9	8.68
Colima	4	3.9	Queretaro	8	7.89
Chiapas	4	4.02	Quintana Roo	5	4.97
Chihuahua	5	4.83	San Luis	6	5.93
Distrito Federal	20	19.93	Sinaloa	4	3.89
Durango	4	4.17	Sonora	7	6.88
Guanajuato	9	9.21	Tabasco	4	4.07
Guerrero	5	4.97	Tamaulipas	7	7.2
Hidalgo	4	4.09	Tlaxcala	2	1.79
Jalisco	9	9.01	Veracruz	5	4.79
Mexico	9	9.14	Yucatan	5	5.25
Michoacan	7	6.99	Zacatecas	6	5.89

1.B.3 Other parameters

Sectoral dispersion productivities θ^j used here are the ones described in Table 1.3.

Elasticities of substitution η^j are aggregated as follow. The two mining sectors and the energy generation one were aggregated into mining (21-22). The eight manufacture sectors are aggregate into the only manufacture sector elasticity (31-33). Table 1.4 shows the elasticities used for the model.

List of sectors: The 12 tradable sectors are Agriculture, Forestry, Fishing and Hunting (NAICS 11), Oil mining (211), non oil related mining ($212-213$), Energy generation (22), Food Product & Beverage and Tobacco Product ($311-312$), Textil and Textil Product Mills, Apparel and Leather and Allied products ($313-316$), Wood, paper and printing ($321-323$), Petroleum & Coal Products, Chemicals,Plastic and Rubber Products ($324-326$), Metal products ($327-332$), Machinery, Computer and Electronic Product, Electrical Equipment and Appliance, Transportation Equipment ($333-336$), Furniture and related products (337), Miscellaneous (339). The non tradable sectors are 12 and are: Construction (23), Wholesale and Retail Trade ($43-$

Table 1.3: Sectoral dispersion of productivities

Sector	θ^j
Agriculture	8.11
Oil	51.08
Non Oil Mining	2.76
Energy Generation	15.72
Food ,Beverage,Tobacco	2.55
Textil, Apparel Leather	5.56
Wood, paper,printing	9.46
Petroleum, Coal Products	4.75
Metal products	6.78
Machinery ,Equipment	10.6
Furniture	5
Miscellaneous	5

Table 1.4: Elasticities of Substitution

Sector	η^j
Agriculture	7.988
Mining(21-22)	5.376
Manufactures(31-33)	1.406
Construction	9.048
Wholesale and Retail Trade	1.923
Transportation	3.750
Information services	0.684
Financial services	1.155
Professional services(52-53)	1.066
Education	2.501
Health Care	2.501
Leisure services (71-72)	2.056

46), Transport and mailing services $(48-49)$, information services (51 without 517), telecommunications (517), financial services (52), real state (53), professional services $(54-56, 81, 93)$, education (61), health care (62), Arts and sports (71), Tourism(72).

1.C Counterfactuals Algorithm

- Guess w_n, r_n and P_n^T for every region/

- Use the system of prices and cost to get x_n^j and P_n^j.

$$x_n^j = [(1-\beta_n)^{(\beta_n-1)(\beta_n)^{-\beta_n}}]^{\gamma_n^j}\Big[\prod_{k=1}^{J}(\gamma_n^{jk})^{-\gamma_n^{jk}}\Big](\gamma_n^j)^{-\gamma_n^j}[r_n^{\beta_n}w_n^{1-\beta_n}]^{\gamma_n^j}\prod_{k=1}^{J}(P_n^k)^{\gamma_n^{jk}}$$

Prices for tradable goods:

$$P_n^j = \Gamma(\xi_n^j)^{\frac{1}{1-\eta_n^j}}\Big[\sum_{i=1}^{N}(x_i^j\kappa_{ni}^j)^{-\theta^j[T_i^j]^{\theta^j\gamma_i^j}}\Big]^{-1/\theta^j}$$

Prices of non tradable goods:

$$P_n^j = \Gamma(\xi_n^j)^{\frac{1}{1-\eta_n^j}}x_n^j(T_n^j)^{-\gamma_n^j}$$

- Use the relationship between Labor and Structures to get the new distribution of Employment across regions.

$$L_n = \frac{1-\beta_n}{\beta_n}\frac{r_nH_n}{w_n}$$

- Get trade shares and gross production for each region and sector.

$$\pi_{ni}^j = \frac{(x_i^j\kappa_{ni}^j)^{-\theta^j}(T_i^j)^{\theta^j\gamma_i^j}}{\sum_{m=1}^{N}(x_m^h\kappa_{nm}^j)^{-\theta^j}(T_m^j)^{\theta^j\gamma_m^j}}$$

$$X_n^j = \alpha^j L_n I_n + \sum_{k=1}^{J} \gamma_n^{kj} \sum_{i=1}^{N} \pi_{in}^k X_i^k$$

- Using X_n^T solve the equilibrium of the oligopoly using the best responses and the entry condition.

$$C_n \sum_{k=1}^{M} q_n^{ek} = c_n^I (q_n^i + \sum_{k=1}^{M} q_n^{ek})^2$$

$$C_n q_n^I + C_n \sum i \neq k q_n^{ei} = c_n^{ek} (q_n^I + q_n^{ek} + \sum_{i \neq k} q_n^{ei})^2$$

$$q_n^{ek} \geq \frac{r_n a_n}{P_n^T - c_n^{ek}}$$

  This step give actualized prices for the telecommunication sector and a value for Λ.

- Use balance trade and free mobility to get a new value for w_n

$$L_n \Big(\frac{w_n}{1 - \beta_n} + \Lambda \Big) = \sum \gamma_n^j \sum \pi_{ni}^j X_i^j$$

  This is repeated until the difference between the guess prices and the ones from the algorithm are close enough.

Chapter 2

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

2.1 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.

[1] Ahmed (August 2015).
[2] Woody (November 2017).

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 chapter argues that external pressures to drug markets affect market structure in this markets and the levels of violence.

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 relationship between the number of active cartels and violence. I found that the heroin market became less concentrated and that there is more violence in municipalities with competing cartels than in the ones with one or none active cartels.

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,

[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`

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 over multiple years is not available. Inspired by 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.

[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.

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 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

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

[8]A full explanation of the algorithms and the techniques used can be found in 2.3 and Appendix 2.B.

[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)

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

Second, I find that the number of homicides per 100,000 inhabitants increases in municipalities with at least two cartels compared to the ones with one or zero cartels. In particular there are 17 to 35 extra homicides after 2010 in a municipality

[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 2.B

[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.

with two or more cartels compare to a municipality equally suitable but with just one cartel. These results suggest that the demand shock increased the potential gains from entering some municipalities and that cartels use violence to increase their market share. 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.

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

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 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 chapter 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 chapter 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.

2.2 Background

2.2.1 The Opioid Crisis

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 the 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. By 2010 several physician organizations pressured the federal and local government to make it harder to abuse and accumulate the pills. As a results, several policies where established to crack down pill mills, and Purdue Pharma introduced an abused deterrent version of OxyContin. This new pill was harder to crush or dissolve, thus deterring the most-dangerous methods of abuse by injection and inhalation. The restriction in the legal supply drove some users to switch to its legal 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).

2.2.2 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] Mexican cartels exported some heroin[17] but it was never their main activity. The percentage of heroin of Mexican origin seized by the DEA went from 22% before 2010, to 51% in 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 military. This project considers nine main Drug Trafficking Organizations recognized by the Mexican prosecutor's office and the DEA.[18]

2.3 Data

The main goal of this chapter is to document how Mexican Drug Trafficking Organizations reacted to the opioid crisis. To achieve this goal ideally I would like to observe when a 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.[19] So in order to measure this difficult to measure phenomena; cartel

[16] A brief history of the drug trade in Mexico and the war on drugs can be found in Appendix 2.A.1 and Appendix 2.A.2.

[17] Heroin is a highly addictive drug processed from opium.

[18] A description of these nine cartels can be found in Appendix 2.A.3

[19] The Mexican prosecutor's office, military, and federal police have their own data on presence, unfortunately they are only available at the state level or are published sporadically. The same is true for the DEA datasets.

presence and opium suitability, I used web scraping and machine learning. The data sets and how they were built are described below.

2.3.1 Cartel Presence

In order to measure cartel presence I need to construct a novel data set. This data set tracks for each of the nine major Drug Trafficking Organizations and for each year between 1990 and 2016 whether each of the organizations was operating in a municipality or not. The algorithm I used to create this data set was the following one.

First, I used a web crawler[20] to scrape Google News Mexico. Google News is news aggregator that collects more than 50000 news sources worldwide. Google does not provide the exact number of sites it tracks for the Mexican version but through the scrape I was able to identify 770 local, 33 national, and 83 international media outlets that publish in Spanish. This web crawler looked for any article between 1990 and 2016 that contained a municipality-cartel pair.

The web crawler collected every article whose main body[21] 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 was 1,201,483. I used a sentence extractor to keep the sentences from these articles that included a municipality-cartel pair.[22] If the article contained a year I assigned the event to that year, if no year was assigned I use the publication year. The number of sentences analyzed was 2,802,224.

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

[21] 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 a municipality sometimes the search engine will return this as a hit. Appendix 2.B includes examples of these type of media pages.

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

Next, I manually classified 5,000 sentences as either presence or not to train a semi-supervised CNN.[23] I used 80% of this sample as the training set and 20% as the test set. A CNN[24] is a deep learning set of algorithms usually use for image classification but also 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.[25] Then several filters are applied. Each filter constitutes of different word window sizes that go over each sentence. This is followed by a discretization operation that reduce dimensionality of the output. This produces a final sentence representation that is classified. The particular CNN used here has an out of sample classification accuracy of 0.86.[26]

To validate this data set for cartel presence, I used two other data sets that also use news articles to measure cartel presence. This will tell us how the algorithm used here compares to other techniques use to collect information from news articles. Finally, I compared the data set with state level data from the DEA in order to provide some external validation measure for the data set created here.

Validation with other data sets created from news outlets

Coscia and Rios (2017) and Professor Victor Manuel Sanchez from the Autonomous University of Coahuila Mexico built different data sets that use news outlets to measure cartel presence. Coscia and Rios (2017) tracked the presence of the same nine DTOs at the municipal level between 1990 and 2010. They also used a web crawler and then code a cartel as being present if the frequency of hits for a particular municipality-cartel exceeds a certain threshold. The correlation between their data

[23]Examples of this sentences can be found in Appendix 2.B.

[24]A simple bag of words with logistic classifier was also calculated and the comparison between these two methods can be found in Appendix 2.B.

[25]A word embedding is a learned representation of text where words that have similar meanings have similar numeric representations.

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

and the one constructed here between 1990 and 2010 is 0.38.[27] The low correlation between these two datasets can be attributed to the difference in validation techniques, relative number of hits versus natural language processing.

Professor Sanchez data set was manually recorded 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 and the one used here is 0.71.

External Validation

The DEA has recorded 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 the data use here at 0.69. For the years 2011, 2013 and 2015 the DEA just reported dominant presence by state and correlation with my data set goes down to around 0.35 for each year. The DEA does not explain what they mean by dominant presence, and the algorithm used here does not aim to classify dominant presence.

The high correlation between the data set used here and the manually collected one provides evidence that the algorithm used here has a high performance compared to a human classification of the articles. Despite the fact that the articles manually coded are probably different from the ones found by the web crawler. The high correlation between the DEA data and the data used here shows that using news articles as a source of illegal activity data might be a good approximation to data provide by the authorities. The advantage of using news articles is that they are reported at a more disaggregated geographical level and with a higher periodicity. These two properties are particularly useful to measure criminal activity. Criminal groups and in particular Drug Trafficking Organizations are continuously changing

[27] All hits before 2000 come from a Google project that digitized newspapers.

their territorial dominance and knowing these fluctuations is key to understand how these organizations operate.

Figure 2.1 shows the evolution of cartel presence between 2004 and 2016. Figure 2.1a shows the mean average number of active cartels between 2004 and 2009 and figure 2.1b shows the mean number of active cartels between 2010 and 2016. The maps show the increase in the number of municipalities with at least one active cartel and the increase in the number of municipalities with multiple cartels present.

2.3.2 Agro-ecological Data

The geographic variation used in this chapter comes from a novel data set that measures suitability to grow opium poppy based on exogenous information on geographic and climatic characteristics. The index built here is conceptually similar to the suitability indexes used by the Food and Agricultural Organization (FAO). While this indexes exist for almost all legal crops, they do not exist for *papaver somniferum*, commonly known as opium poppy. The only available measure is the FAO overall characteristics for *papaver somniferum* to survive.[28]

I used 45 agro-climatic characteristics and all their interactions and regress them on the log of opium yields. Unfortunately, there does not exist historical data on opium production in Mexico.[29] Therefore, I used Afghanistan's [30] opium yields. Since 1990 the United Nations has been collecting data, through surveys and satellite images, on opium yields and hectares cultivated. [31] The index built here used yields by Afghan district between 2000 and 2018.[32] The main agro-climatic variables used are temperature, precipitation, elevation, terrain ruggedness, soil quality, and river

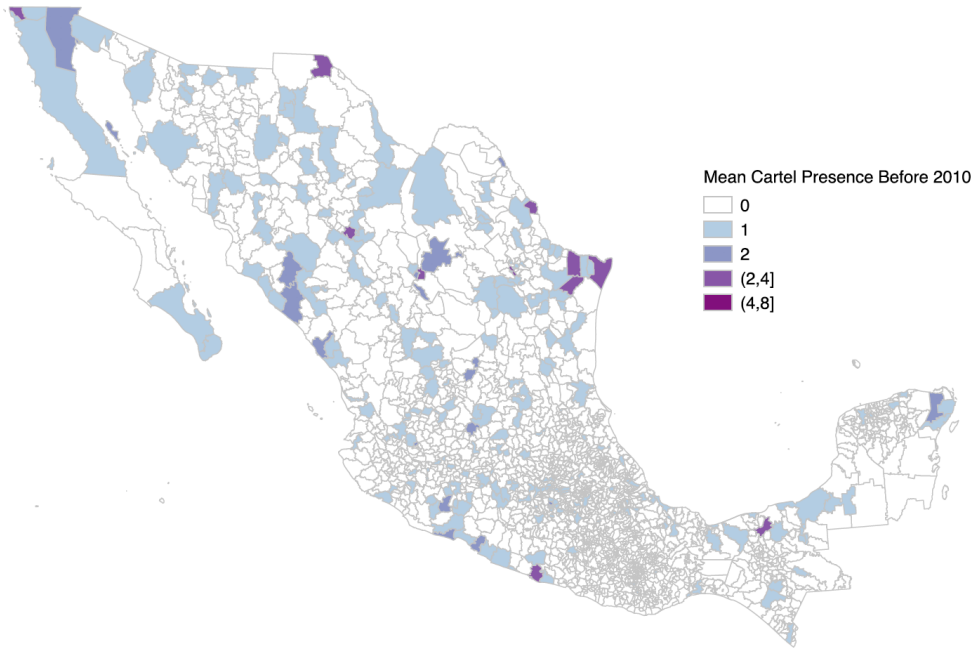
[28] `http://ecocrop.fao.org/ecocrop/srv/en/dataSheet?id=8296`

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

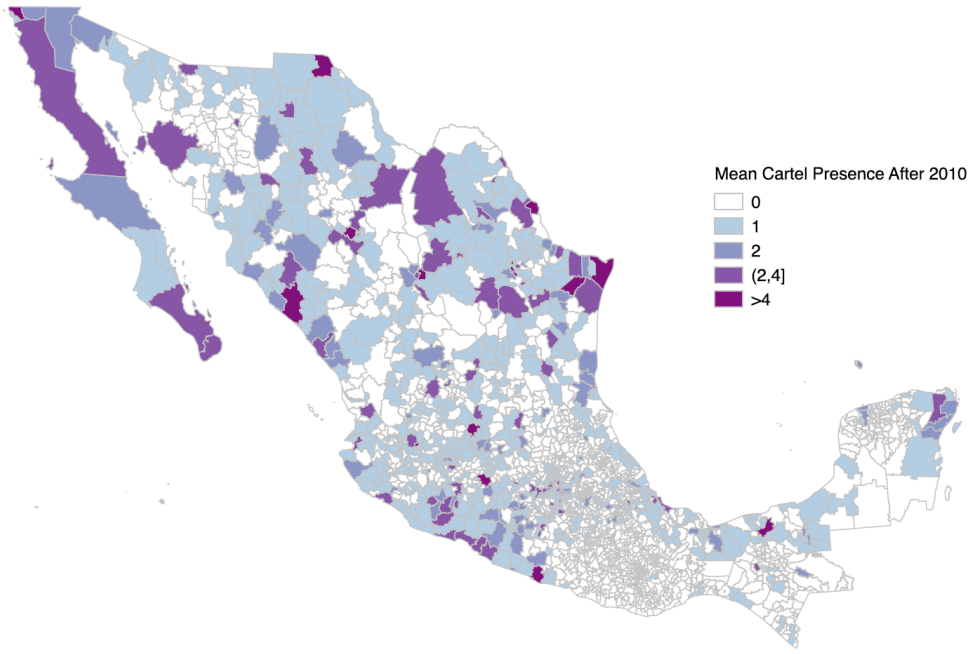
[30] Afghanistan is the world main producer of raw opium.

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

[32] 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).



(a) Mean Cartel Presence 2004-2009



(b) Mean Cartel Presence 2010-2016

Figure 2.1: Cartel Presence

density. A full description of these variables and the data sets they came from can be found in Appendix 2.C.

In order to reduce the number of regressors, there will be 903, I used an elastic net. An elastic net is a penalized regression that reduces the number of regressors Zou and Hastie (2005). I used a 10 fold cross-validation to validate the model.[33] The parameters from this elastic net are then used to predict the log productivity of opium in Mexican municipalities given its agro-climatic characteristics.[34] This measure is then standardized between 0 and 1 for interpretation purposes, so that 1 means perfectly suitable and 0 means not suitable to grow opium poppy.

Figure 2.2 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 2.1 shows that cartel presence and opium suitability are related specially after 2010. Most of the states in the Pacific coast; Sinaloa, Nayarit, Jalisco, Colima, Michoacán, and Guerrero, are highly suitable to grow opium and saw the number of cartels increased specially after 2010.

The Mexican military provides monthly data on how many hectares of opium are eradicated by municipality. I used this data set to provide some external validity for the opium suitability index. The correlation between the index and the mean eradication between 2000 and 2005 is 0.45. This implies that there is at least some eradication in highly suitable municipalities.

2.3.3 Homicide and Demographic Data

The data on homicides per municipality came from the INEGI data. There does not exist a full panel of homicides related to organized crime so I used all the homicides for all the analysis here. Data on population, average years of education, percentage

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

[34] The shrinking and mixing parameters used can be found in Appendix 2.C.

Table 2.1: 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)

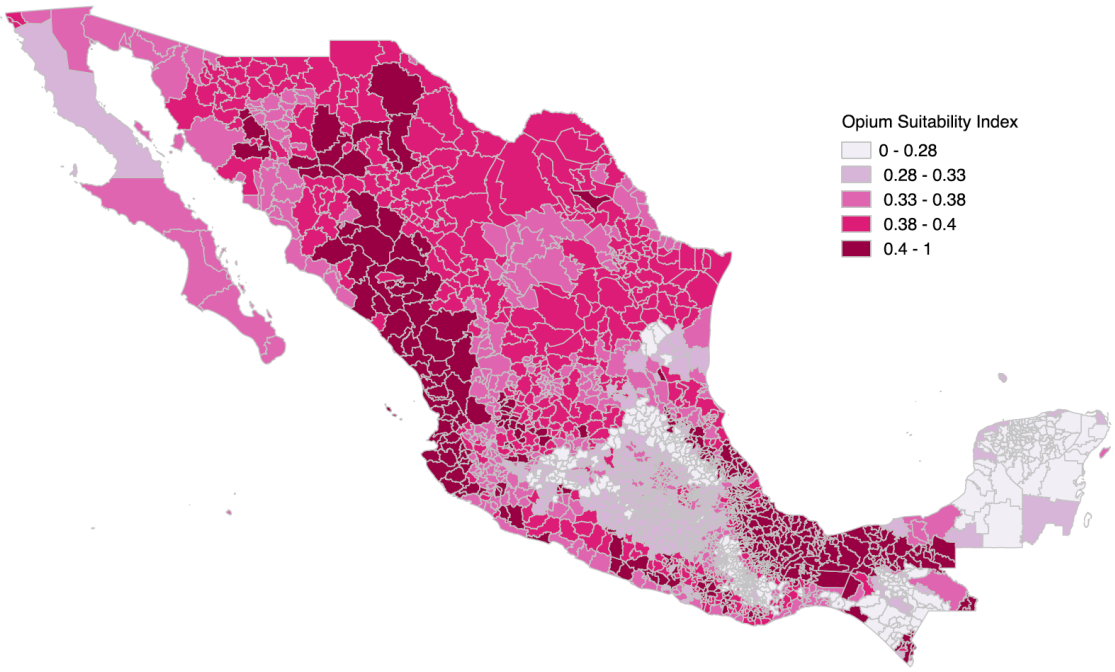
*Notes: This table presents the results of a ordinary least square regression where the dependent variable is the mean eradication of opium poppy, measured in hectares. Controls for police, military presence and includes municipality fixed effects.*p<0.1; **p<0.05; ***p<0.01*

of indigenous population, illiterate population, unemployment, basic characteristics of the households that includes houses with dirt floors, percentage of houses without electricity, sewage or running water and percentage of houses with TV, refrigerator, washer machine, phone, Internet and car come from INEGI 2000, 2005, 2010, and 2015 censuses and intercensal surveys. I also used the CONEVAL data set that reports an index of how marginalize and municipality is and data sets that record political parties of mayors and governors from CIDAC and INAFED.

2.3.4 Drug Time Series

The Mexican National Defense Office publishes data each year on how many hectares of opium and marijuana are eradicated in each municipality and the amount of drugs seizes by the military and the marines. The data on heroin prices came 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.

Figure 2.2: Opium Poppy Suitability Index



2.4 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 Organization 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 effects 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.

2.4.1 Theoretical Framework

This sections provides 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 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 from government interventions might generate.[35] 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 invests 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 a 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 function of its own investment and the investment of all the other competi-

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

tors:

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

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 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.[36]

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 :

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

[36] All the calculations can be found in Appendix 2.D.

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.*

2.4.2 Empirical Strategy

Baseline Econometric Specification

In order 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 affects 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. The reformulation was followed by an increase in heroin overdose deaths and a spike in heroin prices in the United Sates. This seems like a plausible exogenous shock to the heroin market that might affect entry decisions into news 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 2010, the year of the reformulation.

$$Y_{mt} = \sum_{t=2004}^{2016} \beta_t Suit_m * PriceHer_t + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_s t + \epsilon_{mt} \tag{2.1}$$

$Suit_m$ 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 U.S. adjust by purity, inflation, and normalized to 2002 dollars. The Y_{mt} are different measures of cartel presence: the probability of at least one cartel present and the number of active cartels. α_m are municipality fixed effects, γ_t year fixed effects and $\sigma_s t$ state specific trends. Fixed effects control for all individual municipality characteristics that are fixed over time. Controls are 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.[37] The only difference between this specification and an standard event study is that here the treatment is a continuous variable.[38]

[37]Dell (2015) finds that drug related violence increased after close elections, when the winner was a PAN mayor. There is anecdotal evidence that PAN mayors and governors cooperate more with the federal government efforts against drug trafficking.

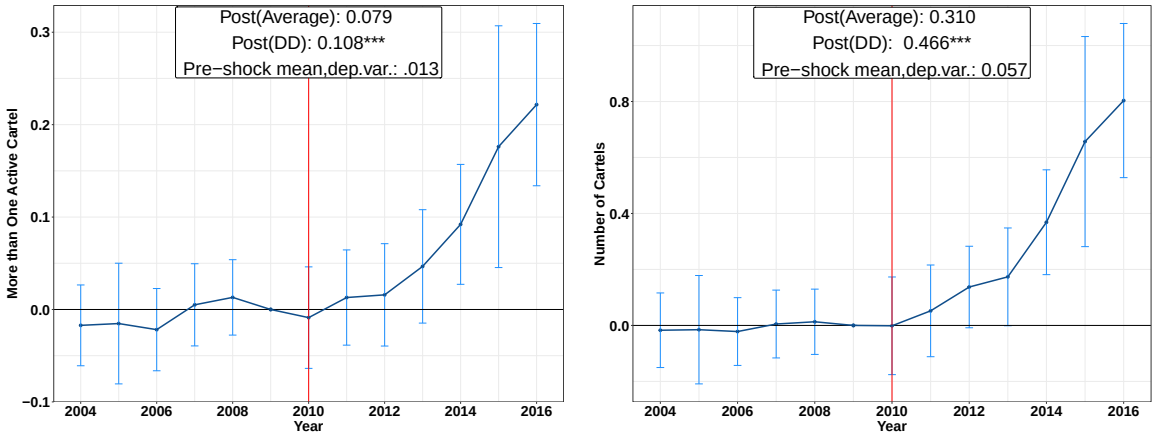
[38]Strategy commonly use to estimate the effect of commodity shocks (Dube and Vargas, 2013).

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 index and heroin prices. Standard errors are clustered using Conley (1999) with a radius of 500 Km. This is to address 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 2.F.

Results

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

Cartel Activity: Figure 2.3a shows the increase in the number of municipalities with more than one active cartel after 2010. To test the relationship between suitability and the increase in cartel presence I used specification (1). Figure 2.3a shows the event study coefficients when the dependent variable is one if the municipality has at least 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



(a) More than one cartel active

(b) Number of active cartels

Figure 2.3: Event Study on cartel presence

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 2.3b 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 2.2 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 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 to 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 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 2.C.

Table 2.2: The effect of the reformulation on cartel activity

	Cartel Activity									
	More than one					Number of Cartels				
Average effect post-2010	0.108*** (0.011)	0.121*** (0.014)	0.064*** (0.012)	0.044*** (0.012)	0.049 *** (0.012)	0.466*** (0.002)	0.537*** (0.049)	0.292*** (0.038)	0.227*** (0.039)	0.241*** (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*

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 in this work 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 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.[39] Examples of these sentences can be found in Appendix 2.B. From the 1,201,483 articles analyzed here 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 helps 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.[40]

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

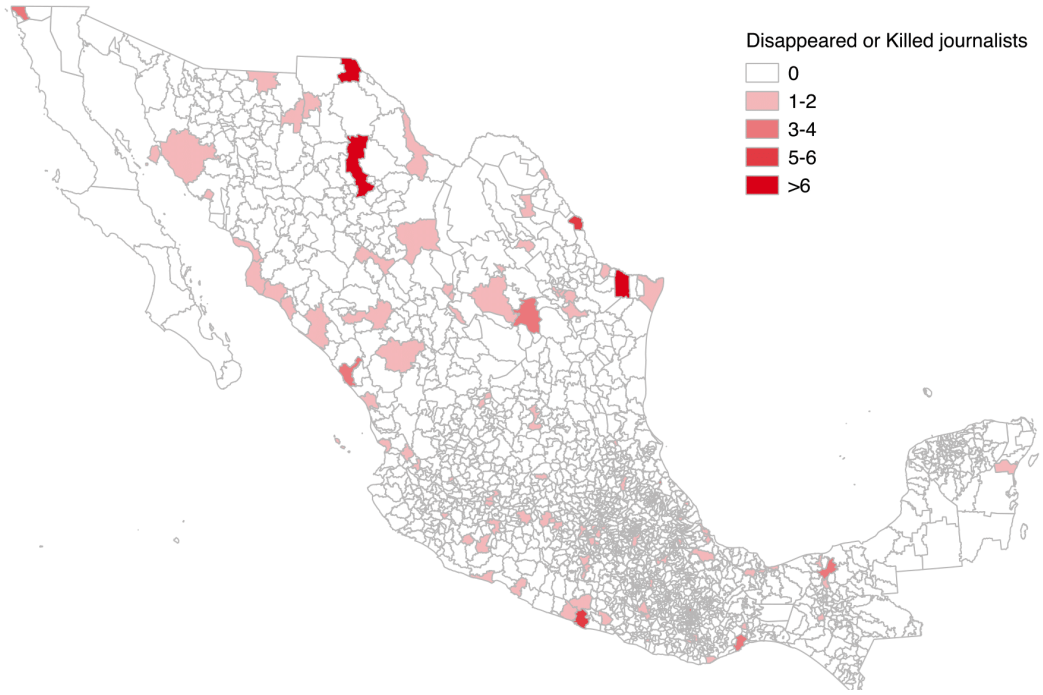
[40]The data set of missing and killed journalist can be found here `https://en.wikipedia.org/wiki/List_of_journalists_and_media_workers_killed_in_Mexico`.

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 2.E. The specifications controls for police and military presence, political party at the municipality and state level, and 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 presence by cartel is also close to zero. The highest one is for Los Zetas at 0.17. These provides evidence that there does not seem to be any particular bias towards reporting or misreporting on a particular organization. Figure 2.4 shows the map of where media workers have either disappeared or murdered between 2004 and 2016. There is not a particular area where they are concentrated. All of the journalists were attacked in a municipality with at least one cartel present but there does not seem to be a particular cartel that is more lethal to media workers.

Despite this, the data set used here might still be bias, in particular downward biased. Journalists and police officers usually report just when something actually happened in a municipality related to a particular organization. Therefor, the data is probably just capturing 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 think it is newsworthy to repost their activities I would not observe these cartels. 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

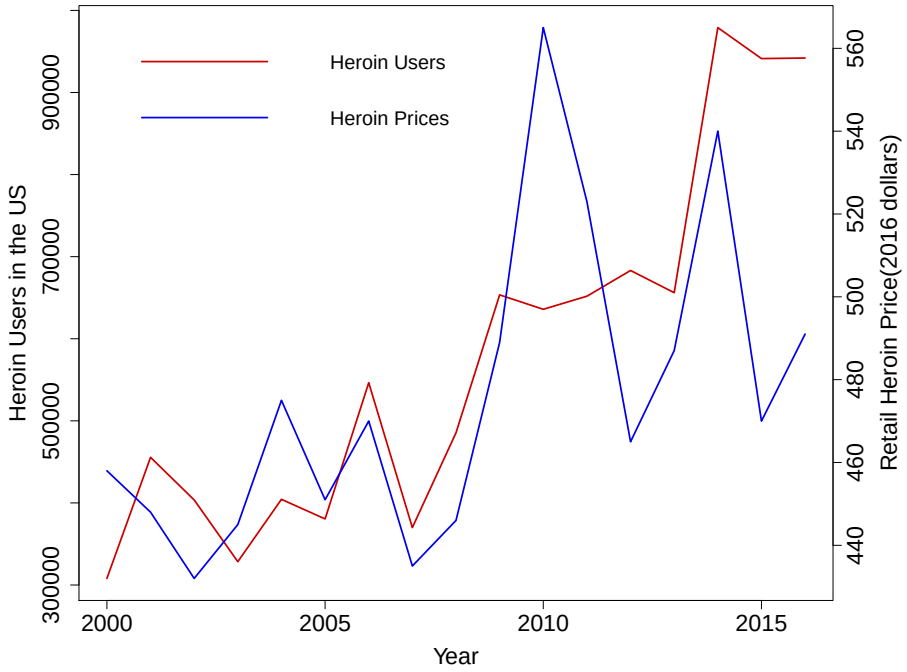
Figure 2.4: Disappeared or Killed Media Workers between 2004-2016



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 2.5 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 overdose deaths from it. Then, it is reasonable to assume that the increase in demand and the subsequent increase in prices attracted more drug traffickers to the heroin market.

Finally, one last concern is that the increase in violence and the multiplication of Drug Trafficking Organizations is a direct effect from the war on drugs. 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 the

Figure 2.5: 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.

beheading of criminal organizations by targeting high rank kingpins. 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 well suited to grow opium poppy or the sharp shift of the heroin market around 2010. In order to address any possible concern regarding government activity I include several controls: 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. State-specific time trends are there to control for any other government policies that might affect cartel activity. The results are robust to all 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 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.

2.5 Number of Cartels and Violence

The results in the previous section provides evidence that the demand shock increased the entry of Drug Trafficking Organizations into suitable municipalities to grow opium poppy. The theoretical framework relates cartel entry, investment in military capacity, and violence. Cartels will decide whether to enter or not a production site and the level of violence in each cite will depend on the number of active cartels and their investment in military capacity. Military capacity is clearly unobservable so in order to measure the effect of the demand shock on the level of violence I will use an instrumented difference-in-difference design. Directly examining the effect of competitive cartels or the number of cartels on violence brings two possible problems: endogeneity and reverse causality. To circumvent these two concerns, I use as an instrumental variable suitability index to grow opium poppy interacted with the heroin price in the United States. These instrument as shown in the previous section increase the number of active cartels but it is not necessarily correlated with the amount of violence in each municipality.

As suggested by the theoretical model if there is an increase in the demand for heroin in the United States, I would expect cartels to expand into suitable areas, increasing the likelihood of violent confrontations between cartels in this particular areas. The second and first stage specifications are given by:

$$
\begin{aligned}
Y_{mt} &= \beta \hat{C}_{mt} + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_s t + \epsilon_{mt} \\
C_{mt} &= \pi Z_{mt} + \psi X_{mt} + \zeta_m + \theta_t + \kappa_s t + \eta_{mt}
\end{aligned}
\tag{2.2}
$$

Here Y_{mt} are the homicide rate per 100,000 inhabitants per municipality. α_m and γ_t are second stage municipality and time fixed effects. $\sigma_s t$ are state specific time trends that account for any policy or change that might affect the state level and not just the municipal one. C_{mt} is the probability of having competing cartels in municipality m at time t. This means having at least two active cartels. β is the main parameter of interest measuring the differential effect of having at least two cartels present on the homicide rate. X_{mt} is the same vector of controls used in the section above. The first stage specification explaining C_{mt} is the second equation in (2.2). In this equation ζ_m and θ_t represent first stage municipality and year fixed effects, respectively. $\kappa_s t$ are state specific time trends. Standard errors are clustered using Conley (1999) with a radius of 500 Km.

The results from this specifications are shown in Table 2.3. The table shows that the increase in the number of homicides per 100,000 is between 17 and 35 after 2010. This increase will be comparing two municipalities that are the same in all aspects except the number of cartels. One with none or one cartel active and the other one with two or more than two active cartels. Column (1) shows the specification without any covariates and just with municipality and time fixed effects. Column (2) adds controls for police and military presence and political party of the mayor and the governor. Column (3) adds baseline specifications, column (4) adds controls and baseline specifications. Finally, column (5) adds state specific time trends. In order for this analysis to be valid I need the parallel trends assumption to be true. A graph that visually shows that the parallel trends assumption hold for high suitable municipalities can be found in Appendix 2.F.

The results from the previous section and this one are both consistent with Proposition 1. An sudden increase in demand for heroin in the United States will drive cartels to enter to suitable municipalities. The entry of several Drug Trafficking Organizations into the same production cite will increase the violence in that particular cite in order to try to capture a higher market share.

Table 2.3: Homicides per 100,000

	Homicides per 100,000 inhabitants				
Post-shock	22.76***	17.83***	35.69**	35.88**	28.02 ***
	(5.64)	(3.65)	(11.29)	(15.17)	(5.16)
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 instrumented difference-in-difference model for the dependent variable homicide per 100,000 inhabitants. The first stage variable is a dummy variable that is 1 when there are competitive cartels, at least to active cartels, in a municipality. Column (1) present the results with municipality and year fixed effects. Column (2) add controls for police presence, military presence, and political party of the mayor and the governor. Column (3) control for baseline characteristics interacted with year fixed effects. The baseline characteristics are population, marginalization rate, and drug related activity in 2000. Column (4) add to the baseline trends the set of controls for column (2). Finally, Column (5) 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*

2.6 Effects of the Demand Shock on Migration and Household Characteristics

In this section I analyze the effect that the external demand shock had on socio-economic outcomes. I use the first specification (1) where the relevant event happens in 2010. First, I ask how demographics such as population, average years of education,

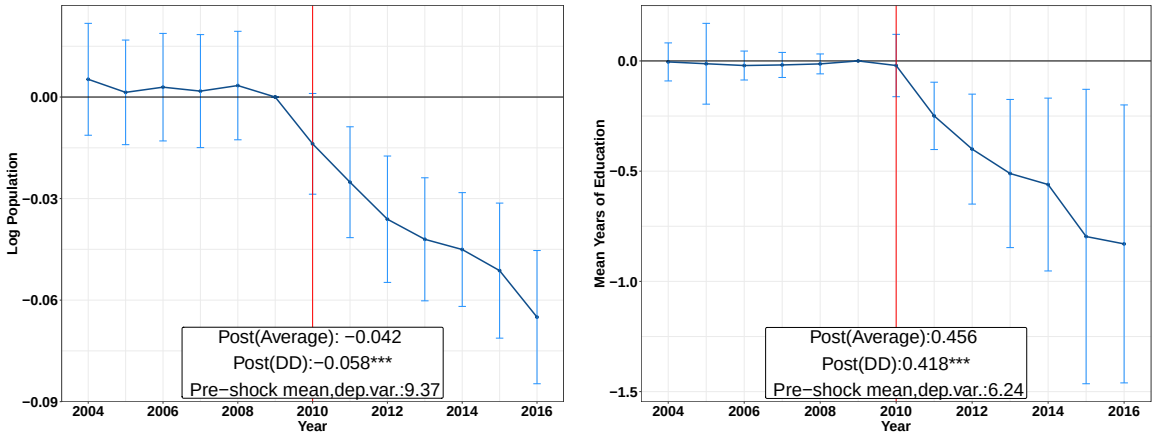
and the percentage of households with dirt floor change after the shock. Finally, I present how the government data on eradication confirms that after 2010, the suitable municipalities were producing more opium than before. These results show that the shock had a direct effect on other outcomes across Mexican municipalities.

2.6.1 Change in Demographics

This section analyses the effect of the shock on different demographic outcomes. I estimate the effect of the shock on population and household composition. The variables analyzed here are the log of the population, mean years of education, and percentage of households with women as a head.[41]

Figure 2.6a shows an steady decrease in the log of the population after 2010 and Figure 2.6b has a similar steady decrease in the average years of education. Figure 2.7, 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 2.F. To understand the magnitude of these coefficients I will compare a municipality in the 75 percentile with one in the 25 percentile of suitability, when heroin prices double in the United States. A municipality in the 75 percentile of suitability will have a 2.7% decrease in th log of the 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.

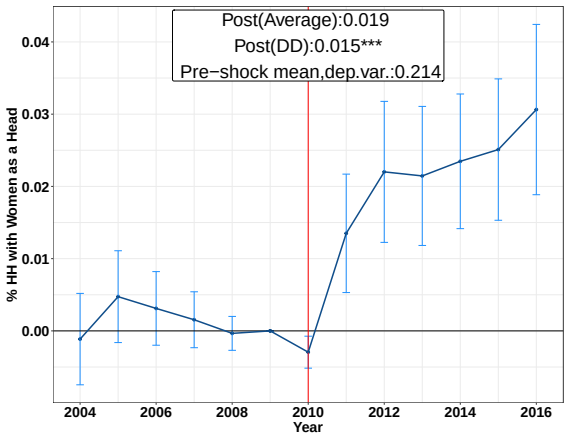
[41]The other variables analyzed were percentage of indigenous population, percentage of people with social security, adult illiteracy, and mean number of occupants per dwelling. These four variables do not show significant changes during the time of the analysis. These variables have an increasing trend during the whole sample or are completely flat during the period analyzed.



(a) Log of Population

(b) Mean Years of Education

Figure 2.6: Demographic outcomes



(a) Percentage of households with women as a head

Figure 2.7: Demographic outcomes

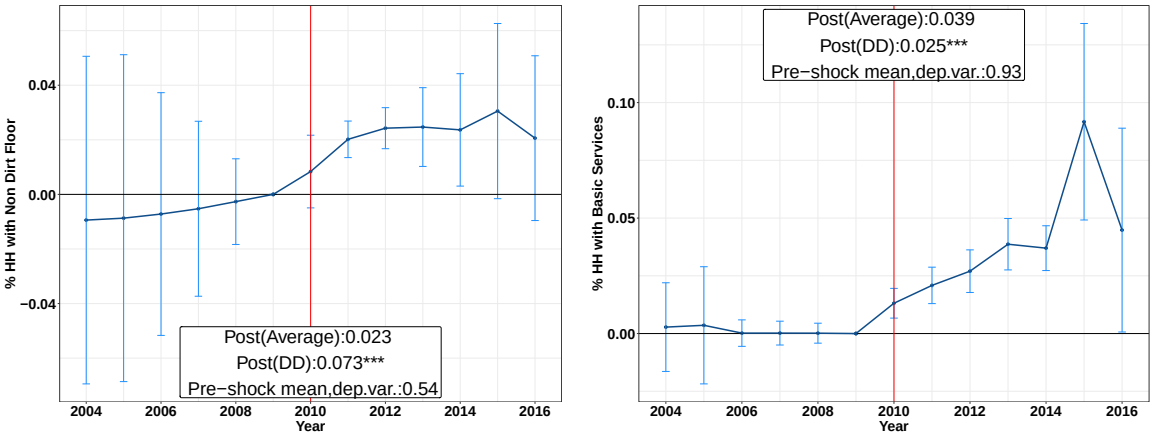
2.6.2 Economic Outcomes

The next set of results suggest that the shock might have had a positive impact in some economic outcomes. The variables analyzed were the percentage of households without dirt floor and the percentage of households with access to basic services (water, electricity, and sewer).[42] Figure 2.8 shows the coefficients from the event study using specification (1). From figure 2.8a there was an increase in the percentage of houses that had floors made of materials different from dirt. Figure 2.8b shows an steady increase in the percentage of households with basic services. 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 2.F. These results suggest that there was an income boost from the increase in heroin prices and that it is 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 dollars by 2014 Stevenson (2015).

2.6.3 Military Eradication

In this section I use the eradication data from the Mexican military to explore if the shock changed the amounts of opium and marijuana seized. Assuming that the military did not became better at eradicating one particular crop during this period

[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.



(a) Households with Non Dirt Floor

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

Figure 2.8: Economic outcomes

and that eradication can be used as a proxy of total production. Figure 2.9 shows the coefficients of specification (1) for the log hectares eradicated of marijuana and opium. There is a 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 2.4 shows the difference-in-difference coefficients with the different controls and fixed effects, the results are robust to all 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]

2.7 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

[43]Figures for seizures of cocaine and methamphetamines can be found in the Appendix 2.F.

Figure 2.9: Log of Hectares eradicated

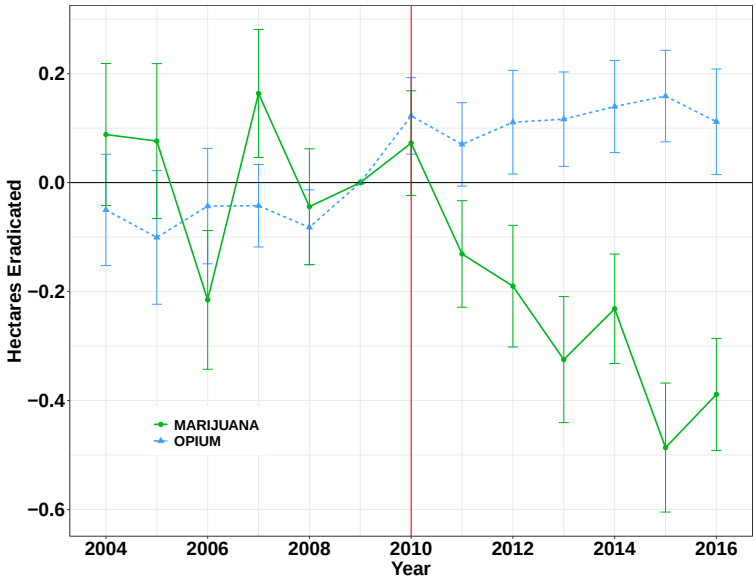


Table 2.4: Opium and Marijuana Eradication

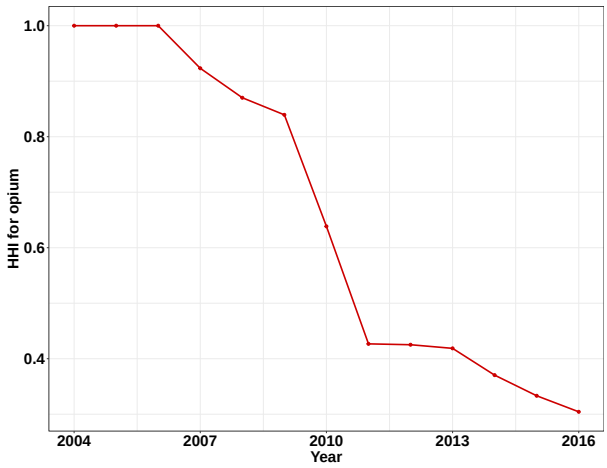
	Eradication									
	log(Hectares Opium Poppy)					log(Hectares Marijuana)				
Post-shock	0.198***	0.157***	0.088*	0.033*	0.040***	−0.220***	−0.192***	−0.235***	−0.210***	−0.166**
Radius 500 Km	(0.001)	(0.045)	(0.038)	(0.008)	(0.004)	(0.002)	(0.048)	(0.047)	(0.047)	(0.054)
Observations	32,202	31,752	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*

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 2.10 shows the Herfindahl-Hirschman Index for the raw opium market. The index is calculated using the cartel presence and the eradication data sets. 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 their operations into this market.

Figure 2.10: HHI Opium



2.7.1 Identifying Expanding and Competitive Cartels

This work consider nine main Drug Trafficking Organizations recognized by the Mexican Military and the DEA as the major actors. The interactions between these or-

ganizations are complex with them expanding, fragmenting, and disappearing. The last decade saw some of them fragmenting due to the government strategy of capturing kingpins. These strategies left power gaps and 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 incentivized 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 drug cartel. These two groups have been fighting with each other for the control of the state of Michoacán. I used the specification below to quantify the effect that the shock had on the presence of each of the nine organizations.

Econometric Specification:

$$Y_{mt}^{c} = \sum_{t=2004}^{2016} \beta_t Suit_m * PriceHer_t + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_e t + \epsilon_{mt} \tag{2.3}$$

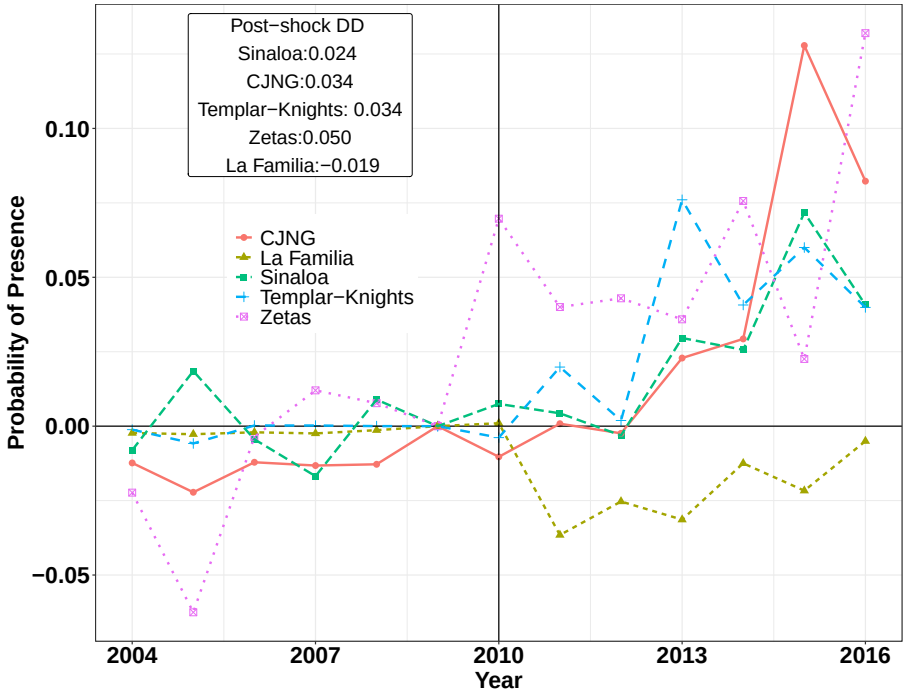
where Y_{mt}^{c} is the probability of having the cartel c active in municipality m and time t. $Suit_m$ is the measure of suitability in the municipality m, $PriceHer_t$ is the retail price of heroin in the United States per milligram of heroin adjust by purity normalized to 2002 prices, X_{mt} is a 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.

2.7.2 Results

The nine major organizations studied in this paper show at least some presence in municipalities well suited to grow opium poppy. Figure 2.11 shows the coefficients from equation (2) 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 Appendix 2.F. To interpret these results lets compare a municipality in the 75 percentile of opium suitability with one in the 25 percentile, when the heroin price doubles in the United States. The probability of the Sinaloa Cartel being present in the 75 percentile municipality is 10.55% higher compared to a municipality in the 25 percentile of suitability. The comparison between this two type of municipality are 7.89% for the Jalisco New Generation Cartel, 2.17% for the Templar Knights and 12.33% for Los Zetas. Finally, the probability of La Familia being present decreases -0.39% each year after the shock in a 75 percentile municipality compared to one in the 25 percentile. The remaining four cartels: Tijuana, Golf, Juarez and the Beltran-Leyva Organization do not show significant increase or decrease in the probability of being present in high-suitable municipalities despite the fact they do enter some opium producing territories. A detailed analysis of what happened with these four cartels can be found in Appendix 2.F. These results suggest that market pressures can also lead criminal organizations to split and fight with previous allies

to get control of valuable territory.

Figure 2.11: Effect of Demand Shock on Individual Cartel Entry



2.8 Conclusion

This chapter provides evidence that Drug Trafficking Organizations react to external market pressures, in particular to exogenous changes in the demand for drugs. I contribute to the literature by adding market pressures and external demand shocks as factors that increase violence and the number of active Drug Trafficking Organizations. The results from this chapter 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 Mexi-

can 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 react to different external pressures is key to implement policies that aim not just to reduce illegal activities like drug trafficking but the negative externalities associated with them.

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Appendix

2.A Background

2.A.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 traces back to the Prohibition era in the United States, when the first criminal organizations established several routes from Mexico to the U.S. border in order to smuggle alcohol (Grillo, 2011).

At the beginning of the twentieth century the U.S. 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, but add things such as 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 trafficking 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 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

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

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.

2.A.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 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.

2.A.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

[45]Feuer (December 2018)

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.

2.B Google News and Natural Language Processing

The algorithm 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 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 2.12 a) shows an example of this. The main article talks about the Sinaloa Cartel being present in the city of La Paz but one of the side articles talks about the municipality of Los Cabos. The search engine will gave a valid hit on this article for the pairs La Paz-Sinaloa Cartel and Los Cabos-Sinaloa Cartel, when the main article is just talking about presence in the first case. The other kind of invalid hits that this step eliminates is the ones where the name of a city or municipality is part of the newspaper name. Figure 2.12 b) shows an example of this. The main article describes a police operation in Coyoacán in Mexico City were they capture several members of the Beltran-Leyva organization. The problem is that the newspaper name is "El Siglo de Torreón" and Torreón is a municipality. Then the web crawler will return this article as the pair Coyoacán-Beltran Leyva and Torreón-Beltran Leyva but just the first pair describes presence of the organization in that municipality.

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



(a) Example 1 (b) Example 2

Figure 2.12: Web Pages Examples

- 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

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

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 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 2.5 shows when and where each cartel appears for the first time in the data set created by the algorithm above. The first Column shows the year the cartels first appeared in the data set, some of this cartels are older but the algorithm did not search before 1990. The second Column shows the first municipality where each cartel appears in the data set and the next four columns show in how many municipalities each cartel was active in 1990, 2000, 2010, and 2016. Table 2.6 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 2.5: Summary of cartel presence

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

Table 2.6: Cartel Presence Summary Statistics

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

2.C 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).

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

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

The suitability index was built by regressing the log of opium yields by year and district in Afghanistan between 1990 and 2018 on the 45 geo-climatic characteristics and all its interactions. To reduce the number of regressors I use an elastic net. An elastic net is a penalized OLS that combines lasso and ridge methods. 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 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.

2.D 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:

$$\frac{R\eta M_i^{\eta-1}}{\sum_{j=1}^{N} M_j^{\eta}} - \frac{ReM_i^{2\eta-1}}{(\sum_{j=1}^{N} M_j^{\eta})^2} - 1 = 0 \tag{2.4}$$

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

$$\eta\left[\frac{N-1}{N}\right] = \frac{M^*}{R} \tag{2.5}$$

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:

$$\eta(N-1)[N(\eta-1)+2\eta] < 0 \tag{2.6}$$

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:

$$N \leq \frac{\eta}{\eta-1} \tag{2.7}$$

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

2.E 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.

$$Y_{it} = \beta C_{it}^{d} + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_s t + \epsilon_{mt} \tag{2.8}$$

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

Table 2.7 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 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 particular cartel that is more dangerous than the other ones. This implies that using news articles to measure cartel presence is a good and is probably close to data that local authorities have.

Table 2.7: Relationship between death and disappeared journalist and cartel presence

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

*Notes: This table presents the results from regressing 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*

2.F Robustness checks

Cartel Activity

Table 2.8 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.

Number of Cartels and Violence

Figure **??** shows years in the x axis and average homicides per 100,000 inhabitants in the y axis for all the municipalities that considered high suitable. Here high suitable means that they are above the 75 percentile of the suitability index. The graph shows visually that until 2009 the trend between municipalities with two or more cartels and the ones with one or zero is parallel. After 2009 there is a clear increase in the number of homicides per 100,000 inhabitants in the municipalities with two or more cartels compare to municipalities with less than two. The trend for these municipalities stay constant for most of the period while the trend in for the municipalities with two or

Table 2.8: The effect of the reformulation on cartel activity

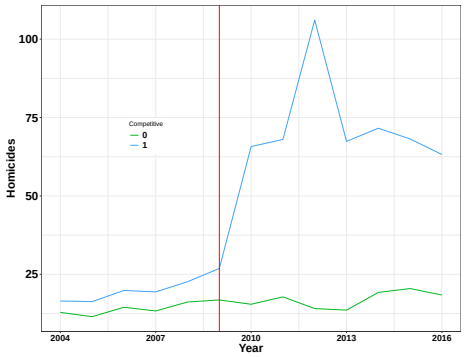
	Cartel Activity									
	Competitive					Number of Cartels				
PshockInst(dd)	0.108***	0.121***	0.064***	0.044**	0.049**	0.466***	0.537***	0.292***	0.227***	0.241***
	(0.02)	(0.021)	(.018)	(.017)	(0.017)	(0.072)	(0.075)	(.058)	(0.057)	(0.061)
Observations	32,202	31,752	32,202	31,752	31,752	32,202	31,752	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*

more active cartels goes up and stays up, with some fluctuations, for the rest of the analyzed period.

The effect of the shock in socioeconomic outcomes

Tables 2.9 to 2.11 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 2.9, log of the population and mean years of education. Table 2.10, percentage of households with a woman as the head. Finally, Table 2.11 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



(a) Parallel Trends

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 2.9: 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

Table 2.10: 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 2.11: No-Dirt Floor and No-Basic Services

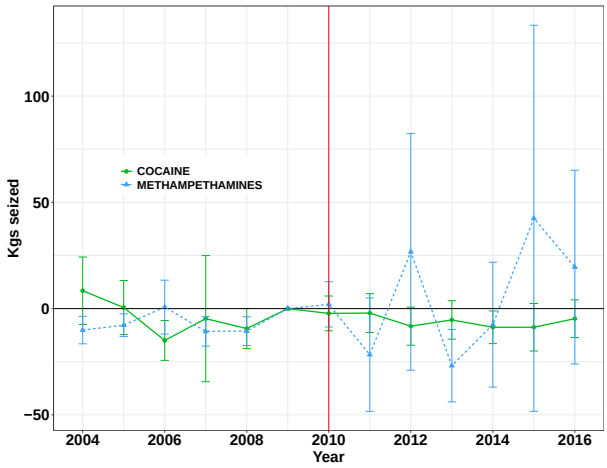
	Economic outcomes:									
	% without Dirt Floor					% of Households with basic Services				
Post2010	0.073***	0.038*	0.081***	0.081***	0.056***	0.025***	0.014*	0.021**	0.013**	0.015***
	(0.009)	(0.017)	(0.013)	(0.013)	(0.016)	(0.000)	(0.008)	(0.008)	(0.002)	(0.001)
Observations	32,202	31,752	32,202	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

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 methamphetamines 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 2.13 shows the coefficients from the event study specification, the quantity of cocaine and methamphetamines 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 2.13: Kilograms seized by the Mexican military



Cartel Competition

The next tables 2.12 to 2.16 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 2.12: 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 2.13: 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 2.14: 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 2.15: 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 2.16: 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

Chapter 3

Cartel Entry, Exit and Violence

3.1 Introduction

All empires are creates by blood and fire.[1]

-Pablo Escobar, during an interview with Colombian journalist Elizabeth Mora in April 1984.

Violence is seen as an intrinsic characteristic of the trade of illicit drugs. Usually, they use violence to settle disputes, discipline employees and provide a semblance of order with suppliers, creditors, and buyers, while also serving to intimidate and attack potential competitors. There is consensus in the literature of this relationship being true. There is not enough evidence of what are the factors or characteristics that determine the levels of violence. Here I will argue that market structure, define as the number of cartels at a particular location, is key in understanding the relationship. The context for this analysis is Mexico during the last twenty years, so institutional context plays an important determinant on the degree of violence Williams and Felbab-Brown (2012).

In this chapter, I use a novel panel data set of cartel presence across Mexican municipalities from 1990 to 2018 to look directly at how entries and exits of Drug

[1] Paez Parada (2010)

Trafficking Organizations affect violent outcomes. In particular, the homicide rate, extortion, theft, and rape. The data set[2] includes nine Drug Trafficking Organizations recognized as major actors in the international drug markets by the U.S. and Mexican governments. The data is a panel by year and municipality that shows if a particular cartel is present or not during that year in that municipality. There are a total of 1,883 municipality-year with net cartel entry and 1,237 municipality-year with net cartel exit. Importantly, the data covers a period in which the heroin market is expanding in the United States. Besides, during this period many municipalities have one or more cartels present, allowing me to study how the change in violent outcomes vary with the number of cartels.

The analysis in this chapter focuses on the years 2005-2016 because the data was collected from on-line news media 2005 is a good starting year for the analysis due to the increase in the number of news outlets with a web presence. The analysis ends in 2016 because it is the year when heroin demand in the United States starts going back down due to the presence of fentanyl Lakhani (May, 2019).

The identification strategy exploits the sharp timing of entries and exits of cartels into municipalities. I exploit the increasing demand for heroin during the period while other drug markets stayed stable in the United States. The main specification looks at changes in homicide rates in municipalities that experience an entry or exit of a cartel relative to other municipalities in the same state and year that do not. The identification relies on the profitability of the heroin market for a particular municipality is not the only element changing the violence. I discuss the determinants of cartel profits and the extent to which they could be correlated with the violent outcomes in a municipality. The primary econometric specification is an event study where the relevant event is the entry and exit of a cartel. The results are presented graphing the event study coefficients. These graphs show non-particular pre-trends

[2]For an explanation of how this data set was generated, see Chapter 2 data section.

before the events and sharp changes in the year of the events. These plots provide evidence of the change in the number of cartels in a municipality driving the changes in violence.

The first variable studied is the effect of cartel entry and exit on the homicide rate. The main concern with estimating this is measurement error from the cartel presence. The data set used here measure cartel presence from the news; this implies that maybe cartels are not being reported in regions where there are not doing anything news worthier. This constitutes classical measurement error, which might lead all the estimates here to be downward bias. In order to address several possible controls that might directly affect homicides in a municipality. These controls include police and military presence, the political affiliation of the mayor of the municipality and governor of the state, and several baseline characteristics. Finally, I add controls for how profitable a particular municipality is for different drug markets. All these support a casual interpretation of the findings.

The first variable studied is the effect of cartel entry and exit on the homicide rate. The entry of the second, third, fourth, and fifth cartel increases the homicide rate per 100,000 inhabitants. For example, the entry of the second cartel increases the murder rate by 36.86%, 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 114.61% increase in the homicide rate after the entry. There does not seem to be any effect after the fifth cartel, but there are too few municipalities with six or more cartels to say this with confidence. The entry of the first cartel in a municipality does not increase violence. This particular result suggest that it is not the presence of illegal activities that generates the violence but the presence of more than one criminal organization fighting for scarce resources. All these results are robust to the different controls and specifications.

The exit of cartels follow a similar pattern as the entry of cartels. The exit of a cartel from a municipality with more than three cartels does not have any particular effect on the homicide rate. The only significant exit is when a municipality with two cartels experiences the exit of one of them. This exit decreases the homicide rate by 15.98% every year after the exit. The last result from the exits is that when a municipality goes from one to zero cartels there is not a significant change in the homicide rate.

Next, I studied the effect of the number of cartels on other criminal outcomes. In particular, extortion, non-violent theft, violent theft, injuries, rape, and kidnapping. The specification used here is a difference-in-difference one that exploits the sharp entry and exit of cartels into municipalities. Here, the only significant result is for extortion that decreases with the number of cartels present in the municipality. The sources of omitted bias for these results is the same as the one describe above. The problem with the results is that different from homicides which are count as long as the government has a death certificate. The data use to measure other crimes come from the police, which implies is a better measure of how many crimes are reported to the authorities and not the actual number of crimes.

This paper contributes to a growing empirical literature trying to understand how criminal organizations affect several outcomes. Polo (1996) builds a model of internal cohesion inside criminal organization and the interaction between increase competition and violence, Mesquita (2018) establishes the relationship between conflict behavior and economic behavior, and Castillo and Kronick (2019) construct a model that focuses on the role of the state in increased violence. The results found in this chapter are consistent with the effect of entry on violent outcomes.

The results presented here are also related with the literature that studies the effects of external and demand shocks on illegal markets. Millán-Quijano (2019) and Castillo et al. (2015) use increases in cocaine prices and link them to increase

violence in Colombia. The results here are consistent with increased profitability in drug markets lead to an increase in drug trade related violence in drug producing countries.

The study presented here differs from past empirical work in the novel data set used, the identification strategy from an increase demand in the heroin market, the ability of the study to disentangle different possible variables that directly or indirectly affect violence. The chapter is organized as follows. Section I below provides background information for the Mexican context. Section II describes the data used in this chapter. Section III lays the main empirical strategies and threats to identification. Section IV presents results on other criminal activity and section V concludes.

3.2 Background

3.2.1 Drug related violence in Mexico

The illicit trade of goods[3] between Mexico and the United States has been going on for years. Regardless of this, the amount of drug-related violence observe right now in Mexico is a contemporary phenomenon not observed in previous decades. A combination of corruption, impunity, and thriving drug markets in the United States the last twenty years have all contributed to this increase in violence across Mexico.

Mexico right now has some of the most dynamic, as well as violent, organized crime groups in the world. They control the manufacture and distribution of several drugs (marijuana, cocaine, heroin, meth, and now fentanyl) have been their primary activity in the last couple of years. Until the early 2000s, the violence related to organized-crime remained low in Mexico. A combination of different factors that included; democratization and increasing pressure from the U.S. to fight drugs led to an increase in violence across the country. By 2006 violence was increasing, especially

[3]Particularly; narcotics, guns, money, and people.

in Michoacan, so the former President Felipe Calderon declared war on drugs. The strategies from the government increase, even more, the violence leading to the most violent years the country has experienced. The period for this chapter includes the war on drugs.[4]

3.2.2 Cartels entry and exit

The main independent variable in this chapter is the change in the number of active cartels in each municipality across time. This chapter considers the nine major Drug Trafficking Organizations[5] recognized by the Mexican Persecutor's office and the DEA. I observe a total of 29,472 municipality-year pairs; there are 26352 with no change in the number of active cartels, 1,883 with net cartel entry, and 1,237 with net cartel exit.

The entry and exit of new cartels into a region have significant effects on socio-economic and violent outcomes. This chapter focuses on changes in violence when these entries and exits occur. Drug Trafficking Organizations are dynamic entities in constant fluctuation across different drug markets and territories.

To justify the identification strategy, one should understand the forces that cause entry and exit of cartels. The primary mechanism behind the entry of a cartel into a new territory is the ability to extract rents. Literature regarding the direct effect of entries and exits is scarce, due to the lack of available data on cartel presence across space and time. Despite this, several examples illustrate the relationship between changes in violence and changes in drug markets in the United States, changes in political power in the territories, changes in enforcement, and changes in local demand for drugs.

[4] All the estimations include controls for police and military presence in order to disentangle the violence from the government enforcement from the violence amongst criminal organizations.

[5] The Sinaloa cartel, the Juarez cartel, the Tijuana Cartel, the Gulf Cartel, Jalisco New Generation Cartel, Los Zetas, La Familia Michoacana, Knights Templar, and the Beltran-Leyva Organization.

Changes in demand for a particular drug in the United States will increase or decrease the value of certain territories, consequently led to cartel entry or exit. Mejía and Restrepo (2013) study how changes in demand for cocaine in the United States affect patterns of violence in Colombia. Shifts in political power at any level will change previous agreements between the criminal organizations and local governments that will derive into a different entry and exit patterns. Dell (2015) provides evidence on how changes in the political party across Mexican municipalities affected cartel presence. Finally, governments' efforts to fight drug production and trafficking can lead to changes in the value of some territories. Castillo et al. (2015) studied how higher cocaine seizures in Mexico affected violence, while Sviatschi (2018) studied how U.S. intervention in the Andean region shifted the production of cocaine from Colombia to Peru.

The shock used in this chapter to affect cartel entry and exit is an increase in the demand for heroin in the United States.[6] During this same period, the cocaine market is stable, with the meth market expanding.Cocaine is not produced in Mexico, just trafficked across the country. Then, unless good places to grow opium poppy are the same ones used to transport cocaine, there should not be any problem with the cocaine market. The meth market is also expanding during this period, although this meth is a synthetic drug that is usually produced near the U.S. border.[7] A sudden increase in demand in the United States leads cartels to enter more profitable regions across Mexico. There are idiosyncratic supply-side factors that affect how profitable a particular region is in the heroin market. These include agro-climatic conditions to grow opium poppies, location between the producing cites and the U.S. border, the number of active cartels in that region, accessibility to chemicals to transform opium into heroin, police and military activity, and political alliances.

[6]For a full description of this shock see chapter 2 background section
[7]I address this in the robustness section below

In the empirical section, I discuss the extent to which the various drivers of entry and exit correlate with violent outcomes and the implication for the interpretation of the estimated parameters.

3.3 Data

3.3.1 Cartel Presence Panel Data

I used the data set created for the last chapter, collected from news outlets between 1990 and 2016. The method of recollection consists of web scraping Google News for any related article that mentions a municipality and one of the major drug trafficking organizations. The data use from this chapter is from 2005 to 2016; most news outlets start having web-pages in Mexico in 2005. In each year, I know the number of cartels, and which of them are present in each municipality. The number of active cartels will be the first variable analyzed.

The analysis in this chapter defines each municipality as production or trafficking cite. I use the municipality because this is the smallest unite for which I can disaggregate violence data throughout the study. The Drug Trafficking Organization will operate in the municipalities in order to either produce or transport their products.

3.3.2 Violence and Demographic Data

The independent variable in this chapter is the homicide rate per 100,000 inhabitants. This data set comes from INEGI data sets on mortality. The particular data set used records every single intentional death for which a death certificated was created and records several demographic characteristics of the death. These characteristics include the municipality of death, the type of weapon used, the age of the victim, and

gender. I used the whole sample of deaths unless otherwise indicated.[8] Demographic data for each municipality come from INEGI censuses, police presence and governance variables also come from INEGI data sets. Finally, the political affiliation of mayors and governors come from CIDAC and INAFED.

3.3.3 Profitability of the heroin market

Mexican Drug Trafficking Organizations are multi-product firms that operate across borders. They are the leading suppliers of marijuana, heroin, cocaine, and methamphetamines in the United States. Profits of a cartel depend on the combination of drugs they produce or transport to the United States.[9] In this chapter, I use data from 2005 to 2010 because of data availability in the cartel presence data set. During this period, the heroin market in the United States expanded.

Between 1990 and 2010, there was an increase in prescription and consumption of legal opioids in the United States. Eventually, this increase in legal opioids availability led some users to start abusing the legal opioids and to several policies[10] that aimed to reduce the abuse of legal opioids. Some abusers change to the illegal counterpart heroin.[11] The policy changes led to an increase in demand for heroin and heroin prices. Drug Trafficking Organizations in Mexico saw this increase in demand and decided to enter the heroin market. Primarily, they enter into municipalities well suited to grow opium poppy.

Therefore, I approximate the profitability of the heroin market by interacting the suitability index[12]to grow opium poppy with heroin prices in the United States. The

[8]There does not exists a complete panel data of homicides from organized crime. The only existing ones stopped being public in 2010, therefore I would not used this data.

[9]Drug Trafficking Organizations also provide services like security and participate in other criminal activities. Across this chapter I abstract for any other activities that generate income for the cartels.

[10]The 2010 reformulation of OxyContin by Purdue-Pharma, the crack down of pill-mills, and the change of opioids from tier two to tier one.

[11]For a longer explanation of the 2010 OxyContin reformulation see Chapter 2.

[12]See Chapter 2

interaction between these two variables approximates how valuable is each municipality for the heroin market.

3.4 The effect of cartel entry and exit on violence

3.4.1 Baseline Specification

In order to estimate the causal effect of entry and exit of Drug Trafficking Organizations on violence, I use as policy change the increased demand for heroin in the United States. I exploit the years around this policy change; in particular, I used data between 2005 and 2016. The policy change was in 2010, and there are not enough reliable data on cartel presence before 2005 due to the lack of newspapers with on-line edition before 2005.

The main specification is an event study 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 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 lacked such conditions, so I expect to see criminal organization fighting over potential market shares.[13]

The main econometric specification used is the following one:

$$V_{mt} = \sum_{\tau=-5}^{5} \beta_\tau \mathbb{1}\{\tau = t - e_m\} + \psi X_{mt} + \alpha_m + \gamma_t + \sigma_e t + \lambda z_{mt} + \epsilon_{mt} \tag{3.1}$$

[13]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 actions. Incorporating these effects beyond political party and military and police presence are left for future research.

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 fixed effects α_m, calendar year fixed effects γ_t. $\sigma_e t$ are state-year fixed effects, which might be relevant because state-level policies that aim to reduce violence might be important drivers of municipal-level violent outcomes but unrelated to specific violent events in a particular municipality and obey more overall trends in state-level violence.

Unless otherwise noted, the vector of controls X_{mt} includes changes in police presence, military presence, political party at the municipal-level, political party at the state-level. A set of baseline characteristics in the year 2000 interacted with year fixed effects that includes; population, average years of education, average hectares cultivated of heroin and marijuana, average seizures of cocaine and meth[14], and the index of marginalization. All of this baseline characteristics are for the year 2000 and all the averages for the drug variables are between 2000 and 2004.

The index z_{mt} denotes the heroin market profitability for municipality m and year t. This variable is the result of multiplying the opium poppy suitability index with the heroin prices in the United States. Assuming not other market is being affect during this period, this is the only profits that are changing for the drug cartels. The parameter λ encodes the extend to which cartel profitability in the heroin market is related to violent outcomes V_{mt} conditional on cartels present, controls, and fixed effects.

[14]Includes any variation of methamphetamines; meth, crank, chalk, and speed.

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 (3.1) 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.

3.4.2 Threats to Identification

Identification relies on event timing being random after controlling for all the observables and fixed effects. The first problem that I need to address is the measurement error in the cartel presence data.[15] Measuring the exact year of the first appearance or disappearance of a cartel in a municipality is key for the identification to work. If the cartel presence variable is just measured when there are violent events, this would not be true, and there will be bias in the estimation. There will be classical measurement error, and β's will be biased towards zero. Then all the estimates presented here can be considered as lower bounds for the true model.

The second concern is any pre-existing trends in violence before the entry or exit of the cartel. All the analyses in this section show visually that there are not pre-trends in the homicide rate before the entry or exit of the cartels.

Finally, the last concern is that the precise timing of entry and exit. Identification is going to be straightforward if $\lambda = 0$; if the variation in the profitability of the heroin market is unrelated to violence after conditioning on observable characteristics and fixed effects. This is plausible if the remaining variations in the cartel possible profits come from cost shocks and other idiosyncratic considerations.

[15]For a complete explanation on possible measurement error in this data set see Chapter 2 threats to identification section.

If $\lambda \neq 0$, then the magnitude of the committed variable bias will depend on how much of the variation in the entry can be explained by variations in z_{mt}. If the profits can explain almost all the variation in entry and exit patterns, then the bias will be big. Otherwise, it will be small. The economics of entry and exit decision means that the latter is more likely the case. The optimal policy of cartel enter is to enter if and only if $z_{ct} \geq z^*$ given all the other characteristics of the municipality. Then an increase in the heroin market will prompt a cartel to enter if it happens to cross the threshold z^*, this means periods when the heroin market is big enough, but the entry does not occur because it does not goes above the cutoff. Even though entries do depend on z_{mt}, the current period shock will explain a small share of these entries.

3.4.3 Results Entry

This section shows three main results. First, the presence of a single cartel does not increase violence. Second, there seems to be a non-linear relationship between the number of cartels and the increase in the homicide rate. Last, it seems that the only significant exit is when a municipality goes from two to one cartel. The figures below show the β's from the specification with all the controls and fixed effects.

Entry of the First Cartel

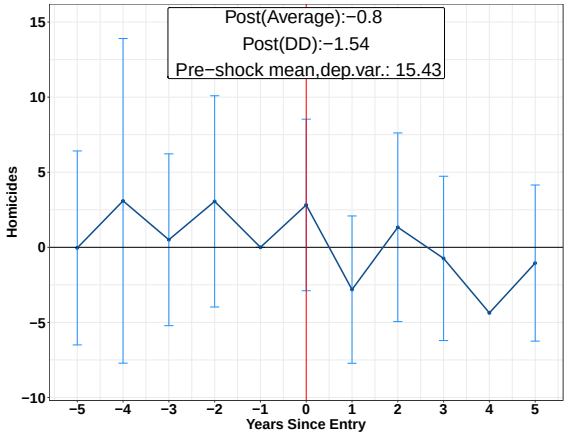
Figure 3.1[16] presents the coefficients from equation (3.1), were the relevant event is the entry of the first cartel into a municipality. From the graph, there does not seem to be any pre-trend in homicides before the entry. The F-test to test if $\{\beta_t\}_{t=-5}^{-}1$ are all equal to zero is 0.2799. The value of the F-test means that I can not reject the null of all the pre-event coefficients to be jointly zero.

There does not seem to be a significant effect from the entry of the first cartel into a municipality. This result is consistent with Biderman et al. (2018), that find a

[16]Standard errors for β_4 are too big to fit this graph.

decrease in violence in São Paulo (Brazil) when a single gang gains monopoly power. This result suggests that it 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 to several specifications that are; one with just fixed effects, one with fixed effects plus controls, one with fixed effects plus baseline characteristics, and the one shown in the graphs that include fixed effects, controls, and baseline characteristics. A table with the same result but using a difference-in-difference specification can be found in Appendix 3.A.

Figure 3.1: First Cartel Entry



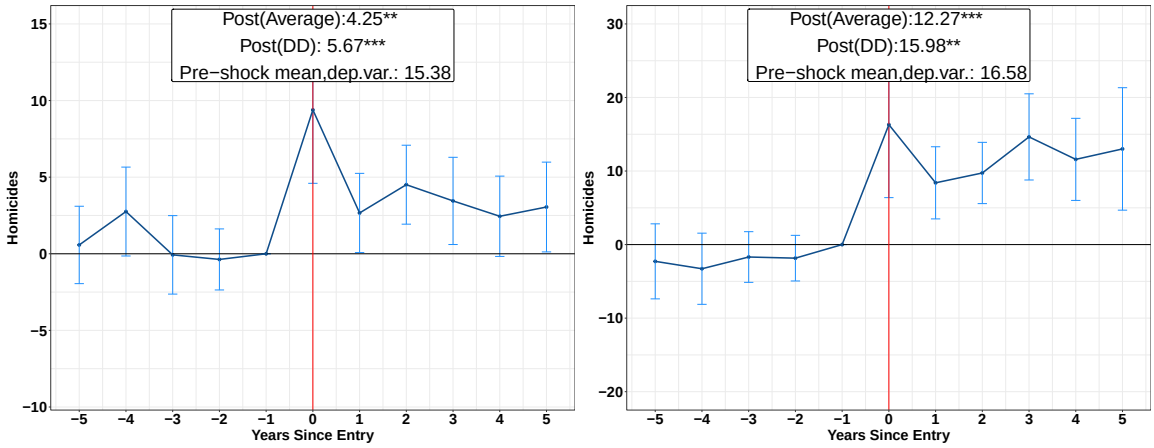
Entry after the First Cartel

The second result from this section is the increase in homicide rate from the entry of the second, third, and so on cartels. Figure 3.2 shows how homicides increase in municipalities that go from one to two cartels and the ones that go from two to three cartels. Figure 3.2a shows that the second entry of a cartel, the homicide rate per 100,000 inhabitants, increases by four homicides. The increase peaks at the year the second cartel enter with 9.39 extra homicides in the municipality. Then, the homicides

stay high, with an average of 3.22 homicides higher than the pre-entry levels for the next four years after the entry of the second cartel. This provides evidence that the year the second cartel enters a location that already has a cartel, there is an initial confrontation that makes the homicides jump for that particular year. The year after homicides drop back down but higher than the pre-entry levels. The graph shows no pre-trend in the homicide rate previous to the entry of the second cartel. The specific F-test implies that the null cannot be rejected, where the null is all the pre-entry β's being jointly zero.

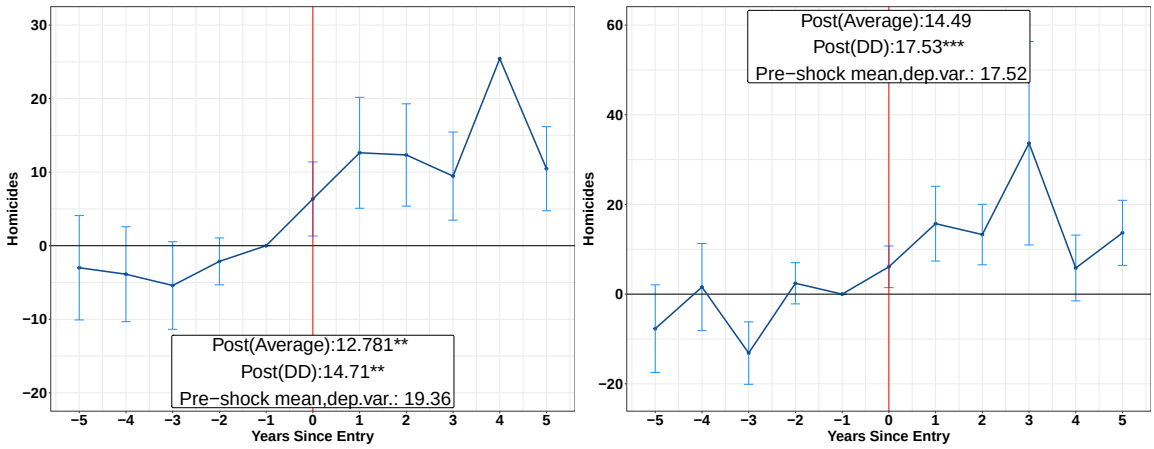
The entry of the third cartel is shown in Figure 3.2b follows the same pattern as the entry of the second cartel with the difference that they year the third cartel enters, there is an increase in homicides of 16.31. In the following four years, the homicide rate stays high, with an average of 11.47 extra homicides after the entry. There does not seem to be any pre-entry trends in the homicide rate for any entry. The F-test is also consistent with no pre-trends. Again, this provides evidence that the most violent year is the year when a new cartel enters a municipality and that the year after this homicides decrease. The results shown in the graphs are robust to different specifications; the tables that show the difference-in-difference results from these specifications can be found in Appendix 3.A.

Figure 3.3 shows the change in homicides after the entry of the fourth and fifth cartel. The entry of the fourth cartel shown in Figure 3.3a, there is not a sharp increase when the fourth cartel enters. The homicide rate increases the year of the entry, but there is a more significant jump the year after the entry. There is an increase on average of 14.06 homicides the years after the entry of the fourth cartel. From the graph, there is no pre-trend in the homicide rate before the entry of the fourth cartel. The F-test confirms the non-existence of a pre-trend. The entry of the fifth cartel increases the homicide rate by 17 homicides. This is the most significant increase from all the entries; Figure 3.3b shows that the most significance increase



(a) Second Cartel Entry (b) Third Cartel Entry

Figure 3.2: Cartel Entry



(a) Fourth Cartel Entry (b) Fifth Cartel Entry

Figure 3.3: Cartel Entry

in the homicide rate occurs a year after the entry and not simultaneously with the entry. The coefficients get noisier after the third year of the entry. The entry of the fifth cartel is the last significant one. The number of municipalities with six or more active cartels is only 14. These sets of results are robust to adding controls for police presence, military presence, political party, baseline characteristics, and the set of fixed effects. The tables that show the difference-in-difference coefficients for the entry of the fourth and fifth cartel can be found in Appendix 3.A.

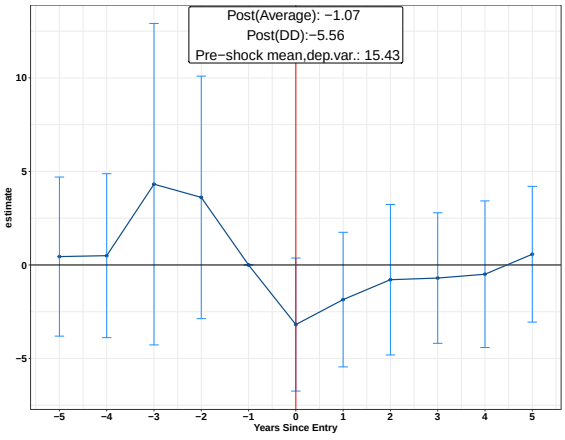
3.4.4 Results Exit

The last result is related to the exit of cartels from a municipality. The graphs below show the β's from specification (3.1) with all the controls and fixed effects.

From One to Zero Cartels

The section above provides evidence that when a municipality goes from having zero to one cartel, there is not a significant increase in the homicide rate. Analogous to this case is the case when a location goes from having one cartel to zero cartels. Figure 3.4 shows a drop in the homicide rate the year the cartel leaves the municipality, but it is not a significant effect. The years after the exit, there seems to be an increase in homicide rate going back to the baseline before the cartel leaves the municipality. This result is consistent with the entry of the first cartel, not generating any additional homicides. This result is robust to different specifications, and the tables that show them can be found in Appendix 3.B.

Figure 3.4: First Cartel Exit



Exit in Municipalities with Multiple Cartels

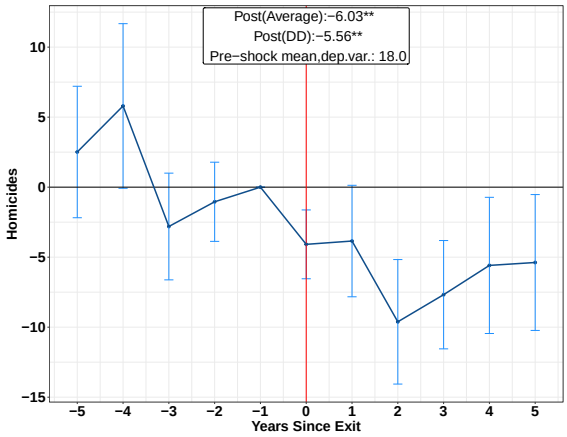
There does not seem to be any significant effect when a cartel leaves a municipality with multiple cartels. The number of municipalities that experience exits is small

compared to the municipalities that experience an entry. Therefore, this section just analyzed the case when a municipality with two cartels experience the exit from one of them. The number of municipalities with three or cartels that experience an exit is just fifty; then, there is not enough power to estimate for these cases with enough confidence.

Figure 3.5 shows the coefficients from specification (3.1) when the relevant event is a municipality with two cartels that experiences the exit of one of them. This graph shows a sharp drop in homicides after the exit of the cartel, and the homicides keep going down after two years of the exit. In particular, the biggest drop on homicides happens two years after with -9.61 decrease in homicides. The average drop in homicides after the exit is -6.03. From the graph, there is not a pre-trend in the homicides previous to the exit of the cartel.

Although this measurement error could be worst for exits than for entries. It might be that journalists stop reporting a particular cartel when it decreases its dominance in one territory, but there will be remnants of active conflict years after the media report the exit. This might explain the considerable drop after two years in the graph and then an apparent stability in the homicide rate. The regression table that shows the estimates for the difference-in-difference specification can be found in Appendix 3.B.

Figure 3.5: Second Cartel Exit



3.4.5 Every Entry and Exit

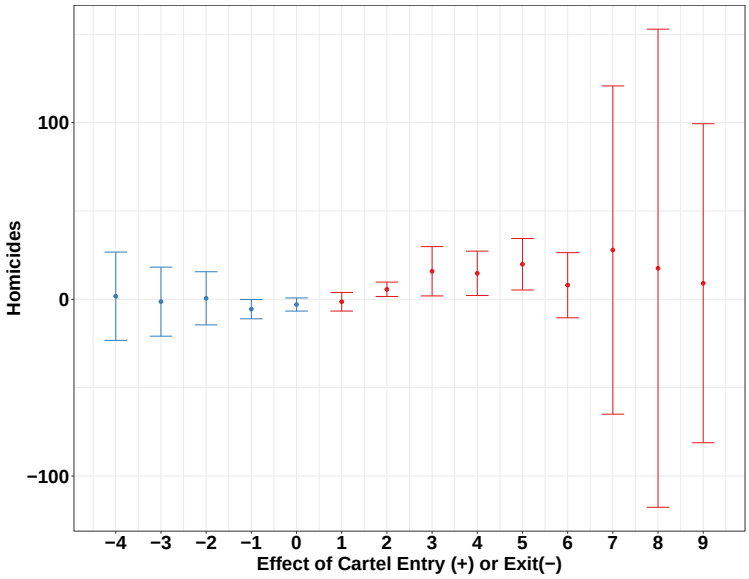
Figure 3.6 shows the difference-in-difference coefficients from equation (3.1), but with the event time, year dummies replace by a dummy variable $PostEvent_{mt}$. The coefficients and error bars in red show the entry of cartels. The graph shows that there is a non-linear relationship between the entry of cartels and the homicide rate. The standard errors of these estimates are more significant as the number of active cartels increases in a municipality. The small number of municipalities with more than five active cartels explains the bigger standard error.

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 of 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. Violence appears to be increasing in the number of active cartels at least until the fifth cartel enters a municipality.

3.4.6 Robustness

The results presented in the section above are robust to four different specifications, and these results are valid as long as there is not another drug market drastically affecting the cartel entry or exit into municipalities. Table 3.1 shows the results

Figure 3.6: Second Cartel Exit



of the difference-in-difference model for the entry events, from the first to the fifth cartel. The results are estimated using the same specification as (3.1), but with the event dummy years replace by a post-entry dummy. The specification includes all the controls, baseline characteristics, profitability of heroin, and fixed effects. I add to this specification a set of controls that account for other drug markets. These controls are the quantity of kilograms seized by the Mexican military each year in each municipality of cocaine, methamphetamines, amphetamines, pseudoephedrine, and labs to synthesize any of them. This set of new controls will rule out that it is other drug markets driving the homicide rate and not the heroin market.

The results presented in Table 3.1 follow the patterns from the results in the section above. The estimates decrease, but they are still significant and go in the same direction. Adding these controls for other drugs market does not seem to affect the main results. The estimates for the drug seizures are all insignificant in the four cases present above; the only one that is significant is having a methamphetamines lab in the municipality seem to reduce the homicide rate. This is true for the cases when the first cartel entries and when the second one enters.

Table 3.1: Controlling for other drugs: Entry

	Homicides per 100,000 inhabitants				
	First	Second	Third	Fourth	Fifth
Homocide Rate	−1.33	5.57**	15.67**	14.53**	19.65**
	(2.63)	(2.30)	(6.91)	(7.36)	(9.43)
Observations	42,624	13,389	7,719	4,409	2,493
Pre-entry mean, dep. var.	15.43	15.38	16.58	19.35	17.31
All FE	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓
Baseline trends	✓	✓	✓	✓	✓

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

Table 3.2 presents the results of the exit events when the controls for other drugs are added. The table shows that there is no change in the results from the section above. The exit of a cartel in a municipality with two of them reduced the homicide rate. The exit of a cartel from a municipality where it is the only cartel present does not affect the homicide rate. None of the introduced controls seems to be significant when the relevant event of study is the exit of cartels.

Table 3.2: Controlling for other drugs: Exit

Homicides per 100,000 inhabitants		
	From One-to-Zero	From Two-to-One
Homocide Rate	−2.82	−5.29*
	(1.86)	(2.77)
Observations	11,713	2,465
Pre-entry mean, dep. var.	18.64	8.0
All FE	✓	✓
Covariates	✓	✓
Baseline trends	✓	✓

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

3.5 Effect of Cartels in Other Criminal Activity

In this section, I analyzed the effect that the change in the number of cartels has in other criminal activity.The data used here covers any crime reported to the authorities

for which an investigation was open.[17] The crimes studied are; extortion, violent injuries, violent theft, non-violent theft,[18] kidnappings, and rape. All these variables will be denoted by V_{mt} and account for totals by year, and municipality.

Let m index municipalities, e index states, and $t \in \{1, ..., T\}$ index years. The outcome of interest is the V_{mt} described above. The key independent variable is n_{mt}, which is the number of cartels active in municipality m and year t. Let the main specification for this section be

$$V_{mt} = \alpha_m + \gamma_t + \sigma_e t + \beta n_{mt} + \psi X_{mt} + \lambda z_{mt} + \epsilon_{mt} \tag{3.2}$$

where α_m is a municipality fixed effect, γ_t is a year fixed effect, $\sigma_e t$ is a state-year fixed effect, X_{mt} is a vector of observable characteristics for municipality m, and z_{mt} is the profitability of municipality m at year t already defined in the section above.

First-difference specification is used to study the relationship between a change in the number of cartels and alterations in other criminal activity in a municipality. This follows the evidence found above that entry and exit of cartels has a significant effect on the homicide rate. Let Δ be the first-difference operator so that $\Delta V_{mt} = V_{mt} - V_{m(t-1)}$. The estimating equation is

$$\Delta V_{mt} = \Delta\gamma_t + \Delta\sigma_e t + \beta\Delta n_{mt} + \psi\Delta X_{mt} + \lambda\Delta z_{mt} + \Delta\epsilon_{mt} \tag{3.3}$$

Unless otherwise noted, the vector X_{mt} includes changes in police and military presence and changes the in political affiliation of the mayors and governors. The standard errors are clustered using Conley (1999) errors with a radius of 500Km.

[17] The data used here is measuring the capacity of the authorities to fight crime instead of actual criminal activity. The data disaggregated at the municipal level are only available since 2011.

[18] The theft category includes burglary, bank theft, car theft, and robbery.

The identification strategy follows the one used in the section above.If the change in profits of a particular region accounts just for a small part of the variation in entry and exit, then the bias in the estimates is low.

Results

Table 3.3 shows the results from specification (3.3) for different crime variables. Column (1) represents the change in extortions in a municipality. This is the only significant result for other crimes which would imply that a positive change in the number of cartels in a municipality reduces the number of people that suffer extortion in that place. The result seems awkward, given the fact that criminal organizations are known for participating in extortions. The negative sign in this coefficient is probably showing a decrease in reporting extortion, remember the data come from police investigations and does not measure actual crimes, and not a real reduction in extortion. The presence of multiple cartels might dis-encourage people to report this kind of crime.

Columns (2-6) show the results for violent injuries, non-violent theft, violent theft, kidnapping, and rape. None of these coefficients is significant to the change in the number of investigating crimes. The non-significance of these estimates may be due to two different things. First, it could be that the number of cartels does not directly affects the reporting behavior of these kinds of crimes. Second, cartels themselves are not involve in any of these crimes. A better data set that measures crime or a theory of reporting is needed to conclude something more insightful about the relationship between the number of cartels and crimes different from homicides.[19]

[19]Data on security perception does not exist at municipal level.

Table 3.3: Other Crimes

	Change in the number of crimes					
	Extortion	Injuries	NV-Theft	V-Theft	Kidnapping	Rape
ΔC	-0.93^{***}	-0.10	-3.26	-7.52	0.028	-0.40
	(0.26)	(0.23)	(6.34)	(4.99)	(0.05)	(0.23)
Observations	12,115	12,115	12,115	12,115	12,115	12,115
Mean , dep. var.	2.26	4.87	116.29	48.27	0.45	4.95
All FE	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓

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

3.6 Conclusions

The relationship between organized crime and violence is not obvious. Policies on how to decrease the negative externalities from organized crime usually assume that illegality breeds violence without further evidence of the particular interactions between these groups that generate violence. In this chapter, I use an external demand shock in the heroin market in the United States to try to disentangle the relationship between the number of Drug Trafficking Organizations present in a municipality and the homicide rate. Focusing on the period between 2005 and 2016, I provide evidence that the number of cartels in a municipality has a robust positive effect on homicide rates. The effect on homicide rate increases with the number of active cartels. This evidence suggests that cartel competition and market structure are essential to understand violent outcomes in regions that produce or transport drugs.

These results are consistent with a model in which Drug Trafficking Organizations affect violent outcomes in a location mainly by fighting over scarce resources. DTOs' decision of entry or exit into a municipality depends on how profitable they think that particular location is. This profit consideration includes investments in violence or threatening violence to other actors. The first cartel does not affect the homicide rate because if a single criminal organization has a monopoly in a location, there is no need to commit any violent event in order to increase market shares. The second,

third, fourth, and fifth cartel that enter a particular location all increase the homicide rate. The difference between these different entries is that when a second cartel enters a municipality with one cartel, the increase of violence peaks the year of the entry but then drops back near the pre-entry levels of violence. The result for two cartels suggests that two criminal organizations might be able to collude to split market shares and consequentially reduce violence in the location. This phenomenon is not true for the entry of the third, fourth, and fifth cartel, where violence stays high at least four years after the entry event.

The effects of exit are symmetric to those of entry when a municipality goes from having two to one cartel present. There is an immediate drop on violence the year the cartel exit with subsequent decreases in violence until it stabilizes at a lower value. There is none effect on violence on exit when the municipalities go from the exit of cartels when there are already three or more cartels in the municipality. Analogous to the entry case, there is not an effect when a municipality with one cartel experience the exit of that cartel. Overall, there is a positive relationship between the number of active cartels and the homicide rate in a municipality. The results are in line with previous literature that establishes reduce violence in territories occupies by a single criminal organization.

All the results here exploit an external shock to the heroin market and estimate the average effects of a change in the number of cartels in a municipality. The results do not rule out the possibility that the entry or exit of particular Drug Trafficking Organizations has effects either larger or smaller than the ones estimated here. This is an important caveat in interpreting these estimates and especially for any policy implications. A more detailed study that might be able to disentangle the more violent cartels or the combinations of cartels that generate the most violence are important to implement policies that aim to reduce violence in drug-producing or trafficking regions.

A second important caveat is the lack of proper measures for drug trafficking activities; across this chapter, I interacted a suitability index to grow opium poppy with heroin prices in the United States to approximate how profitable a region is in the heroin market. This measure might leave out other important characteristics of municipalities that may make them attractive to drug dealers, and without a proper measure of actual opium yields in Mexico, it can be hard to unravel these characteristics. The same is true for the approximations of other markets' profitability, I used the number of drugs seized by the military, but this might just be measuring the state ability to interdict drugs and not be a good proxy for actual production or drugs transport across the country.

Finally, the lack of official data on were special operations against drug dealers happen across the country limits the ability to estimate the actual number of deaths from the increase in the number of cartels. Right now I can say with confidence that violence increase, but the estimate might include some effect from these special operations, despite the fact the results presented here already include controls for police and military presence.

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Appendix

3.A Tables from Cartel Entry

The next Tables 3.4, 3.5, and 3.6 show the coefficients for equation (3.1) but with the event-time-year dummies replaced by a dummy variable $PostEntry_{mt}$, indicating that in year t municipality m experienced the entry 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 (5) present the results with municipality, year, and state-year fixed effects. Columns (2) and (6) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (7) control for baseline characteristics interacted with year fixed effects. The baseline characteristics are population, mean years of education, marginalization index, and drug activity in the 2000. Columns (4) and (8) include baseline characteristics, controls, and all the fixed effects. Significant at $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The sample selection is conditional on having n cartels in $t-1$. There is selection in the sample so that the comparison group is municipalities that stay with n cartels versus the ones that go to $n+1$.

Table 3.4: Entry of the First Cartel

	Homicides per 100,000 inhabitants			
Post-entry	−1.541	−1.597	−1.30	−1.37
	(2.59)	(2.62)	(2.58)	(2.63)
Observations	42,624	42,624	42,624	42,624
Pre-entry mean, dep. var.	15.43	15.43	15.43	15.43
Municipalities FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Covariates		✓		✓
Baseline trends			✓	✓
State trends	✓	✓	✓	✓

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

Table 3.5: Entry of the Second and Third Cartel

	Homicides per 100,000 inhabitants							
	Second Cartel Entry				Third Cartel Entry			
Post-entry	4.9**	5.22***	4.89**	5.67***	13.061*	14.57*	15.98**	15.88**
	(2.007)	(1.95)	(2.15)	(2.03)	(5.77)	(6.09)	(7.03)	(6.97)
Observations	13,389	13,389	13,389	13,389	7,719	7,719	7,719	7,719
Pre-entry mean, dep. var.	15.38	15.38	15.38	15.38	16.58	16.58	16.58	16.58
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓		✓		✓
Baseline trends			✓	✓			✓	✓
State trends	✓	✓	✓	✓	✓	✓	✓	✓

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

Table 3.6: Entry of the Fourth and Fifth Cartel

	Homicides per 100,000 inhabitants							
	Fourth Cartel Entry				Fifth Cartel Entry			
Post-entry	12.43**	13.13**	15.01**	14.71**	17.53**	21.08*	19.01**	19.84**
	(5.22)	(5.25)	(6.38)	(6.28)	(7.52)	(6.80)	(7.19)	(7.28)
Observations	4,409	4,409	4,409	4,409	2,493	2,493	2,493	2,493
Pre-entry mean, dep. var.	19.35	19.35	19.35	19.35	17.31	17.31	17.31	17.31
Municipalities FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓		✓		✓
Baseline trends			✓	✓			✓	✓
State trends	✓	✓	✓	✓	✓	✓	✓	✓

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

3.B Cartel Exit

The next Tables 3.7 and 3.8 show the coefficients for equation (3.1) but with the event-time-year dummies replaced by a dummy variable $PostExit_{mt}$, indicating that in year t municipality m experienced the 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 (5) present the results with municipality, year, and state-year fixed effects. Columns (2) and (6) add controls for police presence, military presence, and political party of the mayor and the governor. Columns (3) and (7) control for baseline characteristics interacted with year fixed effects. The baseline characteristics are population, mean years of education, marginalization index, and drug activity in the 2000. Columns (4) and (8) include baseline characteristics, controls, and all the fixed effects. Significant at $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. The sample selection is conditional on having n cartels in $t-1$. There is selection in the sample so that the comparison group is municipalities that stay with n cartels versus the ones that go to $n-1$.

Table 3.7: From One to Zero Cartels

	Homicides per 100,000 inhabitants			
Post-entry	−3.05	−3.37	−2.78	−2.93
	(1.93)	(2)	(1.84)	(1.86)
Observations	11,713	11,713	11,713	11,713
Pre-exit mean, dep. var.	18.64	18.64	18.64	18.64
Municipalities FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Covariates		✓		✓
Baseline trends			✓	✓
State trends	✓	✓	✓	✓

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

Table 3.8: From Two to One Cartel

	Homicides per 100,000 inhabitants			
Post-entry	-6.11^{**}	-6.01^{**}	-5.85^{**}	-5.56^{**}
	(3.02)	(2.75)	(2.81)	(2.73)
Observations	2,465	2,465	2,465	2,465
Pre-exit mean, dep. var.	18.0	18.0	18.0	18.0
Municipalities FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Covariates		✓		✓
Baseline trends			✓	✓
State trends	✓	✓	✓	✓

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