# Weak laws, informality, and organized crime: An establishment-level approach

Job Market Paper

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**Abstract**

How does imperfect law enforcement affect drug trafficking, predation on firms, informality (tax avoidance), and aggregate output? Using differences at the state level on the implementation of the Mexican War on Drugs, I first provide causal evidence that the escalation of organized crime reduced output by 4% in Chihuahua, a state with significant drug cartels. Next, to understand the mechanisms and the policy implications, I develop a general equilibrium model of occupational choice in which imperfect institutions induce drug trafficking, crime against businesses, and tax avoidance. I use a detailed micro-level dataset on business victimization and data on drug cartels to calibrate my model. I find that imperfect law enforcement results in sizable losses of national output attributed to the misallocation of resources and occupations. In counterfactual simulations, I consider the effects of policies that intend to improve the allocation of resources in the private sector. By shutting down the illegal drug market, labor reallocates to the productive sector, and aggregate output increases by 0.5%. Without crime against businesses, output increases by 2.6%, and without informality, output increases by 11.9%. The last two effects arise through a reallocation of labor, capital, and occupations to the more-productive formal sector.

**Keywords:** Misallocation, aggregate distortions, drug cartels, crime, formal and informal sectors.

**JEL Codes: O11, O17, O43, O47, K40**

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# 1 Introduction

Over the past four decades, countries such as the United States, Colombia, and Mexico have dramatically increased their law-enforcement budgets to counter the production and distribution of illegal drugs under policies typically described as the *War on Drugs*. Intuition suggests that such actions would directly translate into less drug trafficking and indirectly into stronger property rights, given that better-equipped police strengthen the protection of private property. Yet the ongoing Mexican War on Drugs provides us with a counterexample in which a government characterized by imperfect law enforcement experiences a different outcome when it ignores the links between illegal markets and confronts drug cartels.[1] Consumption of drugs decreases marginally; drug cartels and the related violence increase; and crime spreads to businesses that, in response, alter their production decisions and may similarly engage in illegal behavior, such as avoiding taxes (informality) to decrease costs.[2]

Recent studies have stressed the importance of idiosyncratic distortions on heterogeneous producers to explain income differences between countries (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). In this paper, I rationalize those distortions as imperfect institutions that influence the predatory behavior of private agents. In particular, I provide evidence that partial law enforcement expands informality and markets for illegal drugs and increases crimes against businesses. The result is that aggregate output declines as the size and composition of establishments become distorted.

In the first part of the paper, I provide causal evidence of the effects of organized crime on the aggregate economy. To do that, I first exploit state-level differences in the implementation of the Mexican War on Drugs, which triggered drug-related violence and increases in organized crime. I then use the synthetic control methods of Abadie and Gardeazabal (2003) and

[1] In 2006, Felipe Calderón, the newly elected president, declared war on drug cartels. Calderón's war consisted of the deployment of military, navy and federal police units to states with a heavy presence of drug traffickers. His narrative centered on the threat *el narco* posed to Mexican families, which the government would have to combat. That narrative, although arguably justified, contrasted with the decreasing trend of drug-related murders and the low presence of drug cartels before the War on Drugs (see Figure 1). Drug cartels responded to the government offensive with violence and diversified their crime portfolio; the result was that murders, extortions, kidnappings, and property crimes reached an all-time high (Figure 2).

[2] INEGI (2016b,a), the Mexican Institute of Statistics, publishes estimations about the direct costs of crime. The direct costs are related to additional spending on security and health, and the value of property handed to criminals. In 2017, property crimes cost Mexicans 2.5% of GDP (1.65% of GDP from households and 0.86% from firms). These numbers, though, do not consider the indirect costs of crime, like a reduction in production, investment, or exiting the market.

Abadie et al. (2010) and find that in the border state of Chihuahua—a state with a significant presence of drug cartels—, GDP per capita decreased 4.0% after the policy.

To find a suitable control group for the synthetic control methodology, I construct organized-crime indexes for all Mexican states using principal component analysis of the aggregate rates of murder, extortion, and kidnapping. With the indexes, I control for potential *spillover effects* of the policy by discriminating between states that had significant increases in organized crime and states that did not. Moreover, the indexes tackle the underreporting bias present in official statistics.

After estimating the effects of the policy on Chihuahua's GDP *per capita*, I perform additional robustness checks and replicate the exercise for the states of Baja California, Nuevo León, and Tamaulipas, which were, similarly, early adopters of the policy. I also find adverse effects of the policy, but only statistically significant for Chihuahua and Tamaulipas.

Consistent with the previous findings, I build a general equilibrium model of occupational choice with criminal markets to understand the mechanisms and the policy implications at the national level. I base my model on Lucas (1978) and Guner et al. (2008) and extend their framework to include crime against establishments, as in Ranasinghe (2017), and illegal drug markets, as in Castillo et al. (2014) and Castillo and Kronick (2017). The institutional framework, or the weak laws I have referred to, consists of parameters that determine the probability of victimization, the share of informality, and the proportion of drugs that reach the final consumer.

My model generates an endogenous distribution of formal and informal establishments, as in Ordóñez (2014). This enables me to more closely follow the distribution of Mexican establishments and pair my model's predictions with the results of Dell (2015) and Utar (2018), who found links between informality and organized crime in Mexican municipalities.

Individuals differ in their managerial talent, which determines their occupation as workers or entrepreneurs in the formal or informal sector. Informal entrepreneurs employ a low level of capital to avoid detection from the government. That distortionary channel is pivotal since a significant fraction of establishments is informal. Crime is a technology that steals from each entrepreneur a fraction of her output with some probability, which depends on government and private protection.

I model a drug market as a noncooperative two-stage game with endogenous entry of drug cartels. Drug cartels buy and transport drugs over routes they control and sell them to final consumers. The government counteracts drug trafficking through interdiction, which decreases the effectiveness of controlling routes.

My calibration relies on a micro-level dataset on business victimization, the *Encuesta Nacional de Victimización de Empresas 2018*, which is maintained by Mexico's National Institute of Statistics and Geography (INEGI, 2018); the dataset targets key property crime moments.

The mechanisms by which weak law enforcement and illegal behavior affect the economy are the following. When the government partially seizes illegal drugs during transit, drug cartels sell a lower number to final consumers (the non-seized drugs). As a result, the final price of drugs increases, as well as cartels' aggregate profits. The reason is that the consumer demand for drugs is price inelastic. The increase in profits pushes more cartels to enter the market and fight for control of the fixed number of routes, and therefore violence increases.

With partial protection on private property, plants spend more on security, and criminals steal a share of their output. A fraction of formal plants on the edge of profitability switches to the informal sector to decrease costs. That is, they stop paying taxes to remain profitable. Plants can operate undetected in the informal sector since the government cannot detect them if they remain small. Also, since the more productive formal sector reduces its size, the aggregate use of inputs decreases as well, and wages, in turn, contract. The decline in wages pushes a fraction of workers into informality, which further increases the size of the less productive informal sector.

In the final part of the paper, I study different law-enforcement policies aimed at increasing the productivity of the private sector. In the first regime, I shut down drug trafficking and keep crime against businesses and informality. Under this policy, former drug traffickers reallocate into the productive sector, and output increases by 0.5%. Next, I provide full protection for businesses while keeping drug trafficking and informality. The result is that output increases by 2.6%. Finally, I shut down the possibility of operating in the informal sector. Under this scenario, output increases by 11.9%. The positive effects of the last two scenarios arise through a better reallocation of occupations and resources.

My work is closest to Besley and Mueller (2018) and Ranasinghe (2017). Both papers use plant-level data from the World Bank to examine the misallocation effects of crime and security spending and their effects on aggregate productivity. I expand those studies and contribute to the misallocation literature by considering two additional channels not studied together: informality and illegal drug trafficking. In addition, I use a detailed micro-level dataset of business victimization from the Mexican Institute of Statistics (INEGI), which allows me to relate the occurrence of crime to the plant size.

Recent works have studied the effects of drug-related crime in Mexico during the War on Drugs. Robles et al. (2013a) estimate that establishments decreased their electricity consumption in the years after the initial increase in violence. Montoya (2016) finds that in high-crime municipalities, the industrial sector reduced operations. Enamorado et al. (2014) find a negative effect of drug-related crimes on the average income growth of municipalities for the years 2005-2010. Similarly, Balmori de la Miyar (2016) finds that in states with military operations related to drug cartels, GDP *per capita* is, on average, 0.5% lower. My paper expands our knowledge by providing causal evidence of the aggregate effects of the War on Drugs, and a framework that explains the mechanisms and quantifies the general equilibrium effects. Such channels are relevant to understand the effects of different policies aimed at improving the productivity of the private sector.

In addition to the contributions mentioned in previous paragraphs, my paper also contributes to the theoretical literature that studies the aggregate implications of criminal markets under calibrated structural models (Platania and Schlagenhauf, 2000; İmrohoroğlu et al., 2004; Ranasinghe, 2017; Ranasinghe and Restuccia, 2018). To the study of the economic consequences of imperfect institutions that result in predatory risk (Hall and Jones, 1999; Acemoglu et al., 2001; Besley and Mueller, 2018). To the literature on the aggregate economic consequences of armed conflicts (Abadie and Gardeazabal, 2003; Blattman and Miguel, 2010). To the studies on the organization and the negative effects of cartels (Acemoglu et al., 2013; Murphy et al., 2017). And to the consequences and interactions of illegal markets (Dube et al., 2016; Sviatschi et al., 2017; Dell et al., 2019)

# 2 Sample and data used

There are two data sources for this study. I use the first one for estimating the causal effects of the Mexican War on Drugs at the state level. I use the second one for the calibrated model.

## Data sources to study the causal effects of the War on Drugs

I build a quarterly panel for the thirty-two Mexican states for the years 2003 to 2016 that includes economic and crime variables. All series are seasonally adjusted by their source or using the routines of Chodorow-Reich. Furthermore, I deflate all nominal variables using the consumer price index calculated by INEGI. The economic variables and their source are GDP per capita, labor force and unemployment from INEGI; temporary and permanent formal workers from IMSS (Mexican Institute of Social Security); government spending per capita from SHCP (Ministry of Finance); and remittances per capita from Banxico (Mexican Central Bank).

### Economic variables

*GDP per capita.* I construct quarterly series of state GDP per capita using yearly state GDP variables at constant prices, a quarterly index that follows the short-run dynamics of aggregate economic activity at the state level called ITAEE (Indicador Trimestral de la Actividad Economica Estatal), and the annual state-level population projections from CONAPO (Mexican Institute of Population Studies).

I assume that both series of GDP and ITAEE measure the same underlying variable and that they only differ in their scale and frequency; therefore, for every year I match, the variation of ITAEE to that of GDP. After that, I obtain a variable of GDP per capita for each state by dividing the constructed series of GDP by the linearly interpolated population projections.

*Industrial production index.* This unitless index $2013 = 100$ provides information over the generation and distribution of electricity, gas and water, and the production of manufacturing firms. The information appears monthly, and I converted the series to quarters by averaging the observations.

*Formal workers.* Formal workers are those registered at the Mexican Social Institute. The information is monthly, deseasonalized and aggregated to quarters. All variables are divided by the labor force.

*Labor force and unemployment.* The variables come from ENOE (Encuesta Nacional de Ocupación y Empleo). The national survey of occupation and employment of INEGI.

*Government spending.* The data is downloaded from INEGI and refers to the share of the federal budget spent by states. I divided by population size to account for state size. I deseasonalized and deflated the observations.

*Remittances.* The remittances are downloaded from Banco de Mexico (Central Bank of Mexico). The information is quarterly from 2003 to 2018. The series are deseasonalized and deflated as well.

**Construction and description of crime variables**

I obtained crime statistics from the Ministry of Interior and converted them into annualized rates (number of crimes per quarter over 100,000 inhabitants multiplied by four) using population data from Conapo (Mexican Institute of Population). Working with official crime statistics poses a challenge since the statistics are systematically underreported or intentionally misreported.[3] I eliminate possible bias by focusing on the direction of the series instead of their level. To be specific, I assume that the bias is constant through time and states and that changes in crime statistics indicate changes in actual victimization rates. With that in mind, I build a demeaned crime index that encompasses the directions of crimes closely related to organized crime (murder, extortion, and kidnapping) using principal component analysis.

Table 2 displays the results. I keep the first component since all the variables have a positive sign, which indicates that positive changes in all the variables increase the index—as one would expect in an index correlated to organized crime. The first component explains 46 percent of the variance, and the murder rate is the variable with the highest weight on the construction of the index. I ran the analysis on a converted cross section of the panel, and therefore the indexes are comparable between states and time. To have a glimpse of the construction of the organized-crime index, in Figure 4, I plot for Chihuahua and the national the input variables and organized-crime indexes.

Figure 5 shows the map of Mexican states with averages of the organized crime indexes

[3]According to the think tank Mexico Evalúa state governments reclassify in their official statistics intentional murders as manslaughters (see Furszyfer et al. 2017). In addition, victims' mistrust of the authorities inhibit them to report crimes. In around 90% of crimes there was no report or follow up of the authorities. The main reason of not reporting (60% of cases) is related to the authorities (because of fear of extortion by them, waste of time, long and hard procedures, lack of trust and previous bad experiences, see INEGI 2016a and INEGI 2016b).

before and after the War on Drugs. Before the war, only some states in the southern part of Mexico, and the border state of Baja California presented high levels of organized crime. However, during the period after the war, many states had considerable increases in their indexes. These results indicate that the war on drugs had distinct effects through time and space in Mexican states.

## Data used for the calibration of the model

It is hard to have a realistic picture of the state of the illegality of Mexico because crime has an underreporting problem, colloquially known as the *dark figure*. Government statisticians estimate the dark figure to be around 87% for crime against businesses (INEGI, 2018). That is, of all victimized businesses in a given year, only 13% of them approach the authorities. The reasons that business owners provide for not reporting crime are attributable to the authorities in 63% of the cases, and the rest to other causes.[4] To correct for this underreporting bias, INEGI has published the National Survey of Victimization of Establishments, which is a representative survey at the national level that quantifies the total number of crimes on establishments, the underreporting, the perceptions of crime, trust on institutions and of particular importance for this study, the costs and security spending associated to crime.[5]

The results for 2017 indicate that one-third of establishments was a victim of crime (33.7%). The victimization differs by establishments' size: 32.9% of establishments with less than 10 workers were victimized, compared 59.3% of the largest establishments. Figure 14 shows the probability of facing crime for all establishments by size. This number is, by itself, not particularly high relative to other regions. In the European Union, as an example, the same number was 35.4% in 2012, with a minimum range of 25.7% for Hungary and 56.6% (Dugato et al., 2013). However, the type of crimes, the degree of violence, and their effects on businesses are different for the Mexican case.

Figure 15 displays the main crimes against businesses and victimization rates. The crime

[4] The causes attributable to authorities as mentioned by business owners are: fear to be extorted by authorities, waste of time, long and difficult procedures to denounce the crime, lack of trust on authorities, or having previous bad experiences. The other causes are: fear of retaliation by the offender(s), the crime was of little (monetary) value or the owner lacked convincing evidence. Source INEGI (2018)

[5] The survey is stratified and probabilistic. It is representative at the national and state level. The unit of observation are economic units of the private sector excluding agriculture and public sector and units without a physical location. The survey was carried in presence with the highest hierarchy person in the establishment. 32,588 units were surveyed during early 2018. See INEGI (2016a) for additional survey design.

with the highest occurrence is petty theft, with a rate of 0.13 (or 13%). The second one is theft or robbery of merchandise, money, inputs, or final goods with 11%. Next are extortion, fraud, and corruption acts with 5%, theft of transit goods and motor vehicle theft with 4% and vandalism, and other types of theft with 1%. Since the majority of these crimes involve a forced exchange of property, we will ignore vandalism for the calibration in subsection 4.5.

The survey estimates that the total cost of crime is 155.8 billion Mexican pesos (or 8.2 billion U.S. dollars). That number consists of 0.86 percent of the Mexican GDP. Of that number, 55.9 percent are direct losses, and 44.1 are expenses in preventive measures. Figure 16 shows the distribution of security expenses. The majority of changes that businesses do to evade crime are physical. Changing locks, installing alarms and CCTVs, changing doors and windows, and installing fences represent 70%. Hiring private guards represent just 7%. The rest are buying insurance and spending on software with 5 and 3%.

Information about drug cartels comes from official sources, academic studies, and organizations like the United Nations. In subsection 4.5, I provide more detailed information about the size of the industry.

# 3 The aggregate economic consequences of the War on Drugs at the state level

In this section, I provide causal evidence that the Mexican War on Drugs had adverse causal effects on GDP per capita at the state level. The Mexican War on Drugs is a large scale policy aimed to deter drug-related crimes. It was launched days after president Felipe Calderón took office in a military parade in his home state of Michoacán. The initial offensive, called Michoacán Joint Operation, consisted of the deployment of 5,000 soldiers and federal police officers with the command to patrol high-crime areas, take over drug corridors, and eradicate the production of drugs. During the next 6 years of his mandate, Calderon launched additional Joint Operations in other states: in Baja California in January of 2007; In Tamaulipas and Nuevo León in January of 2008; in Chihuahua in March of 2008; and in Guerrero, Durango, Coahuila and Veracruz in October of 2011 (Guerrero, 2012).

The first of the *Joint Operations* had a preventive goal in mind. According to the government narrative, Mexico was on the brink of an escalation of violence that had to be contained.[6] Unfortunately, the narrative became a harsh prophecy, as drug-related violence increased considerably throughout many states. During his presidential mandate, Calderón launched other batches of *Joint Operations* with more of a corrective component in mind.

Figures 6 and 7 plot the levels of organized crime, along with the dates the government declared war on drug cartels and sent units to those states. Before the declaration of war, only Baja California and Durango had considerable increases in organized crime. If we consider a corrective policy one that the government implements after an unusually large and persistent increase in crime, then Coahuila, Durango, Guerrero, and Veracruz experienced corrective policies. The rest of the Joint Operations were preventive. That is, federal troops were not sent there because crime was high, but for other reasons.

In the next section, I provide evidence that the preventive *Joint Operations* had adverse effects on the real economy. I focus on preventive policies for two reasons. First, the evidence points out that the preventive policies were exogenous to the economic and criminal conditions of Mexico in the late 2000s (Dell, 2015; Castillo et al., 2014). Second, the corrective policies were implemented many months after the peak in violence in the affected states. If organized crime affects the real economy, the treatment date (i. e. the corrective policy) is many months after the actual event occurred, so the estimation will not, most probably, pick up any causal effect.

## 3.1 Strategy to identify the causal effects of organized crime on GDP per capita

Many authors have studied the reasons why all crimes increased in Mexico after government intervention. The common denominator is that authorities diverted their efforts to drug trafficking and cartels diversified their crime portfolio to preserve their profits (Ríos 2013, Dell 2015, Lessing 2015, Grillo 2012). The adverse economic effects at the micro-level have been documented as well. Some of the adverse effects comprise lower labor participation, a decrease in hours of operation of businesses, and lower investment and production (Carrasco

[6] In 2001, the leader of the powerful Sinaloa Cartel, El Chapo (*Shortie*) Guzmán escaped from prison and started a campaign to take over territories from other drug cartels. In addition, in the early 2000s, Sinaloa's Cartel old rival, the Gulf Cartel, engaged in violent turf wars by hiring former elite military soldiers, known as *Los Zetas* (Grillo, 2012).

and Durán-Bustamante, 2018; de la Miyar, 2016; Rios and Sabet, 2008; Robles et al., 2013b)

I expand on the results of those authors and quantify the aggregate effects at the state level. To do that, I base my identifying strategy on the assumption that the preventive *Joint Operations* were exogenous to the economic and crime conditions of that time. Dell (2015) and Castillo et al. (2014) argue that the increase in violence was triggered by either political motives—president Calderón won the presidency among fraud claims, and he found on attacking drug cartels a way to legitimize himself—or by growing production costs of cocaine in Colombia, which shifted a share of the cocaine market to Mexico. In either way, both events are exogenous and occurred at the same time, so the causal effects will refer to the same event that triggered increases in crime. However, for this study, my narrative focuses on that the government initiative triggered the increase in crime.

A second assumption I make is that the policies triggered heterogeneous responses among states. That is, the states that did not experience Joint Operations or spillover effects serve as a control group. As Figure 5 shows, there are some states which did not receive the policy, but crime still increased. Those states are of no help to comprise a counterfactual state. To overcome that, I estimate periods of high organized crime and discard those states for the control group. I define periods of high crime if the trend of the standardized organized crime index is above two standard deviations. I construct the trend as a two-year moving average. Figures 8 and 9 show all of the states with their respective trends. I discard the states of Tlaxcala and Morelos. Also, I restrict the sample from 2003 to 2012, which is the last year of the Calderón administration.

For this case study, I choose Chihuahua as the treatment state. The reason is that Chihuahua experienced both the policy and substantial increases in organized crime that were not experienced by the majority of Mexican states. A challenge is that any attempt to identify the causal effect of the policy must purge the effects of the Great Recession, which occurred in close dates. Figure 3 plots Chihuahua's GDP per capita along with its murder rate. We can see that the decrease in GDP per capita and the increase in the murder rate coincided with the 2007 financial crisis [7].

To overcome that challenge, I choose a suitable donor set of states whose pre-treatment

[7] In the appendix a construct additional robust checks for the states that experienced the preventive policy; particularly, for the states of Baja California, Nuevo León and Tamaulipas. In all of the mentioned states the policy had negative effects, but it was only statistically significant for Tamaulipas.

outcomes followed the ones of Chihuahua and shared the same business cycle. Besides, since the Great Recession was an external shock to the whole Mexican economy, the implicit assumption is that the states in the donor pool of states are not only synchronized with each other but with the U. S. business cycle, which is where the recession originated.

There is evidence that Mexican states share a common business cycle. Miles and Vijverberg (2011) find that the economy of Mexico became more synchronized to the U. S. economy after the passage of NAFTA. In addition, using time-series decompositions of the coincident indexes of the United States and Mexican states, Delajara (2012) finds synchronization on the cycles of those variables. The synchronization between Mexican states and the U. S. business cycles is stronger in northern states.

## 3.2 The Method of Synthetic Controls

This section follows the synthetic control methods exposed in Abadie and Gardeazabal (2003) and Abadie et al. (2010). Let $Y_{st}^{nw}$ denote non-war GDP per capita for state $s$ in period $t$. That is, GDP per capita in the absence of the treatment (the policy) for states $s = 1, ..., J+1$, and time $t = 1, ...T$. Denote $s = 1$ to the state that received the intervention and denote $Q_{war}$ as the quarter in which the policy was launched at the state level and $Q_1$ as the first quarter in our sample; thus the number of preinterventions periods is $T_o = Q_{war} - Q_1$, with $1 \leq T_0 \leq T$. Let $Y_{st}^{w}$ be GDP per capita for state $s$ exposed to the intervention at time $t$, for $t \in \{T+1, T\}$. I assume that the onset of the war did not have any preintervention effects on GDP per capita for any state, so $Y_{st}^{nw} = Y_{st}^{w}$ for all the $J+1$ states and for all $t \in \{1, ..., T_0\}$.

Let $\Delta_{st}$ denote the impact of the treatment for state $s$ at time $t$, and therefore we can express GDP per capita of the states that were affected by the policy as:

$$Y_{st} = Y_{st}^{nw} + \Delta_{st}. \tag{1}$$

The causal effect is $\Delta_{st} = Y_{st} - Y_{st}^{nw}$. Notice that $Y_{st}$ is the only observed variable in equation (1). Abadie et al. (2010) propose to estimate $Y_{st}^{nw}$ using a factor model of the following form:

$$Y_{st}^{nw} = \delta_t + \boldsymbol{\theta_t Z_s} + \boldsymbol{\lambda_t \mu_s} + \varepsilon_{st}, \tag{2}$$

where $\delta_t$ is an unknown factor with constant factor loadings across states, $\boldsymbol{Z_s}$ is a $(r \times 1)$ vector of observed covariates not affected by the War on Drugs, $\boldsymbol{\theta_t}$ is a $(1 \times r)$ vector of unknown parameters, $\boldsymbol{\lambda_t}$ is a $(1 \times F)$ vector of unobserved common factors, $\boldsymbol{\mu_s}$ is an $(F \times 1)$ vector of unknown factor loadings, and the error term $\varepsilon_{st}$ is transitory, specific for each state and has mean zero.

For the period after the intervention, the synthetic control estimator measures the causal effect as:

$$\Delta_{1t} = Y_{1t} - \sum_{s=2}^{J} w_s^* Y_{st}, \tag{3}$$

in which $s = 1$ denotes the state that received the intervention and $w_s^*$ is a vector of optimally chosen weights for the untreated states $s = 2, ..., J$. The weights are restricted to take non-negative values and to sum 1. Let $\boldsymbol{X_1}$ be a vector of preintervention characteristics for the exposed state, $\boldsymbol{X_0}$ its counterpart for the unaffected states and define $\boldsymbol{W}$ as the vector of weights to estimate. The weights are chosen to minimize the norm,

$$||\boldsymbol{X_1} - \boldsymbol{X_0 W}|| = \sqrt{(\boldsymbol{X_1} - \boldsymbol{X_0 W})' \boldsymbol{V} (\boldsymbol{X_1} - \boldsymbol{X_0 W})}, \tag{4}$$

subject to the restrictions mentioned before and in which $\boldsymbol{V}$ is a symmetric and positive semidefinite matrix. For this study, I choose $\boldsymbol{V}$ to minimize the mean squared prediction error given by:

$$\text{MSPE} = \sum_{t=1}^{T_0} \left( Y_{1t} - \sum_{s=2}^{J+1} w_s^* (\boldsymbol{V}) Y_{st} \right)^2 . \tag{5}$$

## 3.3 Chihuahua's GDP is lower after the government intervention

Table 3 displays the estimated state weights. Synthetic Chihuahua is a combination of Aguascalientes (0.057), Mexico City (0.250), Guanajuato (0.317), Jalisco (0.001), and Yucatán (0.375). The rest of the states have an optimal weight of zero. Table 4 shows the predictor balance between observed GDP per capita, the synthetic control, and the pool of donor states. In general, the variables that comprise synthetic Chihuahua follow the observed ones closely, except for remittances per capita. Chihuahua receives fewer remittances than the average

Mexican state, and therefore a linear combination of those variables will struggle to match it closely.

In Figure 10 (a), I plot Chihuahua's GDP per capita along with its synthetic control. Synthetic Chihuahua tracks observed Chihuahua very closely before the *Joint Operation*. The average log difference before the policy is close to zero (-0.0043). After the policy, we observe a sharp contraction in GDP per capita, which corresponds to the onset of the Great Recession. However, the recovery of Chihuahua is lower than the recovery of synthetic Chihuahua. The results suggest that the policy amplified the harmful effects of the Great Recession. When the presidency of Calderón ended in 2012, the log difference of Chihuahua and its synthetic control was close to -0.04. That is, Chihuahua's GDP per capita was close to 4 percent smaller than it should have been absent the policy.

In Figure 10 (a), I plot the log-difference between Chihuahua and its synthetic control and the organized crime index. Notice how the organized crime index is an inverted mirror image of the log difference of GDP. When organized crime increased, the difference in GDP decreased.

### 3.4 Statistical significance of the results

Inference in comparative case studies that rely on synthetic controls with aggregate data differs from the traditional approach. In regression-based studies, for example, the standard errors measure the uncertainty of the sample on explaining the aggregate data. Although in this framework, I use aggregate data, there is still uncertainty related to the ability of the synthetic control to reproduce a counterfactual Chihuahua. The divergence observed in Figure 10 (b) may be just prediction error, and any model would have shown the adverse effect. One problem here, though, is that large sample inferential techniques are not suitable since the difference between Chihuahua and its synthetic control comprises of only two data points per quarter (Cunningham, 2018). To overcome that situation, I perform permutation methods as in Abadie et al. (2010) and Buchmueller et al. (2011), which date back to Fisher (1936).

The permutation tests, or placebo tests, consist of the randomization of the treatment to each state in the donor pool. Figure 10 (c) shows the difference of observed GDP per capita for each state and its placebo synthetic control (that is, each donor state with the treatment).

The dark line is the difference for Chihuahua. In general, Chihuahua has a good fit before the treatment. After the treatment, the effect is largest for Chihuahua. Both effects give some certainty that the policy is not a prediction error.

Furthermore, I calculate exact *p-values* by obtaining the root mean squared prediction error (RMSPE) for the post and pre-treatment periods and compute the ratios of both for each state. The RMSPE is calculated as:

$$\text{RMSPE} = \left[ \frac{1}{T - T_0} \sum_{t=T_0+t}^{T} \left( Y_{1t} - \sum_{s=2}^{J+1} w_s^* Y_s t \right)^2 \right]^{\frac{1}{2}} \tag{6}$$

Then, I sort them and find the rank of each state ratio. The order of the state determines the exact *p-value*. Chihuahua's place is the second, which results in a *p-value* of 0.09 (2 divided by 22 states). Although it is larger than the standard used *p-value* of 0.05, that number is determined mostly for the small number of Mexican states that entered in the estimation (22 states).

### Discussion

In this section, I provided evidence that the *Joint Operations* of the Mexican War on Drugs preceded increases in organized crime, and had adverse causal effects on the aggregate economy. The second step is to understand the mechanisms and quantify the additional effects of crime and potential policies.

The causal effects presented above are informative, indeed, but partial and prone to possible biases. The results are partial since, by construction, I rely on a donor set of Mexican states which have their own (positive) levels of crime. A counterfactual Chihuahua is not a Chihuahua without the problems of drug trafficking, but a Chihuahua with the (average) drug trafficking problems of the states in the donor pool. There is a possibility that the states in the donor pool present distortionary levels of organized crime as well, but not as intense as Chihuahua.

In addition, possible biases might arise for the following reason. Although I controlled for violence spillover effects, I rely on official statistics, which, as I mentioned in the introduction, present underreporting. When the government announced the first Joint Operations, criminals operating in states with a heavy presence of cartels and, in anticipation of further *Joint*

*Operations*, might have switched their operations base. As crime is mostly underreported, if the policy contaminated other states, then the data are not entirely informative.

In the rest of the paper, I build a theory that considers the empirical facts and the causal effects studied previously. First, after the Mexican War on Drugs, and although the government fought drug cartels with more resources, all crimes increased, and drug-related violence and cartels expanded. Second, the informal sector was affected as studied by Dell (2015) and Utar (2018), and third, the government policy had adverse effects on the aggregate economy. The model I present in the next section accounts for those facts and, since I use data on business victimization corrected by the underreporting bias, I will be able to address the concerns previously mentioned, as well as to offer policy guidelines.

# 4 A model of occupational choice with criminal markets.

The model is a *span-of-control* in the spirit of Lucas (1978) and Guner et al. (2008). Individuals, according to their managerial skills, supply their labor as workers or run establishments as entrepreneurs. I extend the framework by including an endogenous distribution of formal and informal establishments, as in Ordóñez (2014); crime against establishments, as in Ranasinghe (2017); and extend the framework of Castillo and Kronick (2017) to include general equilibrium effects into their illegal drug markets model.

Criminals operate a costly technology that targets each entrepreneur with some probability and steal a personalized level of output. Entrepreneurs may decrease that probability by purchasing private security.

Cartels buy illegal drugs from a representative producer and sell them to final consumers. To do that, they transport those drugs through routes they control by hiring workers. More routes allow cartels to sell more drugs to final consumers.

There are three types of institutions in this economy. Their goal is to provide public security, to track and punish entrepreneurs in informality, and to inhibit the number of drugs that reach final consumers. These institutions are time-invariant and known by all agents.

## 4.1 Preferences and endowments

Individuals are heterogeneous in their talent (or managerial skill) $s \in S = [\underline{s}, \overline{s}]$ and form a continuum set of measure one. Talent $s$ is inalienable, invariant, and distributed according to the pdf $\mu(s)$.[8] All individuals comprise a representative household that lives forever, values consumption, accumulates capital, and chooses occupations for each member at each period. Preferences are given by

$$\sum_{t=0}^{\infty} \beta^t u\left(C_t\right), \tag{7}$$

in which $C_t$ denotes aggregate consumption in time $t$, $\beta \in (0,1)$ is the discount factor, and $u(\cdot)$ is the per-period utility function. The household accumulates capital by increasing investments $I_t$ that follows the motion

$$K_{t+1} = I_t + (1-\delta) K_t, \tag{8}$$

in which $\delta$ denotes the depreciation rate of capital.

Every period each household member has one unit of time which she supplies inelastically to her occupation: entrepreneur in the formal sector, entrepreneur in the informal sector, or worker.

### 4.1.1 Entrepreneurs

Entrepreneurs produce $y$ units of consumption good by renting $k$ units of capital at price $r$ and hiring $n$ workers at the wage rate $w$. Production takes the form of $f_s(k,n) = s k^{\alpha_k} n^{\alpha_n}$ with $\alpha_k + \alpha_n < 1$. Entrepreneurs pay a fixed fraction $\tau_y$ of output as taxes, and each $s$ gets a fraction $\tau_c$ of output stolen with probability $F$ that depends on the rule of law, $\lambda_R \in [0,1]$, and spending on protection, $z \geq 0$. The rule of law is the probability with which the state prevents crime against businesses. Higher values represent a stronger rule of law and lower values increase the victimization probability. Security spending complements the rule of law, but it is costly. The cost is given by $bz^{\psi}/\psi$, in which $b > 0$ is a scale parameter and $\psi$ is an elasticity parameters. The victimization probability has the following form:

[8] $s$ denotes both talent and index.

$$F = 1 - \lambda_R \left(1 + z^{\lambda_z}\right). \tag{9}$$

Entrepreneurs may avoid paying taxes by switching to the informal sector where they have to remain small (in capital) to operate undetected by the government. The government detects informal entrepreneurs with probability $\rho(k)$, and takes away their revenues as punishment. Punishments last only one period, and entrepreneurs who are caught have a fresh start after that. The probability of detecting an informal entrepreneur $s$ is:

$$\rho(k_s) = \begin{cases} 0, & k_s \leq k_{caught} \\ 1, & k_s > k_{caught}, \end{cases} \tag{10}$$

with $k_{caught} > 0$. The government policy allows entrepreneurs to produce using a capital level below $k_{caught}$ and enjoy the benefits of tax avoidance. An informal entrepreneur that produces more than $k_{caught}$ only exists in an off-equilibrium path.[9] In equilibrium all informal establishments rent capital less than or equal to $k_{caught}$ irrespective of their talent.

Since there are no time interdependences, entrepreneurs solve a static problem in every period. A formal entrepreneur solves the following maximization problem:

$$\pi_s(\mathbb{P}, \tau_c) = \max_{n,k,z\geq 0} \left(1 - F\tau_c\right)(1 - \tau_y)y - wn - rk - \frac{bz^{\psi}}{\psi}, \tag{11}$$

in which $\mathbb{P} = (w, r)$. Notice that the price of the consumption good is the numeraire.

An informal entrepreneur that rents some level of capital below $k_{caught}$ solves:

$$\pi_s(\mathbb{P}, \tau_c) = \max_{n\geq 0, 0\leq k<k_{caught}, z\geq 0} \left(1 - F\tau_c\right) y - wn - rk - \frac{bz^{\psi}}{\psi}. \tag{12}$$

Similarly, an informal entrepreneur constrained on capital solves the following problem:

$$\pi_s(\mathbb{P}, \tau_c) = \max_{n,z\geq 0} \left(1 - F\tau_c\right) y - wn - rk_{caught} - \frac{bz^{\psi}}{\psi}. \tag{13}$$

[9] The intuition is the following. Imagine an establishment that rents a capital level higher than $k_{caught}$. Every period the government detects it with probability 1. With non-negative prices of inputs, production is costly. The government seizure of revenues results in negative profits, which lead for the entrepreneur to change occupation.

### 4.1.2 Workers

Workers supply inelastically their time to entrepreneurs and to criminals and drug cartels, which will be defined below. Workers are randomly chosen who to work for. That is, workers put their hours in a *bag,* and anyone in need grabs them, pays the competitive wage, and uses them.[10] Workers' earnings are, therefore, equal to the competitive wage rate $w$.

### 4.1.3 Criminal group

A criminal group operates a costly technology that targets all entrepreneurs and steals a fraction $\tau_c$ of their output with probability $F$, defined in (9).
For each entrepreneur (both formal and informal) the criminal group solves every period the following static problem:

$$\pi_c(s; z, P) = \max_{0 \leq \tau_c \leq 1} \left[1 - \lambda_R \left(1 + z^{\lambda_z}\right)\right] \tau_c y_s - \frac{a\tau_c^{\rho}}{\rho}, \tag{14}$$

where $a, \rho > 0$ are scale and elasticity parameters. Both formal and informal entrepreneurs are different in the level of production and the security units they purchase, therefore the fraction of stolen output will differ between entrepreneurs.

## 4.2 The illegal drugs sector

I model the cartel economy as a non-cooperative two-stage game with endogenous entry. In it, players' payoffs depend on their actions and on all players'. In the first stage, potential drug cartels may enter the market if it is profitable. In the second stage, if a drug cartel enters, it buys $x$ drugs from a drug producer, transports them through $R$ routes it controls and sells $q$ of them to final consumers. Drug cartels differ in their fixed costs of operation. Controlling more routes allows cartels to move more drugs to final consumers. The level of interdiction $e$ reduces the movement of drugs. The interaction between route saturation and interdiction implies that the amount of produced drugs is lower than the drugs final consumers buy, that is: $x \leq q$.

[10] I am not modeling individual decisions to join crime since the final goal of this paper is to quantify the aggregate misallocation. Adding that layer of complexity is a venue for future research if one wants to understand further distortionary channels through the household side.

#### 4.2.1 Drug producer

A representative drug producer sells $X_s$ drugs at price $p_x$. He hires $n_x$ workers to produce using the following technology:

$$X_s = A_x n_x^{\alpha_x}. \tag{15}$$

where $A_x > 0$ and $0 \leq \alpha_x \leq 1$. The drug producer pays the competitive wage $w$ and his profits are given by:

$$\pi_x = p_x A_x n_x^{\alpha_x} - w n_x. \tag{16}$$

#### 4.2.2 Drug cartels

There is a discrete number $J$ of potential cartels which differ in their time-invariant fixed costs of operation that they draw in period 0 from a discrete uniform distribution $\mathcal{U}\left\{c_f^{\min}, c_f^{\max}\right\}$.

There is a continuum of routes with measure one. A cartel $i$ hires $h_i$ workers to control routes and pays them the competitive wage rate $w$. Routes are distributed according to the following Tullock contest function:

$$R_i = \frac{h_i^{\alpha_h}}{\sum_i^E h_i^{\alpha_h}}, \tag{17}$$

where $\alpha_h$ is a decreasing returns parameter common to all cartels, $E \leq J$ is the number of cartels that enter the market. Cartel $i$ sells $q_i$ drugs to final consumers and has the next formulation:

$$q_i = \left(R_i^{-1} e + x_i^{-1}\right)^{-1}, \tag{18}$$

where $e$ is the level of interdiction.

Profits are given by:

$$\pi_i = p_q q_i - w h_i - p_x x_i - c_{f,i}, \tag{19}$$

and cartels in every period choose the number of drugs they buy and the workers they hire to control routes. Notice in equation (18) that without interdiction (that is, when $e = 0$), cartels are able to sell to consumers the same amount of drugs they buy, that is, $q_i = x_i$. Also, the profit function for cartel $i$ in (19) implies that profits depend indirectly by other cartels' actions through $p_x$, and directly through the contest function. This interaction implies that each cartel has a best response function for the actions of other cartels.

Cartels enter the market if they make non-negative profits. The number $E$ of cartels that operate on the drugs market is determined by the distribution of fixed costs.

### 4.2.3 Consumers of drugs

The demand of drugs is fixed and given by:

$$Q = Ap_q^{-B}, \tag{20}$$

where $A > 0$ is the level, $p_q$ is the price that consumers pay for drugs and $B > 0$ is the price elasticity.

## 4.3 Timing of events

The interaction between criminals in both markets (goods and illegal drugs market) imply some strategic behavior for all agents. For this paper, I use the concept of Nash Equilibrium.

At time zero, the household has some initial capital, the government sets the institutions, and each household member draws his or her talent. At every time $t$, criminals observe the talent of each member and set a personalized theft for any labor, capital, security, and occupational choice they make. Theft only triggers if the household member becomes an entrepreneur.

In anticipation of crime, household members have their best-response function. They make occupation choices by comparing the after-theft profits with the wage income. After that, Entrepreneurs make their production and security decisions, and workers supply their labor. Production takes place, and criminals steal from entrepreneurs. At the same time, drug cartels observe prices, buy drugs from producers, hire workers to contest the routes, and sell drugs to final consumers.

At the end of the period, entrepreneurs, workers, criminals, and drug cartels bring their income to the household, to make consumption and capital decisions.

## 4.4 Steady-state competitive equilibrium

A steady-state equilibrium is a distribution of talent $G(s_{\min}, s_{\max})$, a distribution of occupations (workers, informal and formal entrepreneurs), production decisions $\{n_s, k_s, z_s\}$ for formals and informals, a distribution of fixed costs for the drug cartels $\mathcal{U}\left\{c_f^{\min}, c_f^{\max}\right\}$, $E$ number of cartels that enter the market, cartel decisions $\{n_i, x_i\}$, $X$ drugs produced and $Q$ drugs bought, $K$ units of capital and $C$ units of consumption, and prices $\mathbb{P} = \{w, r, p_x, p_q\}$, such that:

- Household maximizes utility given in (7).
- Each $s$ chooses occupations that maximize their income.
- Formal entrepreneurs maximize profits given by (11):
- Informal entrepreneurs maximize profits given by (13):
- Criminals maximize profits given by (14):
- Each cartel maximizes (19).
- The representative drug producer maximizes profits given by (16):
- $E$ cartels enter the market.
- Aggregate quantities are consistent.

## 4.5 Calibration

There are three groups of parameters to calibrate. The first group targets the moments of the distribution of establishments in Mexico. The second group targets victimization levels, costs of property crimes on establishments, and security spending. The last group targets the size of the market for illegal drugs.

**Moments related to the distribution of establishments** There are 9 parameters related to the distribution of establishments: $\alpha_k, \alpha_n, \delta, \tau_y, s_{\min}, s_{\max}, \beta, k_{caught}$ and shape. I set those parameter values following Ordóñez (2014). His model abstracts from crime on establishments, though. Later in this subsection, I show that including crime in the author's framework still allows me to match closely the necessary moments.

#### Moments related to crime against establishments

There are six parameters related to crime against businesses: $b, a, \psi, \rho, \lambda_z$ and $\lambda_R$. Ranasinghe and Restuccia (2018) estimated for Colombia a probability function similar as 9. I take two of the parameters the authors calculated and set $b = 7.422$ and $a = 19.35$, which represent scale parameters of the security cost establishments pay and the extortion cost the criminal group pays. My implicit assumption is that the returns to crime in Mexico are different than Colombia's, but not the level of them.

To calibrate the other four parameters related to crime, I use the business victimization survey ENVE from INEGI (2018). The target moments are the following: the sum of all property handed to criminals as share of GDP is 0.481%. Total spending on security by all establishments as a share of GDP is 0.379. The total cost of crime (property lost + security spending) of establishments with less than 100 workers as a fraction of GDP is 0.725%. Finally, the prevalence of crime of all establishments is 0.337 (or 33.7%).

#### Moments related to drug trafficking

There are 8 parameters related to drug trafficking: $B, e, \alpha_h, A, A_x, \alpha_x, c_f^{\min}$ and $c_f^{\max}$. The minimum value of the distribution of fixed costs can be set to any number, since $c_f^{\max}$ determines the total number of cartels that enter. I set it to $c_f^{\min} = 0$. I set the price elasticity of drugs to 0.61. That number comes from the World Drug Report 2016 from Bussink et al. (2016).

I use diverse sources to calculate the moments related to the markets for illegal drugs. The Department of Homeland Security estimates that Mexican drug cartels generate profits of around 19 to 29 billion dollars. I use the average of the two, which represents 2.1% of Mexican GDP in 2017. The number of workers associated with the whole drug industry comes from Rios and Sabet (2008). The authors estimate that around 300,000 people work producing drugs (0.56% of the labor force) and 168,000 work in other chains of drug trafficking as hitmen, drivers or security providers. That number represents 0.31% of the labor force.

I did not find estimations about the revenues of Mexican drug producers, but I use the number for Colombia from (reference), which is 0.4% of GDP. In 2018, the Mexican government estimated that 37 drug cartels operated throughout the country Monroy (2019). I use that number as a target moment. Finally, to pin down the effectiveness of interdiction, I use estimations from the United Nations Office on Drugs and Crime. They determined that around 43 to 68% of illegal drugs do not reach their final destination. I use the average of both ciphers. Table 5 summarizes all mentioned targets.

#### Jointly calibrated parameters and model validation

The rest of the parameters have direct or weak effects on distinct variables; therefore, I calibrate them jointly. Table 6 shows the parameter values and their data source. In general, the model replicates relatively well the target moments. Table 5 compares the model moments with their data counterparts. Notice that I am not directly targeting the moments of the distribution of establishments in Mexico, and still, the model approximates those moments with a certain degree of accuracy. Including crime to the framework of Ordóñez (2014) still allows me to match reasonably well the distribution of Mexican establishments.

Besides, the model predicts well the cost of crime and the security spending of establishments by size. Figure 17 plots the model predictions with the observed values from ENVE. I I did not target directly those moments, but still follow the observed ones.

## 5 Results of the calibrated model

The key parameters that determine the institutional framework are: $k_{caught}$, $\lambda_R$, $B$ and $e$. The calibrated values are $k_{caught} = 10.5$, that is, informal entrepreneurs who rent capital below 10.5 will go undetected. $\lambda_R = 0.499$, that is, the government provides half of the maximum level of property rights. $B = 0.61$, which results in a price-inelastic demand for illegal drugs. $e = 5.171$, which is related to interdiction efforts. Interdiction efforts comprise different factors, including spending on interdiction, a better trained police, etc. However, it does not have a concrete interpretation related to a particular factor.

The occupational choice is plotted in Figure 18. Low-skilled individuals become workers (those with skill levels below 1.5), since the value is the highest. Individuals with managerial skills between 1.5 and 2 become informal entrepreneurs, and those with skills above 2 become formal entrepreneurs.

## 5.1 Effects of illegality at the individual level

Criminals observe each entrepreneur and tailor the intended amount of output they will steal (that is, the best response function $\tau_c$). Figure 19 (a) plots the intended fraction they will steal from informal establishments and (b) from formal ones. Criminals intend to steal more from higher-skilled informal establishments since they produce more than lower-skilled ones, but they cannot afford enough security to counteract the offensive, as formals can [see Figure 19 (c)]. Low-productive informal establishments produce less, so the criminal group sets them a lower $\tau_c$. In addition, low-productive formal establishments are more targeted than their higher-productive counterparts. Although higher productive formal entrepreneurs produce more—and hence, they are a more valuable *prey* for criminals—they can afford more security to counteract crime [Figure 19 (d)].

Figure 20 displays the realized share of output that criminals steal from each establishment. The patterns are the same as the ones in the paragraph above: higher-skilled informal establishments and lower-skilled formal ones bear the highest cost of crime.

In addition to the previous direct costs, crime indirectly distorts the occupational choices and use of inputs. Figure 21 plots the ratios of inputs and output in the calibrated economy (crime economy) over their counterparts in a counterfactual economy without crime. With crime, low-skilled informal establishments hire more labor, and high-skilled informal establishments hire less. The net result is that the low-skilled informal establishments produce more, and the high-skilled informal establishments produce less. The misallocation channel in the informal sector becomes evident: resources move from high productive informal establishments to low productive ones.

The middle productive formal establishments in the crime economy employ less capital and workers (Figure 21 b). On the other side, formal establishments who are relatively more productive rent more inputs and produce more. Crime induces middle-sized formal producers to use fewer resources and high productive ones to use more. Finally, and in conjunction with the previous effects, crime induces occupations to misallocate.

Some formal establishments that face higher costs because of crime, and operate on the edge of profitability, switch to the less-productive informal sector to remain profitable. In addition to the channels mentioned above, increases in security spending reduce the aggregate use of inputs, and wages, in turn, contract. The decrease in wages further pushes a fraction of workers into informality, since the value of becoming an informal manager is higher than the value of being a worker. The net effect is that the share of the informal sector expands, and informal establishments rent an even more significant level of inputs.

## 5.2 Policy analysis. Full enforcement of laws

In this section, I compare steady states under different full law enforcement scenarios. That is, I increase the size of the respective parameter that governs the degree of illegality until the illegal behavior disappears. I conduct two exercises. In the first one, I shut down the illegal channels and keep the tax rate fixed. In the second one, I shut down the same illegal channels but find the tax rate that leaves the tax revenue unchanged.

I set an arbitrarily large value for the parameter $e$, which is related to the level of spending on interdiction. The thought experiment is to picture a world in which the government finds a way to eradicate drug trafficking. The second column of Table 7 shows the percentage change from the calibrated economy for different aggregate variables. The effects on the aggregate variables are close to zero: aggregate capital increases by 0.54%, labor decreases by 0.14%, and output increases by 0.51%. The mechanisms that generate those changes arise from an increase in the share of entrepreneurship, as some individuals who used to work for cartels become low-skill managers. Total security spending and stolen output increase by almost 2%, as the share of businesses increases.

In the third column of Table 7, I eliminate crime against businesses by providing full government protection, that is, I set $\lambda_g = 1$. Shutting down crime reduces the informal sector by 6.4%. Since businesses no longer get their output stolen, a fraction of medium-skilled entrepreneurs can now afford to pay taxes and operate in the more-productive formal sector. The expansion of the formal sector increases the use of inputs, which, in turn, increases the wage rate. With a higher wage rate, the value of becoming a worker increases, and therefore some previous informal entrepreneurs become workers. The combined effects reduce output by 2.58%. Also, the increase in the wage rate reduces drug-related profits by 0.74%, since drug cartels now pay higher wages to their hitmen.

In the fourth column, I set $k_{caught} = 0$; that is, the government catches and punishes any entrepreneur who chooses not to pay taxes and eliminates any possibility to operate in the informal sector . The changes in the aggregate quantities are the largest under this policy. The entrepreneurship rate decreases by almost 57% as a large number of informal entrepreneurs become workers. With the disappearance of the unproductive informal sector, capital expands 20.3% and labor 12.9%. Surprisingly, the wage rate decreases by 12.7% since the government now taxes a larger share of output. With cheaper labor, drug cartels hire more workers, but their profits decrease. The reason is that with more workers, cartels fight more intensively for the drug routes. The aggregate cost of crime (security spending and stolen output) increases by almost 200% since the economy increases its size.

In the last column of Table 7, I shut down all the illegal channels. Under this policy, capital increases by 28.2%, labor by 13.2% and output by 14.8%. The changes result from a combination of all the channels mentioned in previous paragraphs.

To counteract the additional distortionary effects of the government taxing a more significant level of output when the illegal channel disappears, I replicate the previous exercises, while keeping the tax revenue constant. The results are similar, but the magnitudes differ (Table 8). Shutting down all illegality increases capital by 63.5%, labor by 13.8%, and output by 24.7%. The positive effects amplify since the tax rate decreases by more than half. The substantial increase in aggregate capital more than offsets the increase in labor and, therefore, wages expand.

These numbers may seem large at a first glimpse; however, they are similar to what other authors have quantified in studies that consider the same illegal channels, but in a separate way. See Ordóñez (2014); Ranasinghe (2017); Ranasinghe and Restuccia (2018); Besley and Mueller (2018).

The previous policy exercises show that governments should not prioritize their police efforts on fighting drug cartels, but they should redirect them to protect businesses and punish informality. If governments want to decrease the consumption of drugs for reasons not related to aggregate output, as in this case (for example, for health or moral reasons), they should focus on the demand for drugs, or target drug cartels profits, which are the channels that sustain the drug trafficking market.

### 5.3 The Mexican War on Drugs through the prism of the model

Under my interpretation and in harmony with previous research and the results shown in this work, I rationalize the Mexican War on Drugs as a permanent increase in interdiction, $e$, and a permanent decrease in property rights, $\lambda_g$. The intuition behind that reasoning is that the government operated under fixed resources and, accordingly, when it mobilized the finite police units against drug trafficking, it provided less protection for producers. Since I am not explicitly modeling a function that maps law enforcement resources into institutions, I will make use of a comparative statics approach to analyze the war on drugs. In it, I will find steady-state equilibrium values for different levels of interdiction and government protection, and connect the predictions of the model with a narrative of the events related to the Mexican War on Drugs.

First, I start with the effects on drug trafficking of a permanent increase of interdiction. Figure 22 plots the production and consumption of drugs as interdiction varies. When the level of interdiction increases, the consumption of drugs decreases. Before the war on drugs, Mexico had a low level of $e$, and after the policy, the economy transitioned to some steady-state with higher $e$. Since the demand for drugs is price-inelastic (refer to Table 6), the lower number of drugs that reach consumers causes an increase in the price of drugs. The increase in the price of drugs expands the aggregate revenues and profits of drug cartels. Figure 23 shows the equilibrium price and profits of drug cartels for different levels of interdiction.

Higher illegal profits create incentives for new cartels to enter the market and contest those profits. Figure 24 (a) plots the number of drug cartels for different interdiction values. The model predicts that for low levels of interdiction, the number of cartels increases. Besides, drug cartels hire additional workers to contest those larger profits. Figure 24 (b) plots the number of workers trafficking drugs as interdiction varies. The number of workers in drug trafficking, which is my proxy for violence, increases with interdiction, just like during the War on Drugs. The number of workers producing drugs decreases with interdiction because cartels buy fewer drugs as consumption decreases.

And second, I analyze the aggregate economic effects that result from a permanent reduction in government protection. In Figure 25 (a), I plot the aggregate use of inputs and output of informal establishments, as a ratio between an economy without crime and an economy with various degrees of government protection, and hence, positive levels of crime. In quadrant (b), I plot the same variables for formal establishments. With lower government protection, the input use of informal establishments increases and of formals decreases. Informal entrepreneurs are less efficient than formal ones. With lower levels of property rights, labor and capital are misallocated from formal to informal establishments, causing the total input use and output to decrease, as in quadrant (c).

What are the channels behind the results in the previous paragraphs? First, as property rights decrease, the victimization of firms increases, which induces establishments to react in two ways. The first one is that they decrease their scale of operation, and the second one is that they spend on extra security to protect themselves against crime. Both effects reduce the rental of inputs and output contracts. In addition, the occupational choices distort as well.

Formal entrepreneurs on the margin of profitability switch to the informal sector to remain profitable, and the economy experiences an influx of formals to the informal sector. A second influx to informality arises because of general equilibrium effects. Quadrant (d) of Figure 25 shows that wages decrease with lower government protection. Some workers endowed with a relatively higher entrepreneurial talent switch to informality to increase their income since the value of being a worker decreased. The whole misallocating mechanism is plotted in Figure 26, in which the occupational choices are plotted. The share of entrepreneurs and, in particular, of informal entrepreneur increases with lower government protection.

The previously mentioned effects have multiplying effects on aggregate output. Figure 27 plots the fraction of output that gets stolen and the change in output relative to an economy without crime. With lower government protection, the cost of crime increases, and the economy contracts.

# 6 Conclusions and future work

In 2007 the Mexican government attacked drug cartels using police and military resources. Violence and organized crime increased, as criminal groups diversified into other crimes to preserve their profits, and governments diverted their resources from non-drug-related crimes to drug-related ones. Besdies, the adverse effects of the policy permeated to the real economy.

In states profoundly affected by drug-related violence, like in the border state of Chihuahua, I found that GDP *per capita* decreased four percent after the government intervention.

In a calibrated exercise for the Mexican economy, I show how weak laws distort occupational choices and production decisions of businesses, and have significant adverse effects on steady-state output. In a series of simulation exercises, I show that governments should tailor their police resources to tackle crime that affects businesses or decrease informality. If the demand for illegal drugs is price inelastic, interdiction policies have the risk of creating violence and distorting the economy. If governments aim to decrease the consumption of illegal drugs, they should focus on consumer-side policies, or target the illegal profits of drug cartels.

This paper has three main limitations. To keep the model and estimation tractable, I abstract from including crime against households. New empirical studies have examined the links between organized crime and labor markets. For example, BenYishay and Pearlman (2013) find that in violence-stricken Mexican states, the increase in homicides leads to a reduction in the number of hours worked. Velásquez (2015) finds that in municipalities with high levels of violence, increases in homicides negatively affect women's labor force participation and working hours. Arias and Esquivel (2012) estimate that for every 10 per 100,000 drug-related homicides at the national level, unemployment increases by 0.5%, and the fraction of self-employed decreases by 0.4%. Including the mechanisms by which crime affects households' decisions is an avenue for future work.

The second limitation is that I do not model the individual decisions to engage in criminal behavior. Since the ultimate goal of this paper is to study the aggregate effects, ignoring this aspect is of not of great concern. However, if the interest lies in policies that target groups prone to crime, future iterations should explicitly model crime decisions.

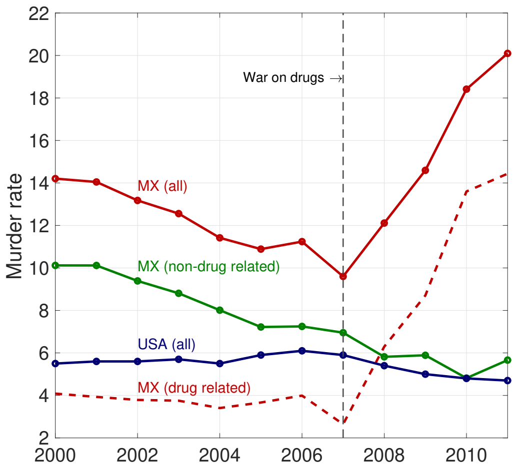
And the final limitation is that my framework does not inform about optimal law-enforcement policies that maximize welfare. In this paper, the institutional framework is given and recovered during the calibration. In reality, governments face tradeoffs between increasing the tax burden and providing more institutions—and potentially distorting the economy with *additional taxes*. Or providing fewer institutions and reducing the tax burden—and potentially distorting the economy with *fewer institutions*. In this paper, I am only able to inform about the potential benefits of the policies on steady-state output.

# Appendix. Figures and tables

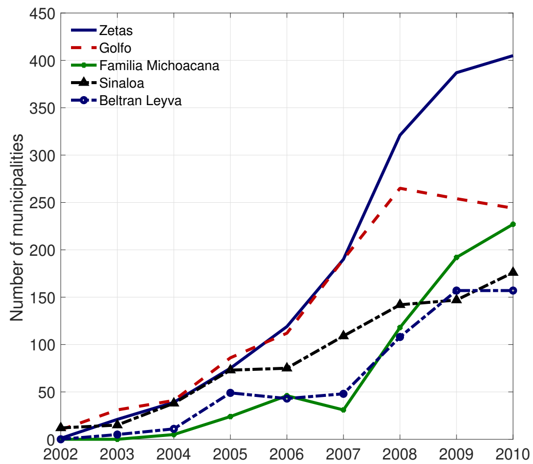
# Figures

Figure 1: Drug-related crimes and cartels before and after the War on Drugs

(a) Murder rate




(b) Presence of drug cartels

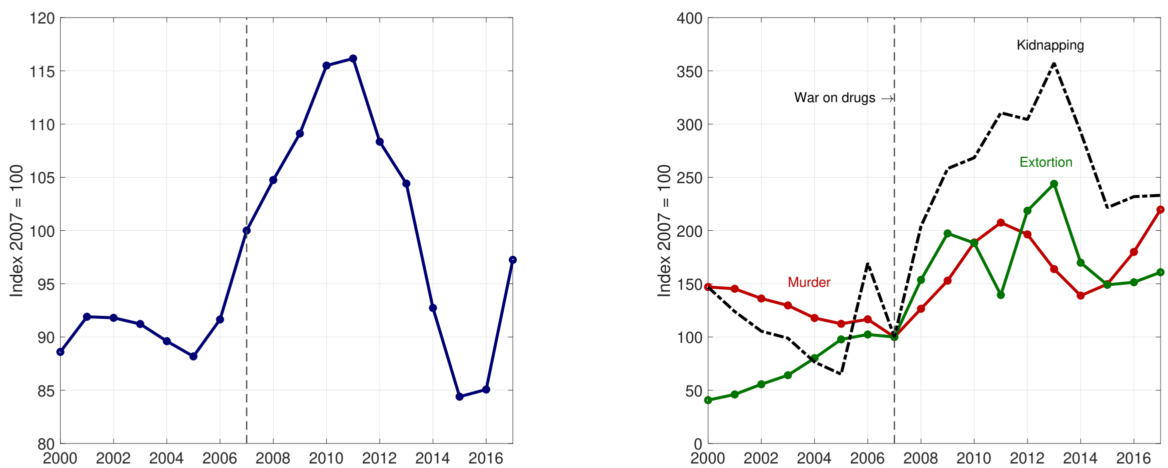



**Note.** Figure (a) shows Mexico's murder rate (number of murders per 100,000 inhabitants) compared with rates in the U.S. Before the War on Drugs in late 2007, Mexico's murder rate was converging to the U.S. rate. After the war, Mexico's murder rate increased considerably. The increase in homicides is explained by drug-related murders, as the non-drug related murder rate continued its downward trend and reached levels similar to the U.S.
Figure (b) plots the presence of drug cartels in Mexican municipalities. The database was compiled by Coscia and Rios (2012) using blogs and news outlets. After the policy went into effect, cartels' presence increased in Mexican municipalities.
*Source*: For Mexico, the Ministry of the Interior, Molzahn et al. (2012) and Enamorado et al. (2016). For the U.S., the Federal Bureau of Investigation.

Figure 2: Recent crime rates of Mexico.

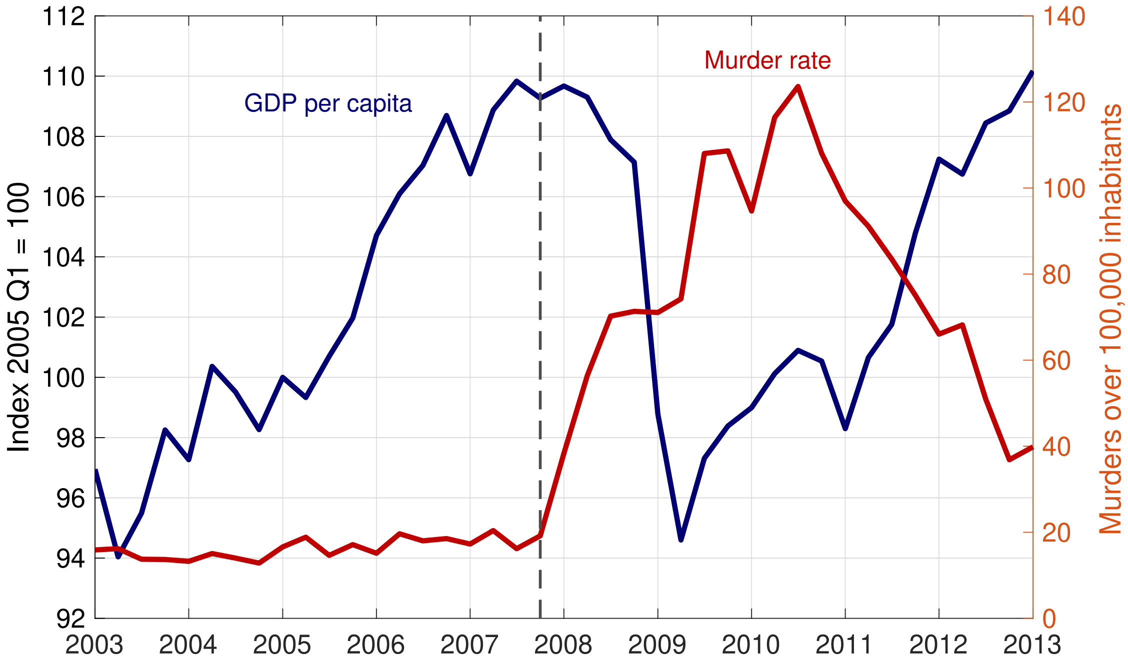
(a) Property crime

(b) Crimes related to organized crime




**Note.** The figure shows the official crime rates (occurrences per 100,000 inhabitants) of property crime (left) and murder, theft, extortion, and kidnapping (right). After the onset of the War on Drugs, all crimes reached all-time highs. These plots, however, should be interpreted with caution, since official statistics present biases that arise from underreporting and false statistics. See footnote 3 for the source of these biases. However, if we assume that the bias is constant through space and time, these graphs are still informative because they demonstrate the direction and magnitudes of the changes in crimes.
*Source*: Mexican Ministry of Interior and INEGI.

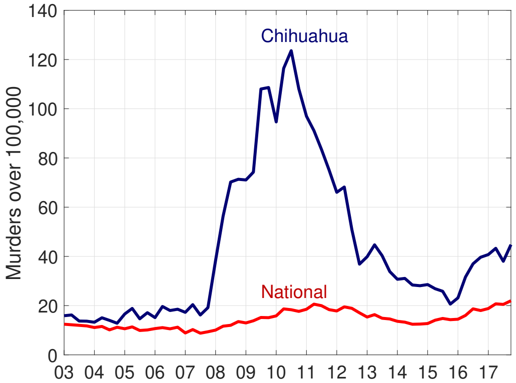
Figure 3: Murder rate and GDP per capita of Chihuahua



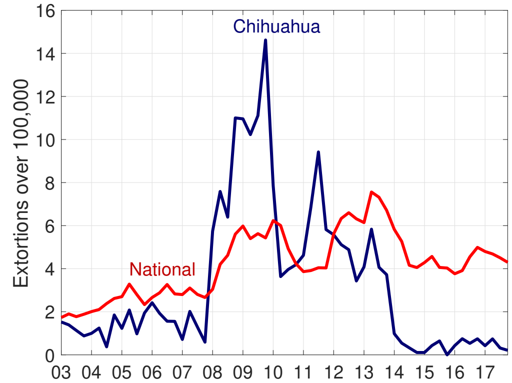

**Notes**. The figure shows the murder rate of Chihuahua and its GDP per capita (index 2005 Q1 = 100). The War on Drugs coincided with the 2007 Great Recession, which had considerable effects on the Mexican economy and, particularly, on the economies of northern states such as Chihuahua (see Banco de México, 2011). To estimate the causal effects of organized crime on the aggregate economy, one needs to isolate the effects of the War on Drugs on Chihuahua's GDP from the effects of the Great Recession.
*Source*: INEGI and the Secretary of the Interior of Mexico.

Figure 4: Organized-crime index and its components of Chihuahua and Mexico

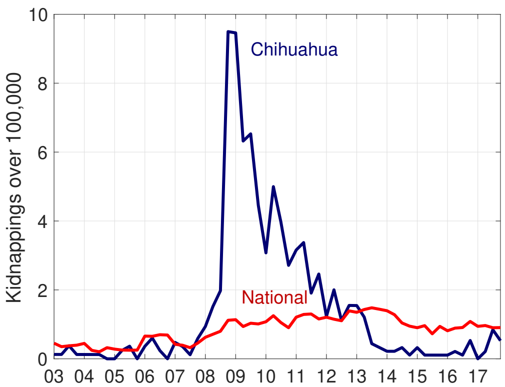
(a) Murder



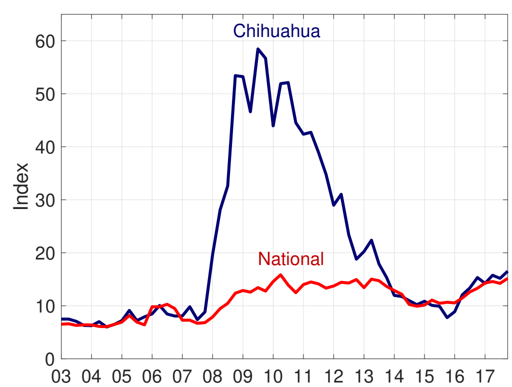

(b) Extortion




(c) Kidnapping




(d) Organized-Crime index



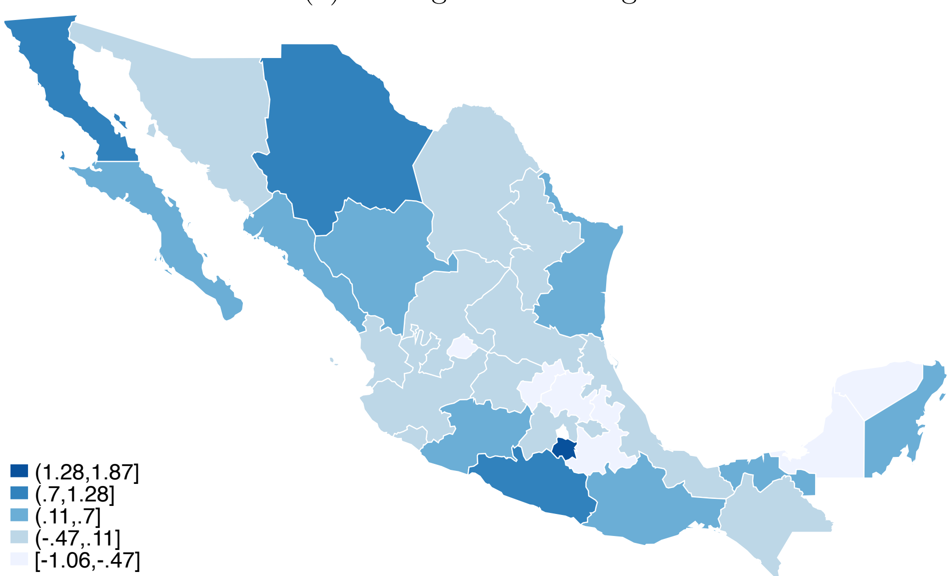

**Note**s. The figure depicts the three variables—murder, extortion, and kidnapping rates—that constitute the organized-crime index for Chihuahua and Mexico. Notice how Chihuahua's rates differ considerably with the national ones.

*Source*: Own estimations using data from INEGI and the Secretary of the Interior of Mexico.

Figure 5: Standardized values of the organized-crime index.

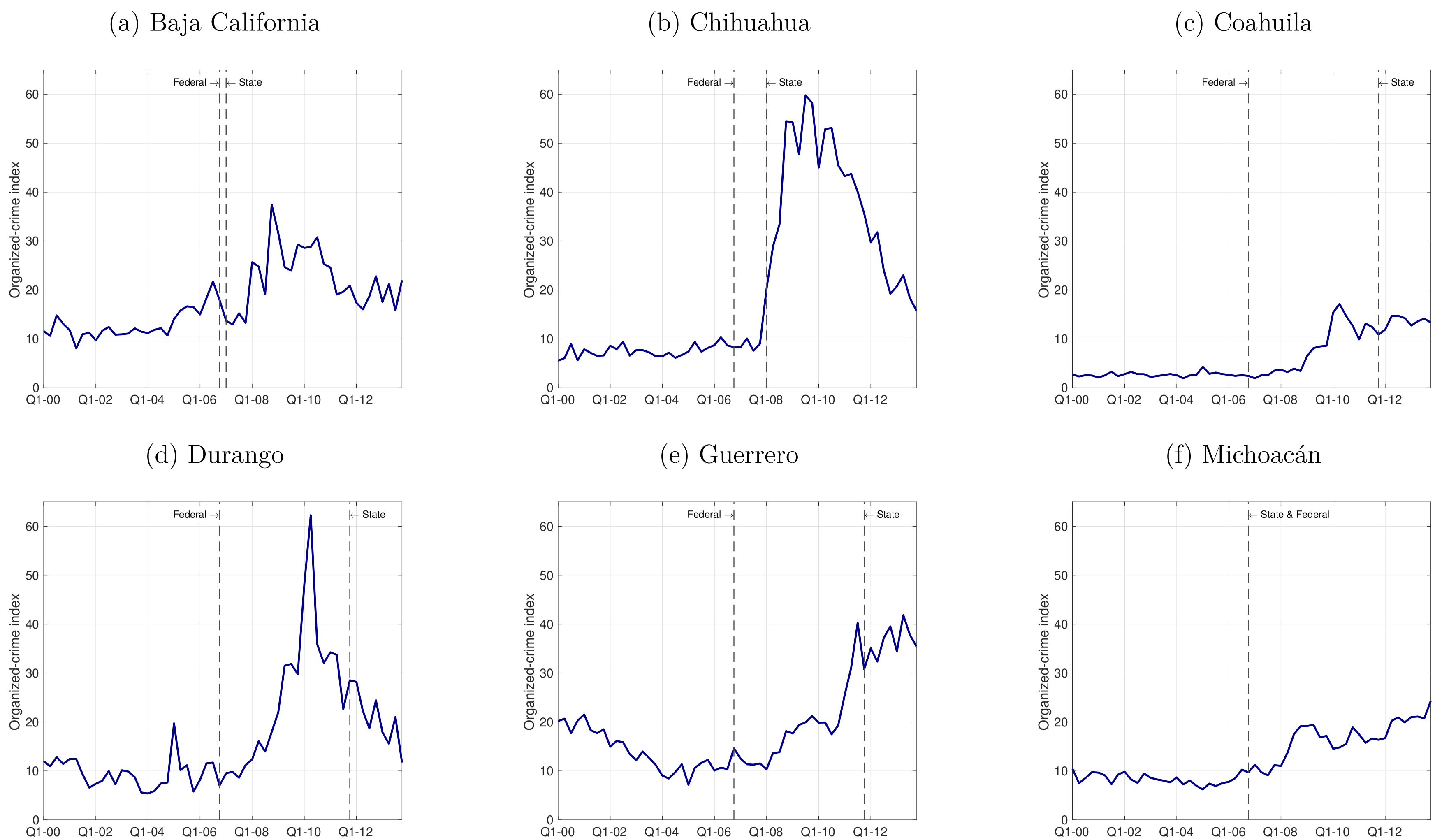
(a) Before War on Drugs


(a) During War on Drugs



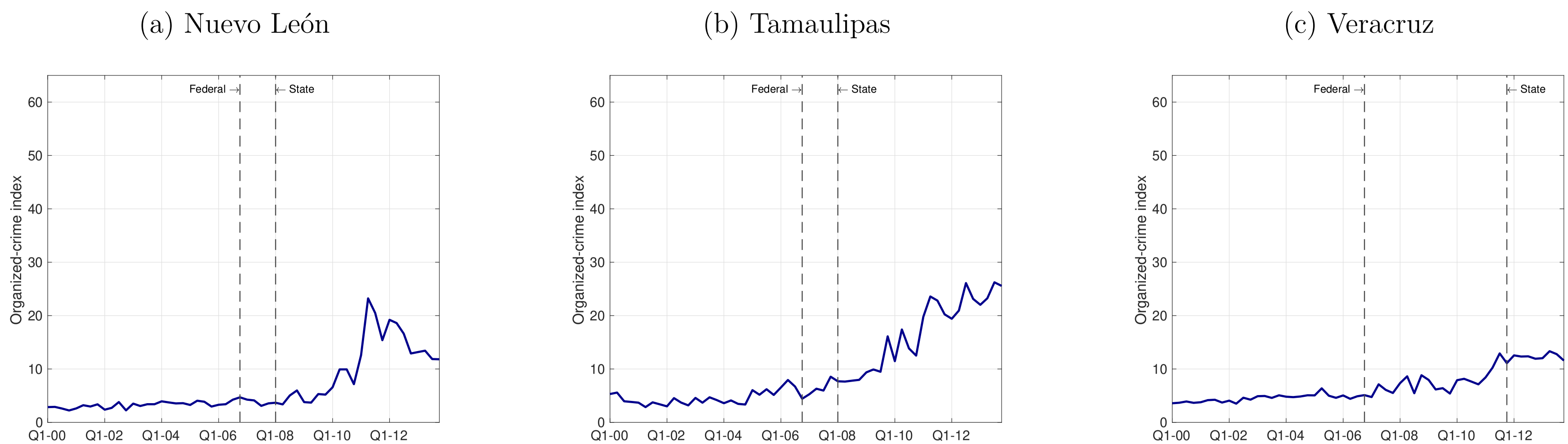

**Notes**. The maps display the standardized values of the organized-crime index for all Mexican states before and during the War on Drugs. Before the war, only a handful of states had large values of organized crime (darker blue shades), and the majority of states had low values of the said index (light blue tones). The situation reverses during the War on Drugs. A large number of states display darker tones of blue, and only a handful display light blue tones.
*Source*: Own estimations using data from INEGI and the Secretary of the Interior of Mexico.

Figure 6: Organized crime before and after the policy.




**Notes**. Subfigures (a) to (f) display the organized crime index for Mexican states in which the federal government launched the *Joint Operation*. The organized-crime index is constructed using principal component analysis on the murder, extortion, and kidnapping rates. The indexes are comparable between time and states. The *Joint Operation* consisted of the deployment of military and federal police units on states with a significant presence of drug cartels. The federal government declared war on drug cartels in December of 2006 (denoted as Federal in the subplots) and launched the *Joint Operations* on distinct periods (denoted State in the subplots).
**Source**. Own estimations using data from INEGI.

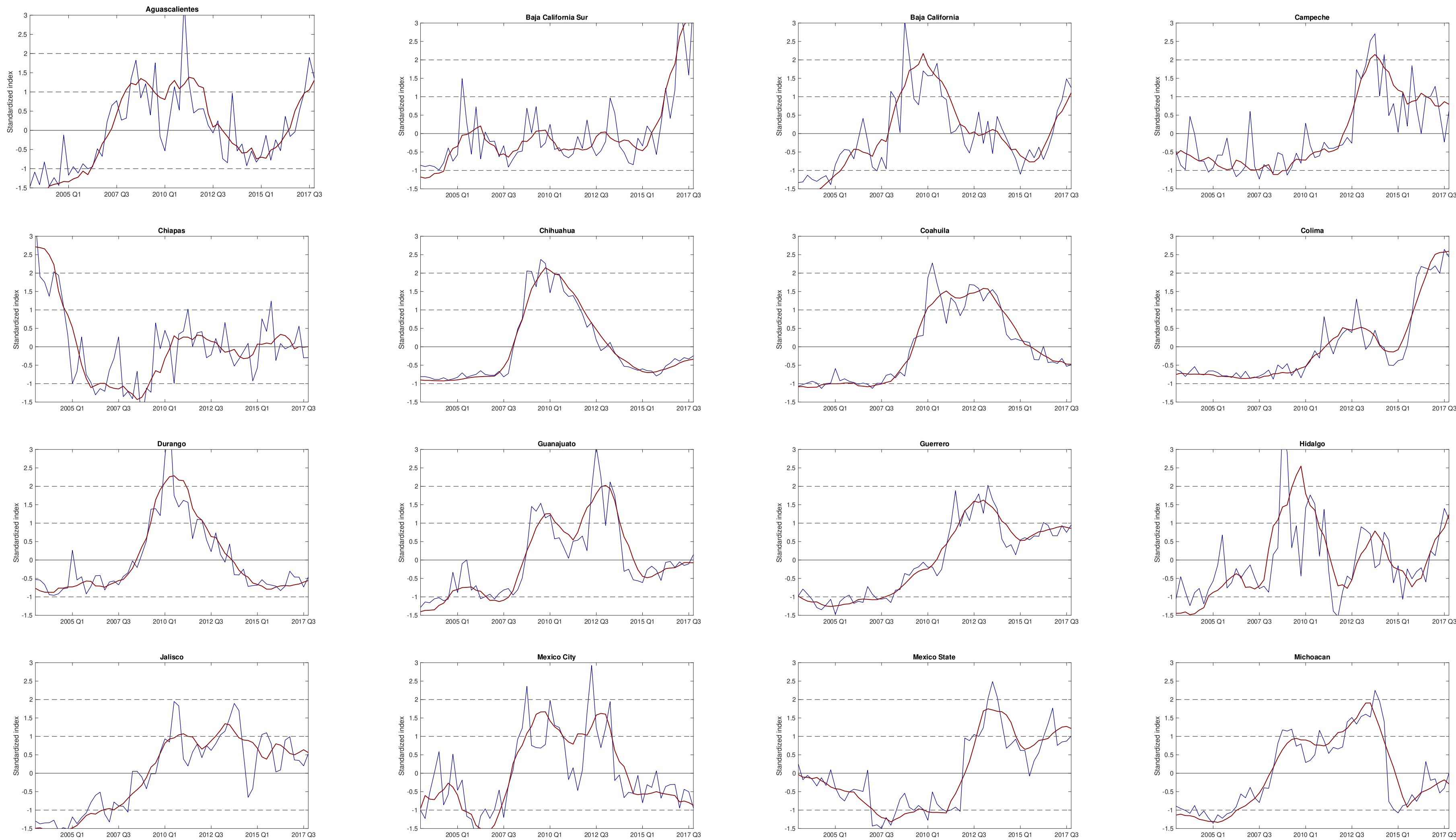
Figure 7: Organized crime before and after the policy.




**Notes**. Subfigures (a) to (f) display the organized crime index for Mexican states in which the federal government launched the *Joint Operation*. The organized-crime index is constructed using principal component analysis on the murder, extortion, and kidnapping rates. The indexes are comparable between time and states. The *Joint Operation* consisted of the deployment of military and federal police units on states with a significant presence of drug cartels. The federal government declared war on drug cartels in December of 2006 (denoted as Federal in the subplots) and launched the *Joint Operations* on distinct periods (denoted State in the subplots).

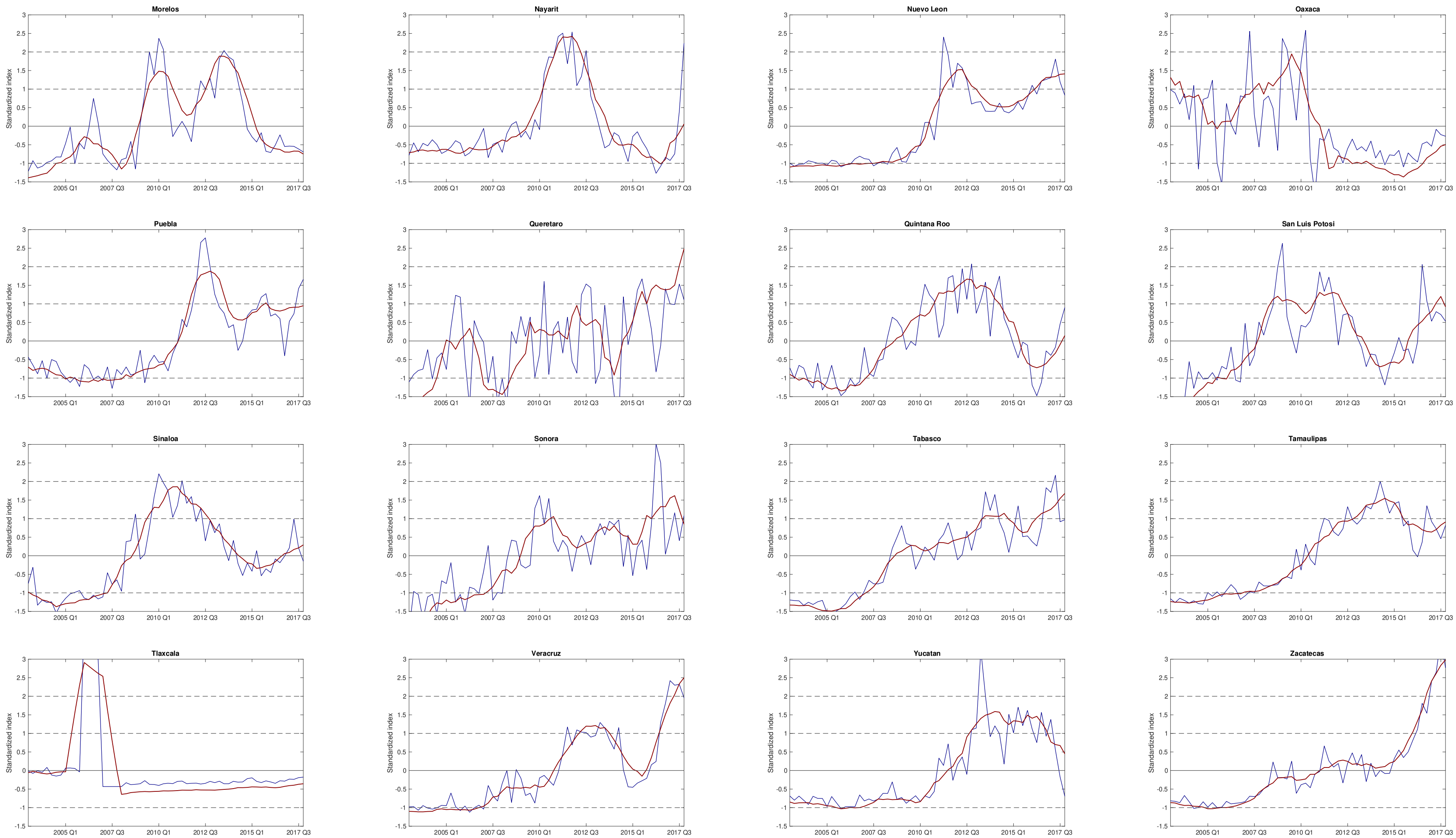
**Source**. Own estimations using data from INEGI.

Figure 8: Standardized values of the organized-crime index before the War on Drugs (Aguascalientes to Michoacán).



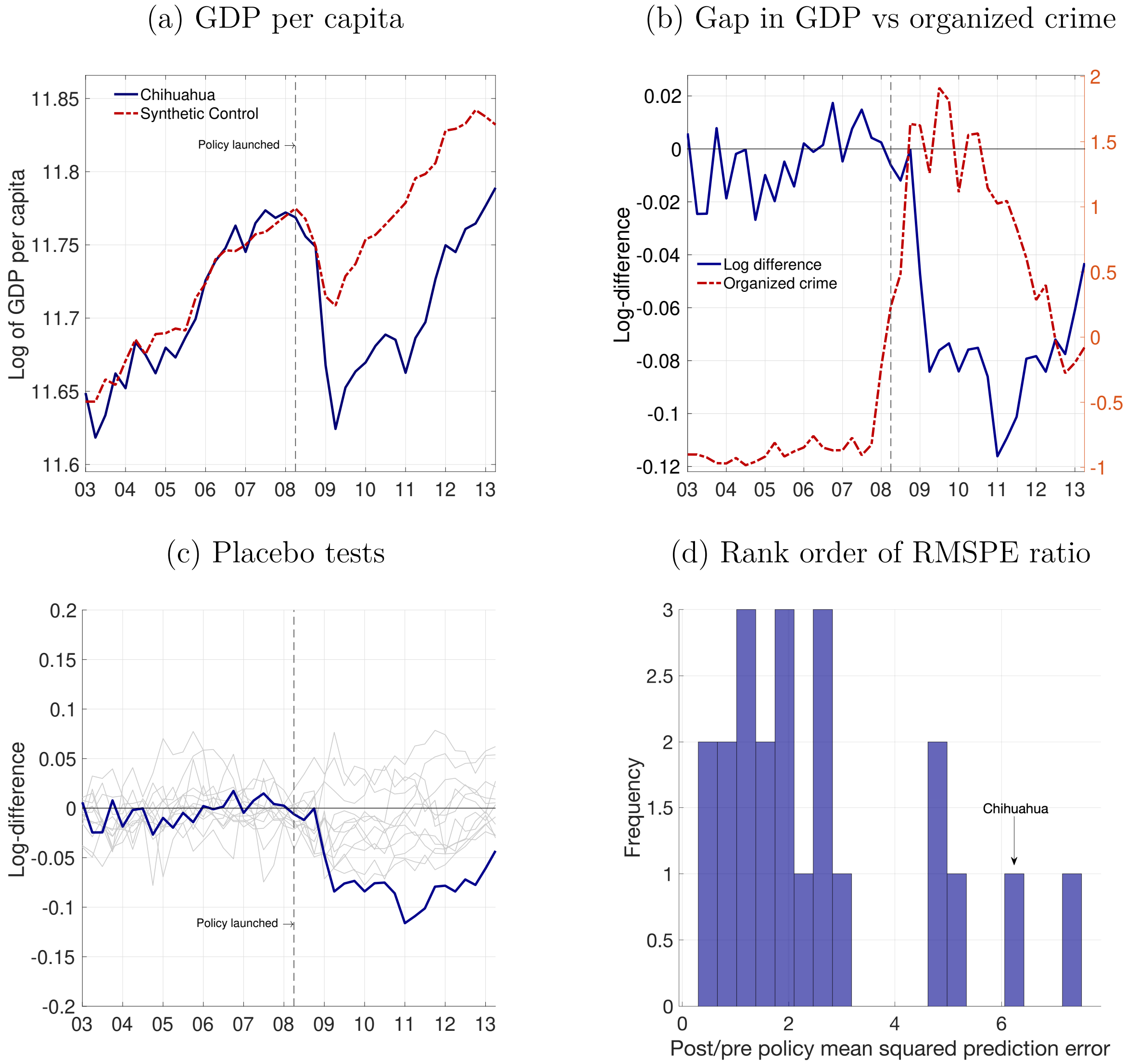

Sources: Own calculations using data from INEGI and CONAPO.

Figure 9: Standardized values of the organized-crime index before the War on Drugs (Morelos to Zacatecas).




Sources: Own calculations using data from INEGI and CONAPO.

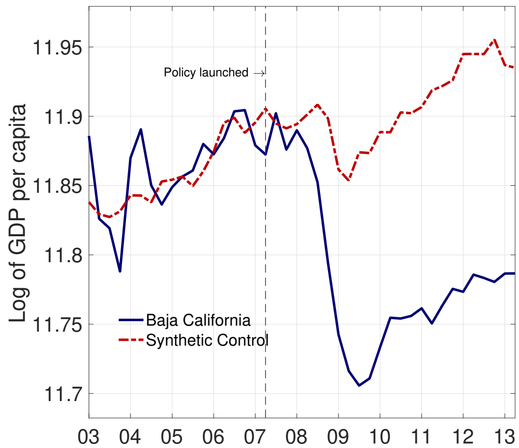
Figure 10: Chihuahua's GDP per capita vs synthetic Chihuahua



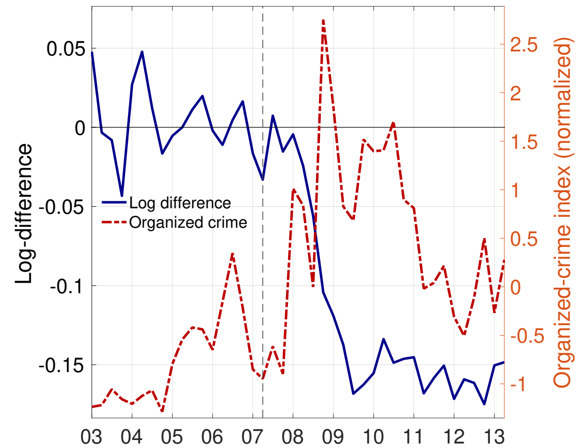

**Notes**. Panel (a) displays GDP per capita of Chihuahua and its synthetic control. The dashed horizontal lines represent the dates when the Mexican government announced the War on Drugs and when it launched the *Joint Operation* in the state. Panel (b) plots the log-difference of Chihuahua with its synthetic control. Panel (c) displays the Placebo tests, which consist of assigning the treatment to each of the states in the control group. In Panel (d), I show the rank order of the ratio of the RMSPE before and after the treatment.

Figure 11: Baja California's GDP per capita vs synthetic Baja California

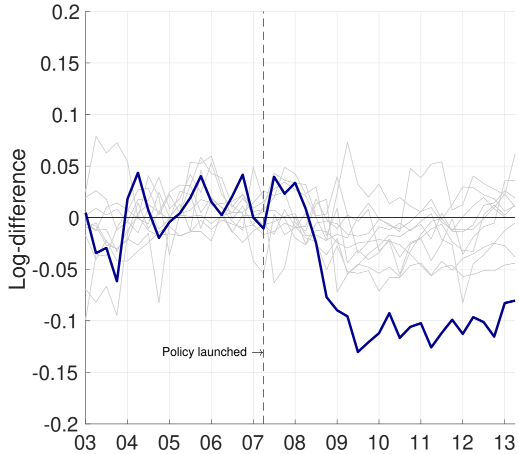
(a) GDP per capita



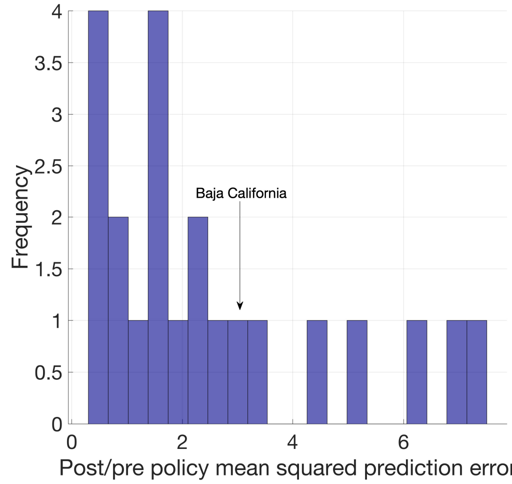

(b) Gap in GDP vs organized crime




(c) Placebo tests



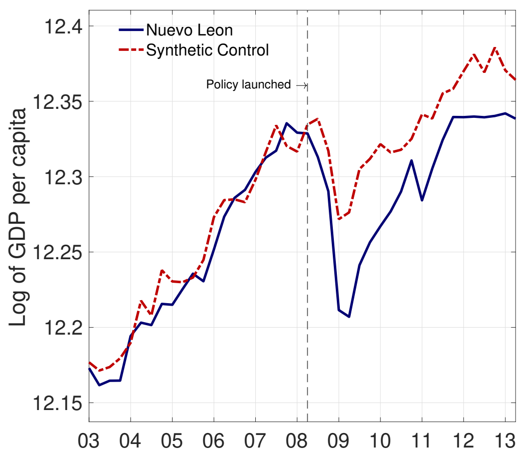

(d) Rank order of RMSPE ratio



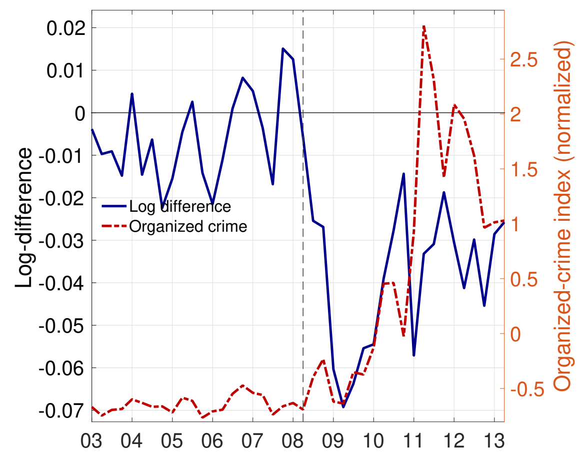

**Notes**. Panel (a) displays GDP per capita of Baja California and its synthetic control. The dashed horizontal lines represent the dates when the Mexican government announced the War on Drugs and when the *Joint Operation* was launched in the state. Panel (b) plots the log-difference of Chihuahua with its synthetic control. Panel (c) displays the Placebo tests, which consist on randomizing the treatment to each of the states in the donor pool. In Panel (d) I show the rank order of the ratio of the RMSPE before and after the treatment.

Figure 12: Nuevo León's GDP per capita vs synthetic Nuevo León
Standardized values.

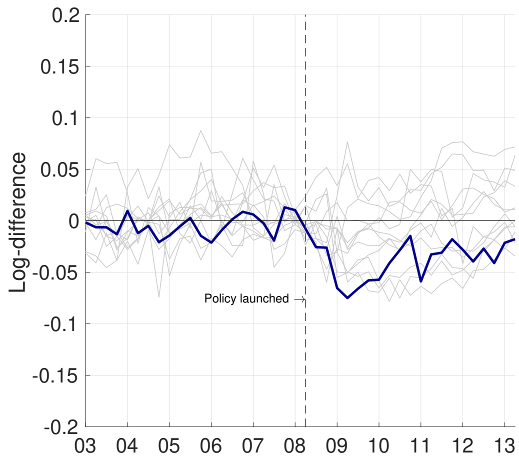
(a) GDP per capita



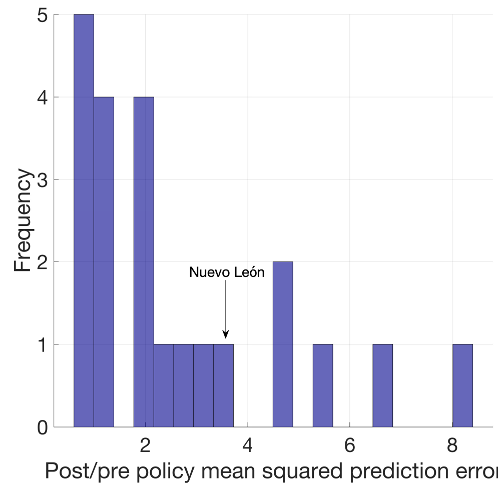

(b) Gap in GDP vs organized crime




(c) Placebo tests

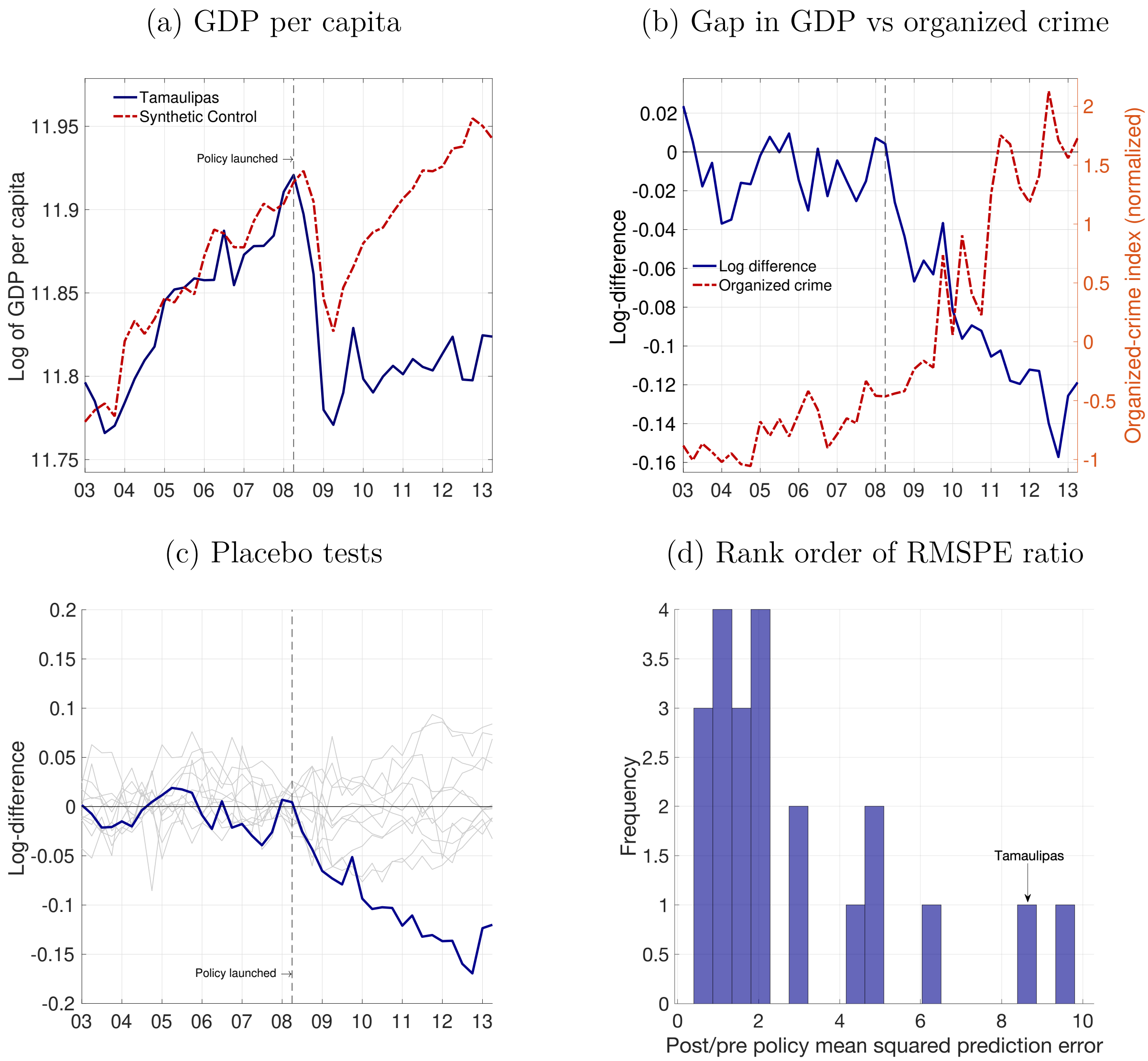



(d) Rank order of RMSPE ratio



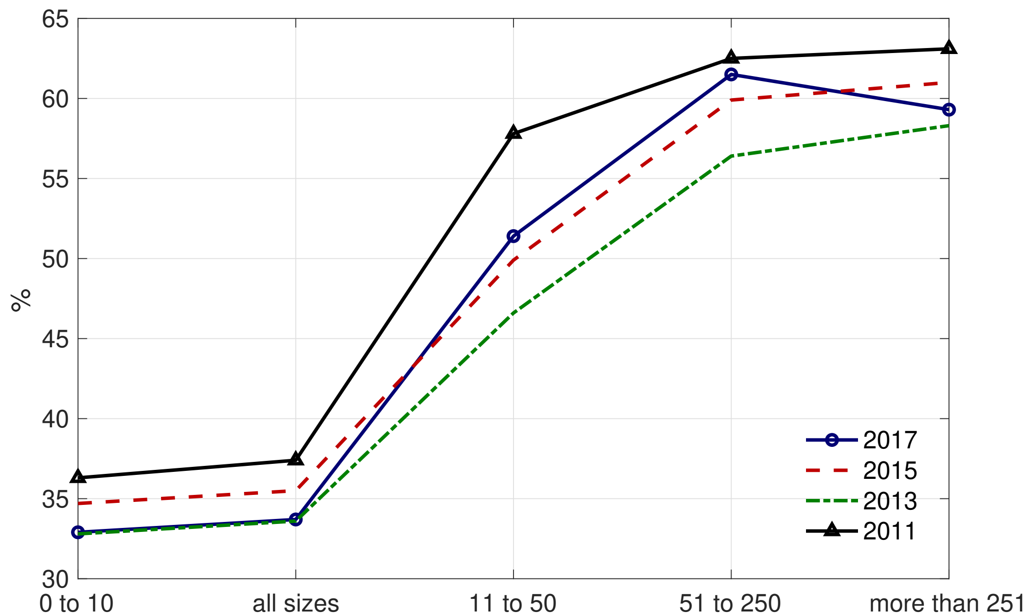

**Notes**. Panel (a) displays GDP per capita of Nuevo León and its synthetic control. The dashed horizontal lines represent the dates when the Mexican government announced the War on Drugs and when the *Joint Operation* was launched in the state. Panel (b) plots the log-difference of Chihuahua with its synthetic control. Panel (c) displays the Placebo tests, which consist on randomizing the treatment to each of the states in the donor pool. In Panel (d) I show the rank order of the ratio of the RMSPE before and after the treatment.

Figure 13: Tamaulipas' GDP per capita vs synthetic Tamaulipas
Standardized values.




**Notes**. Panel (a) displays GDP per capita of Tamaulipas and its synthetic control. The dashed horizontal lines represent the dates when the Mexican government announced the War on Drugs and when the *Joint Operation* was launched in the state. Panel (b) plots the log-difference of Chihuahua with its synthetic control. Panel (c) displays the Placebo tests, which consist on randomizing the treatment to each of the states in the donor pool. In Panel (d) I show the rank order of the ratio of the RMSPE before and after the treatment.

Figure 14: Victimization rate by business size

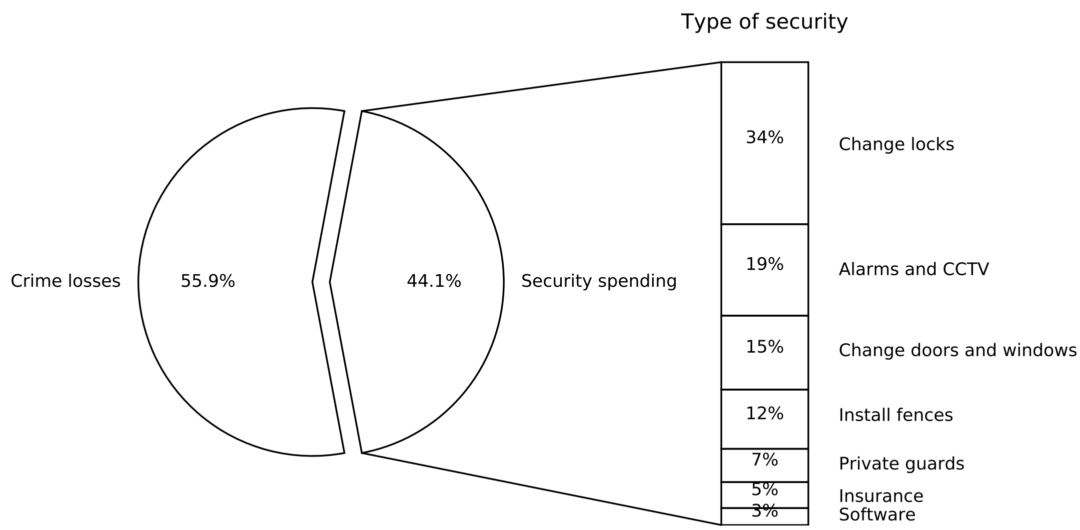



**Notes**. The figure displays victimization rates of establishments by their size (number of workers) from 2011 to 2017. The victimization levels have remained stable over time. Smaller establishments face a lower probability of crime and larger establishments lower probability.
*Source*: Encuesta de Victimización de Empresas (ENVE) for years 2012, 2014, 2016 and 2018.

Figure 15: Business victimization rate by type of crime


**Notes**. The majority of crimes against establishments involved a forced exchange of property (property crimes). Vandalism, which does not involve a transfer of property, had a victimization rate of just 1%.
*Source*: Encuesta de Victimización de Empresas (ENVE) for 2018.

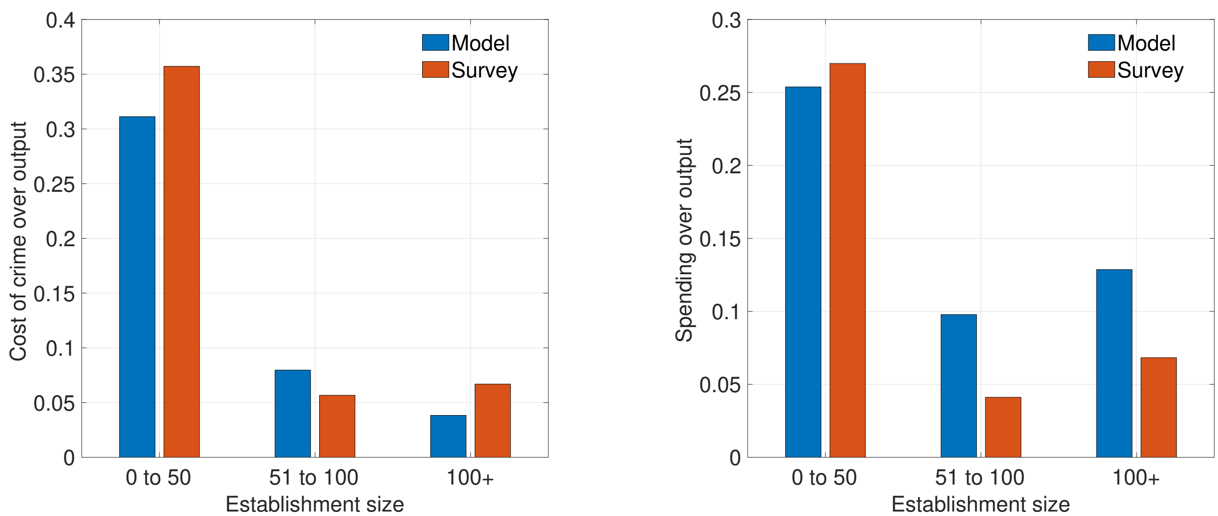
Figure 16: Distribution of costs by crime and distribution of security spending by type




**Notes**. In 2017 crime against establishments cost 0.86 percent of Mexican GDP. Of that number, 55.9% were direct losses (value of property lost), and the rest consisted of additional spending on security. The main components of security spending are: changing locks, installing alarms and CCTV, changing doors and windows, and installing fences.
*Source*: Encuesta de Victimización de Empresas (ENVE) for 2018.

Figure 17: Model moments vs survey moments.

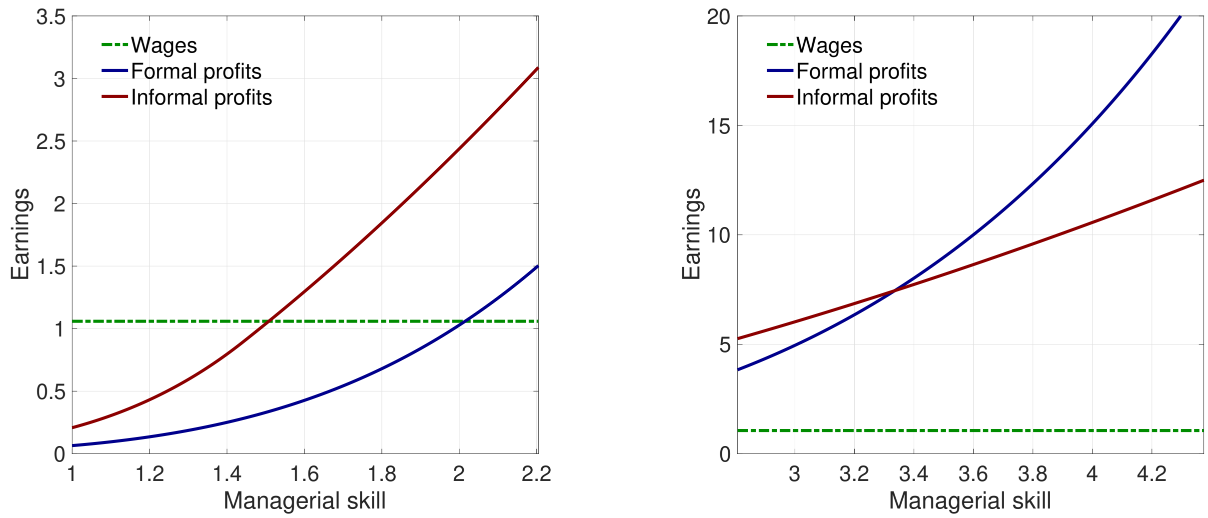
(a) Cost of crime (b) Security spending




**Notes**. Figure (a) plots the total value of property lost as output share by establishment size, and figure (b) plots total security spending as output share. The blue bars correspond to the results from the model, and the red bars are the observed moments from the ENVE survey. The results from the estimated parameterization follow the survey counterparts closely.
*Source*: Model predictions using data from INEGI (2018)

Figure 18: Earnings by managerial skill

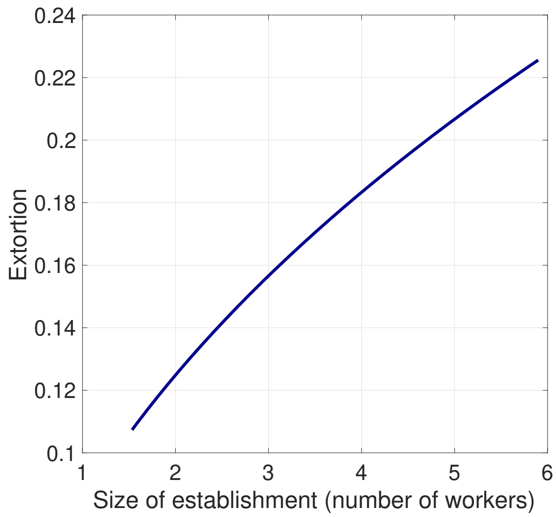
(a) Individuals with low skills (b) Individuals with high skills



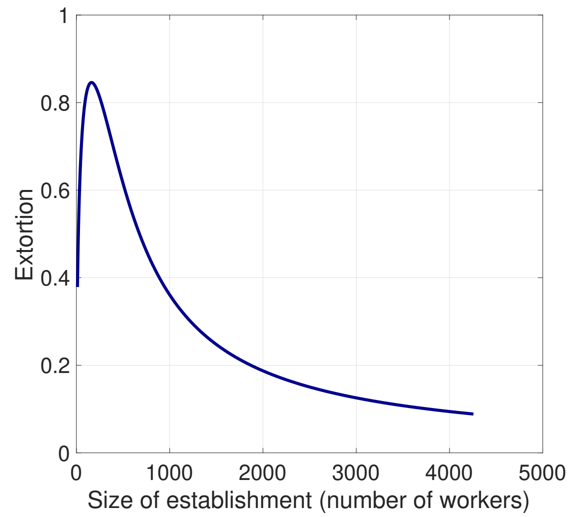

**Notes**. Individuals with low managerial skills select into workers. Some individuals with low managerial skills become informal entrepreneurs; that is, they operate a technology but choose not to pay taxes. They operate in the informal sector by renting a low level capital to avoid government detection. Individuals with higher talent obtain more substantial profits by producing and renting high levels of capital. That is, they choose to pay their taxes since it is profitable to do that.

Figure 19: Best response of the criminal group and establishments

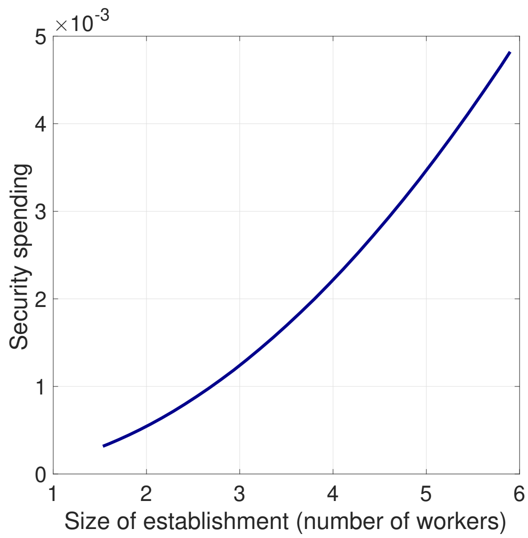
(a) Intended output stolen from informals



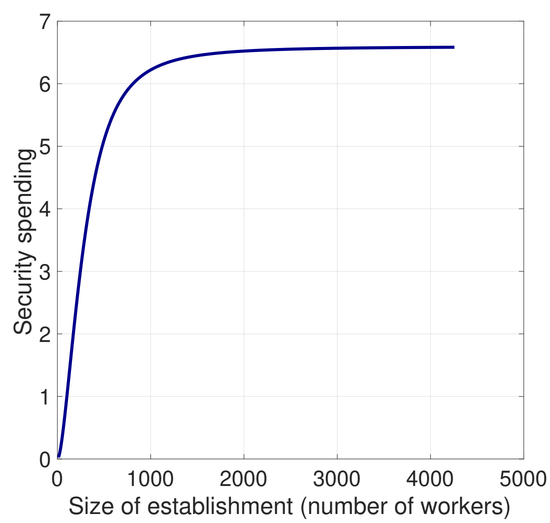

(b) Intended output stolen from formals




(c) Security spending from informals



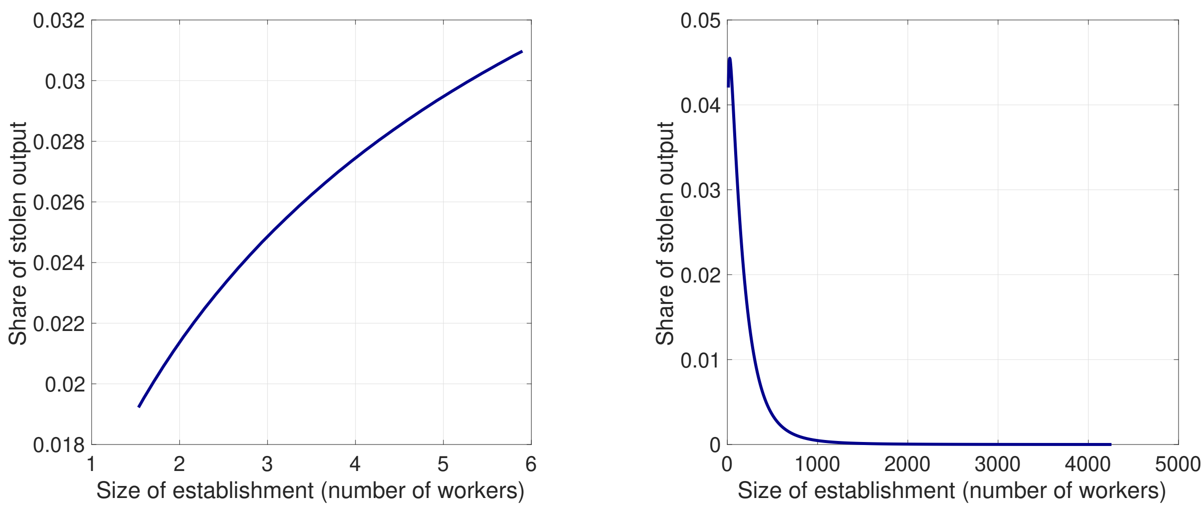

(d) Security spending from formals




**Notes**. Plots (a) and (b) show the best response of the criminal group, that is, the level of output that it intends to steal from informal establishments (top left), and formal establishments (top right). Small-sized informal establishments and large formal establishments are less targeted. Small informal establishments produce limited resources to steal, and large formal establishments buy more security to protect themselves. Larger informal establishments and middle-sized formal establishments bear the highest costs of crime. In the lower half of the plot, I show the best response of the informal and formal establishments, that is, their security spending. Larger establishments, both formal and informal, buy a more substantial level of security.

Figure 20: Share of stolen output by condition of the establishment.

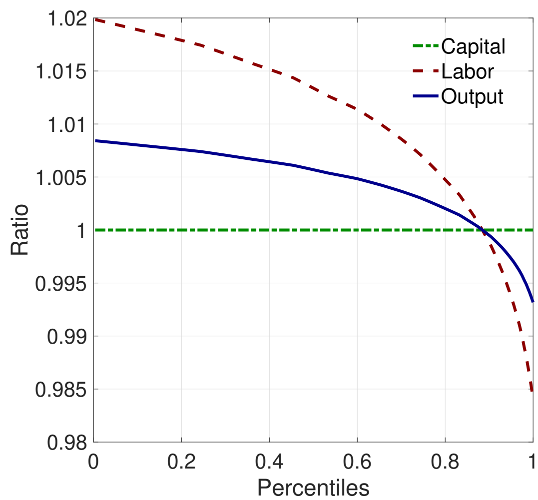
(a) Informal (b) Formal

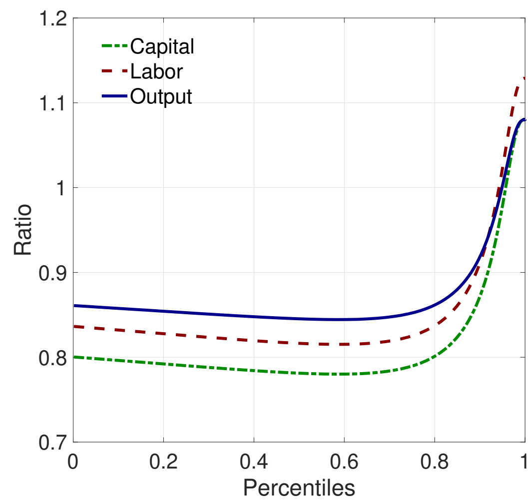



**Notes**. The figure shows the percentage of output that criminals steal. It is expensive for criminals to steal from each establishment; therefore, low productive informal establishments are less affected, since the potential reward is low (that is, they produce a low level of output). Similarly, high productive formal establishments are less victimized. The reason is that, although these establishments produce a large amount of output, they can afford private security to counteract the effect of criminals. High-skilled informal and low-skilled formal establishments are more affected since they produce a more significant level of output, but still, they cannot afford the necessary security to shield themselves against crime.

Figure 21: Inputs and output by condition of the establishments.
Ratio of crime economy over non-crime economy

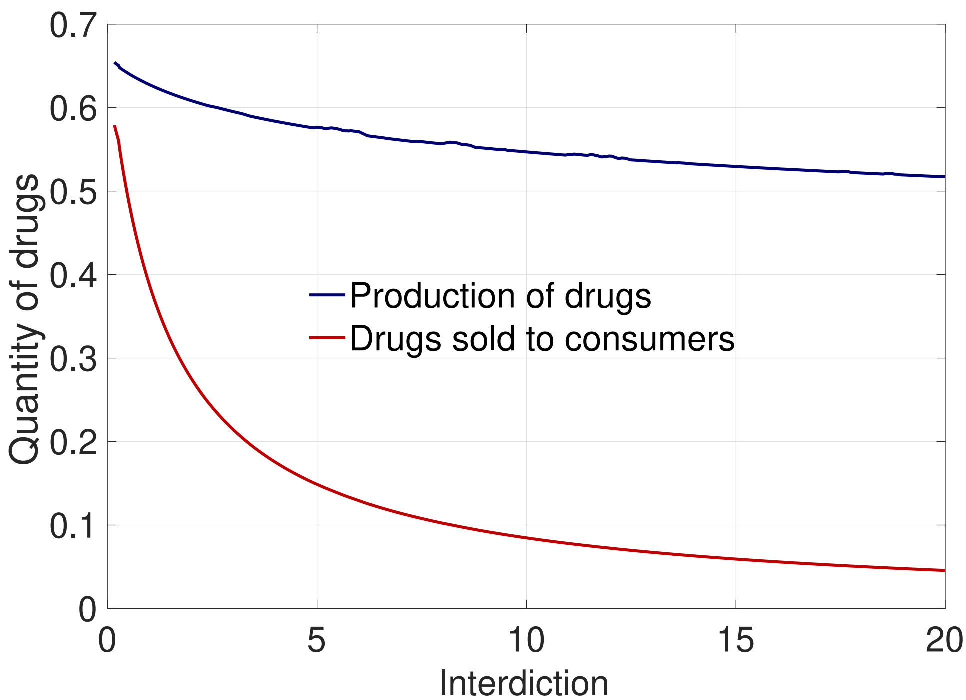
(a) Informals (b) Formals




**Notes**. The figure shows the ratio of input usage of informal establishments (left) and formal establishments (b). Crime on businesses has distortionary effects on the economy. First, victimization causes some formal establishments on the edge of profitability to switch to the informal sector to decrease costs. Besides, larger establishments spend on security to counteract the aggressions instead of using those resources to produce. As a result, the aggregate use of inputs decrease and wages, in turn, decrease. The decrease in wages further pushes a fraction of workers into informality, since the value of being an informal manager is now higher than the value of becoming a worker. The net effect is that the share of the informal sector expands, and establishments rent more inputs, compared to an economy with no crime (graph in the left). Middle-sized formal establishments bear the highest cost of crime. As a result, their input usage decreases. Since wages decrease, large formal establishments rent more inputs (graph in the right).

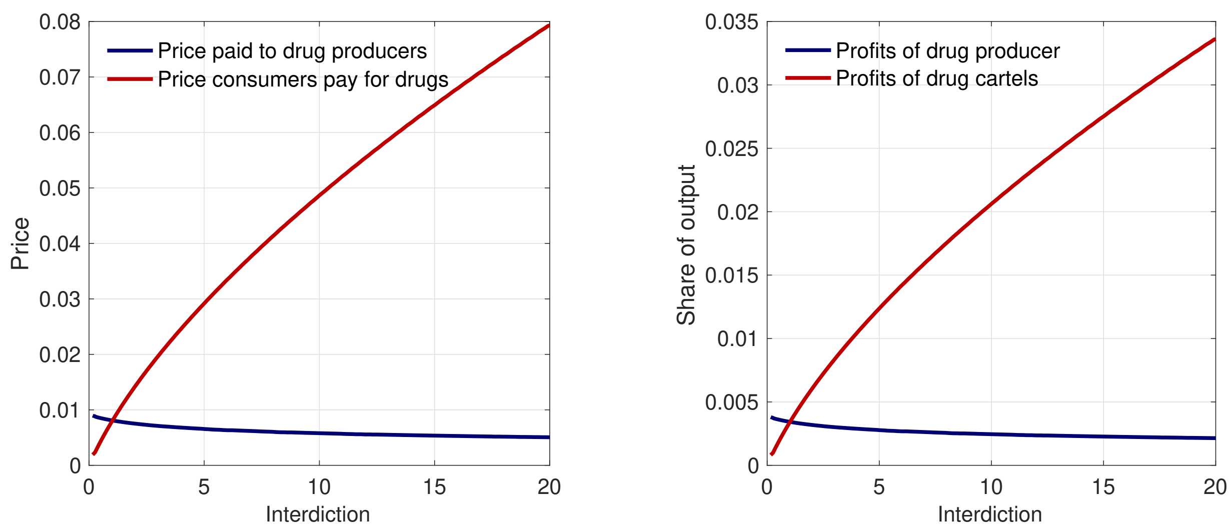
Figure 22: Production and consumption of drugs by interdiction




**Notes**. The figure plots the number of drugs produced (blue line) and the number that reaches consumers (red line). The difference between both lines corresponds to the number of drugs that the government seizes through interdiction. As interdiction increases, the production of drugs barely changes, and the consumption of drugs decreases asymptotically.

Figure 23: Price of drugs and aggregate profits of drug cartels

(a) Prices of drugs (b) Aggregate profits of drug cartels

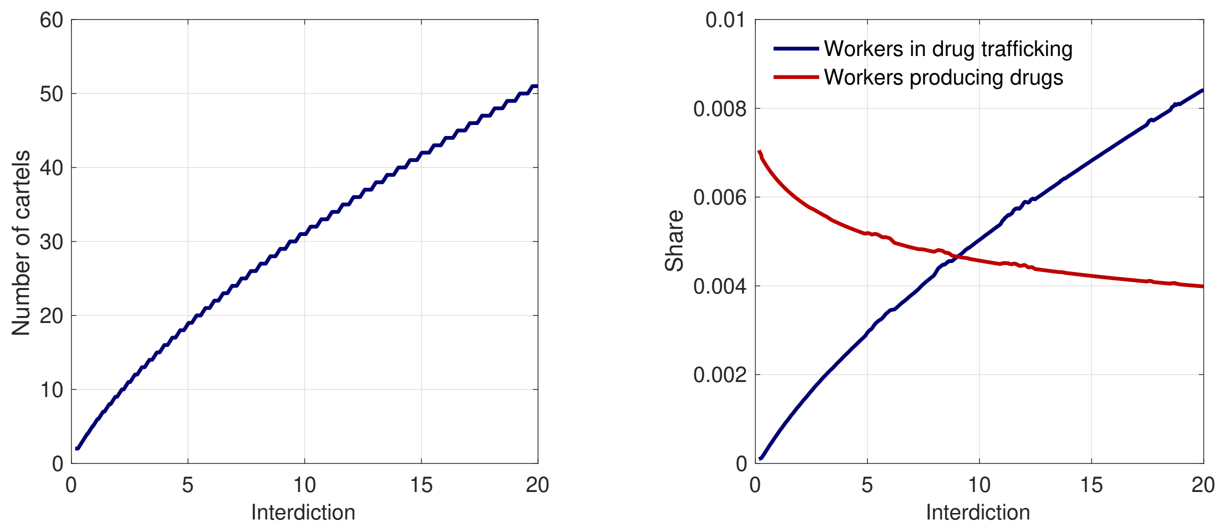



**Notes**. Quadrant (a) plots the price of drugs (blue line) and the consumption price of drugs (red line) as interdiction varies. Quadrant (b) plots the profits of the drug producer (blue line) and the profits of all drug cartels (red line). With more interdiction efforts, the price and profits of the drug producer remain stable. However, the price that final consumers pay for drugs and the cartels' profits increase considerably. Both increases are a consequence of the price inelasticity of the demand for drugs.

Figure 24: Number of cartels and workers as interdiction varies.

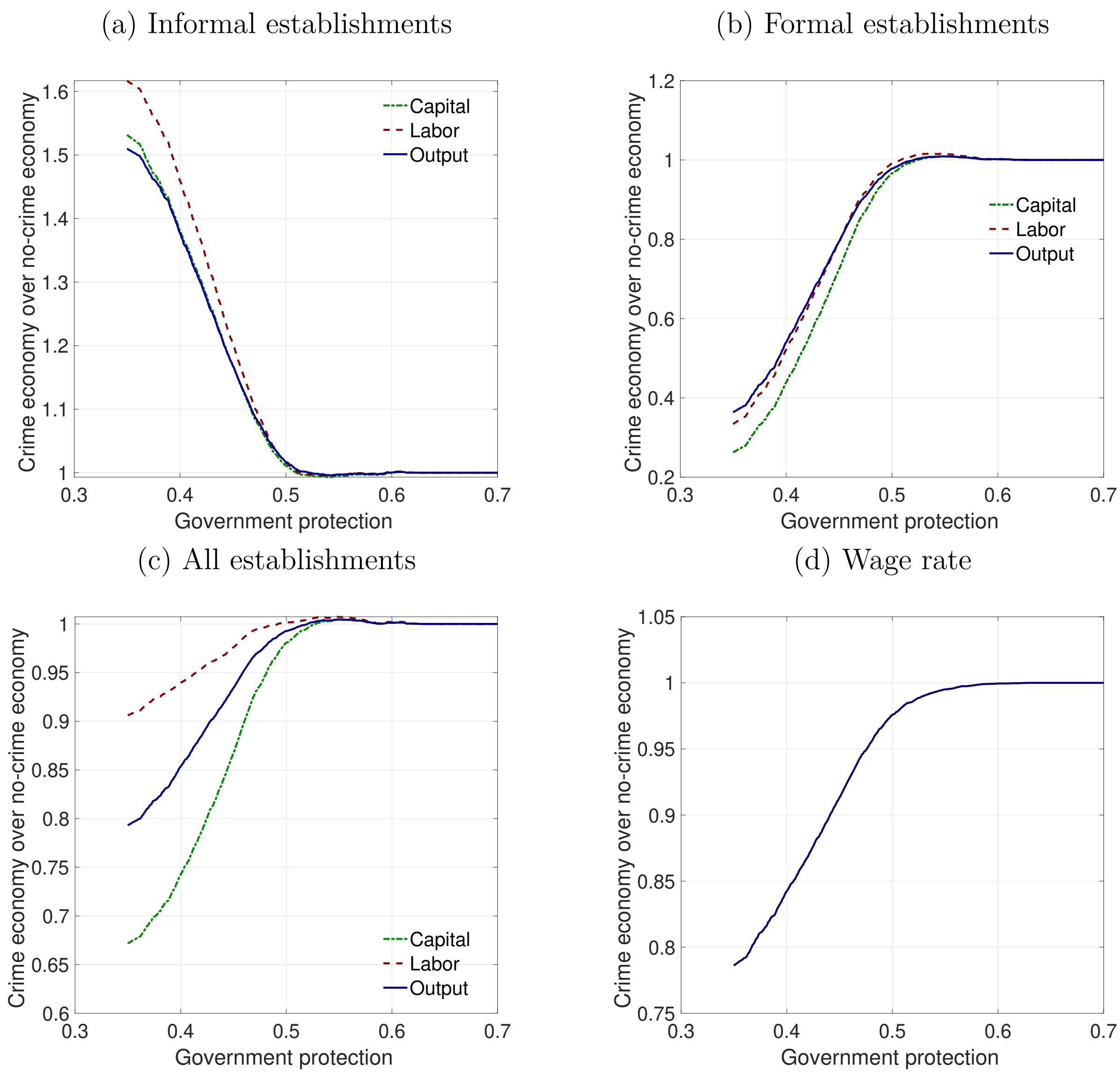
(a) Number of drug cartels

(b) Workers in drug cartels




**Notes**. In quadrant (a), I plot the number of drug cartels as interdiction increases and in quadrant (b) the workers (as a share of the labor force) involved in drug trafficking and production. Starting from a low number of drug cartels, when interdiction increases, the number of drugs that reach final consumers decreases. Since the demand for drugs is price inelastic, the price of drugs and the aggregate profits of cartels increase. This increase in profits pushes new cartels to enter the market to contest the fixed amount of routes. To contest those routes, drug cartels hire more workers.

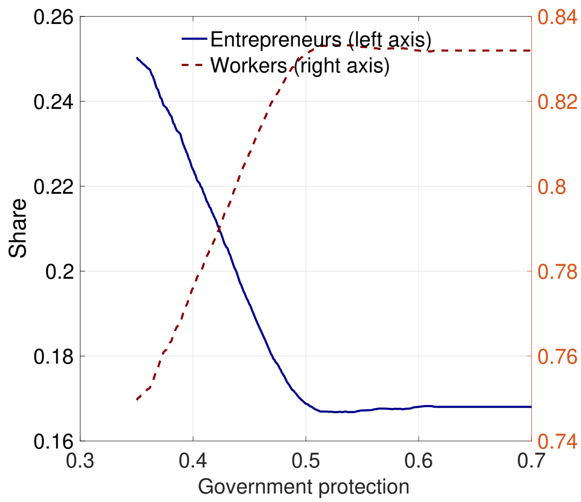
Figure 25: Aggregate inputs and output, and wage rate as government protection increases.



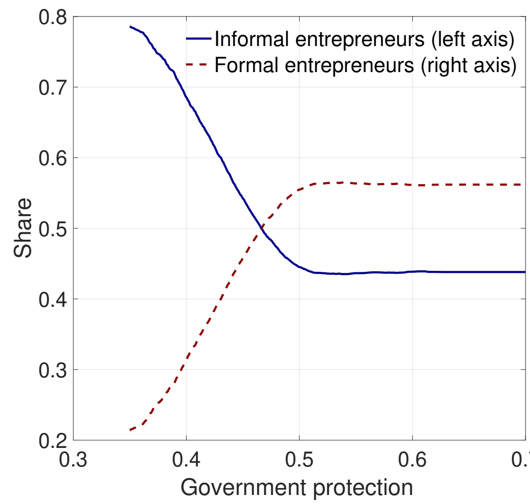

**Notes**. In this figure, I vary the parameter $\lambda_g$, which controls government protection on establishments. With lower government protection, crime on establishments increase. The increase in crime *i)* lowers the aggregate input use, which results in a contraction of wages [quadrant (d)], and *ii)* distorts the occupation choice, as the additional crime-related costs push a fraction of formal entrepreneurs into informality. Also, the decrease in wages forces some workers to join the informal sector. The overall effect is that resources misallocate as the more inefficient informal sector employs more inputs [quadrant (a)], the more efficient formal sector employs less inputs [quadrant (b)], which results that the aggregate use of inputs and production decrease [quadrant (c)].

Figure 26: Occupational choice with different levels of government protection
Shares

(a) Occupations shares

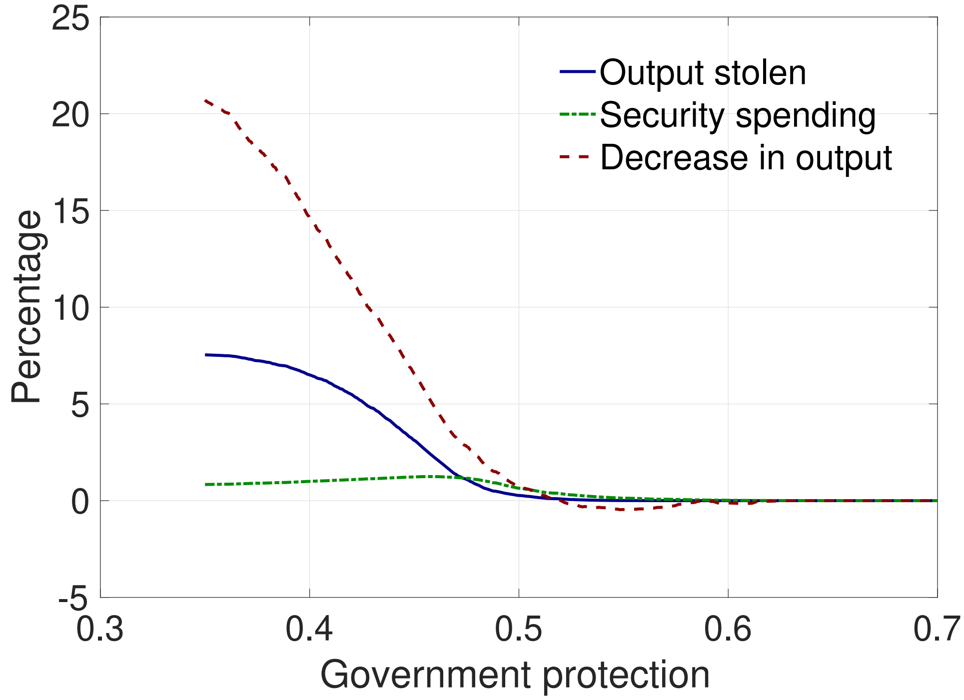



(b) Informality and formality shares




**Notes**. In Panel (a), I plot the worker and entrepreneur shares as government protection increases. When the government provides more protection, entrepreneurs bear lower costs, which allows them to employ more inputs. In the aggregate, the rent of more inputs increases the wage rate, which pushes some individuals in the informal sector to now work for wages. In panel (b), I plot the distribution of formal and informal entrepreneurs for different values of government protection. When the government provides more protection, some informal entrepreneurs switch to the more productive formal sector. Since the costs of crime decrease, some entrepreneurs can now afford to pay taxes and produce without the restriction on capital.

Figure 27: Cost in output by government protection




**Notes**. In this figure, I plot the cost of crime for different values of government protection and the decrease in steady-state output relative to an economy without crime. With low protection, criminals steal more output from entrepreneurs. Notice that crime has a substantial multiplicative effect on output. When the government is low ($\lambda_g = 0.4$, for example), criminals steal close to 6% of output, but the economy decreases by 15%.

# Tables

Table 1: Murder rate before and after the Mexican War on Drugs

| State | (a) Q1 2003 - Q4 2006 | (b) Q1 2007 - Q4 2016 | (c) % change |
|---|---|---|---|
| Aguascalientes | 3.4 | 7.7 | 123 |
| Baja California | 13.6 | 19.8 | 45 |
| Baja California Sur | 10.2 | 12.5 | 23 |
| CDMX (Mexico City) | 10.2 | 12.7 | 25 |
| Campeche | 3.3 | 5.5 | 68 |
| Chiapas | 7.5 | 6.7 | -11 |
| Chihuahua | 7.6 | 26.6 | 251 |
| Coahuila | 2.6 | 9.0 | 246 |
| Colima | 3.3 | 11.3 | 237 |
| Durango | 8.8 | 19.4 | 120 |
| Guanajuato | 4.6 | 8.3 | 82 |
| Guerrero | 10.9 | 25.1 | 131 |
| Hidalgo | 5.0 | 6.7 | 34 |
| Jalisco | 6.9 | 12.4 | 80 |
| Mexico | 7.6 | 9.0 | 18 |
| Michoacán | 7.9 | 15.0 | 90 |
| Morelos | 17.0 | 29.0 | 71 |
| Nayarit | 4.7 | 7.6 | 61 |
| Nuevo León | 3.5 | 10.8 | 205 |
| Oaxaca | 15.3 | 13.2 | -13 |
| Puebla | 3.7 | 6.3 | 68 |
| Querétaro | 4.1 | 4.4 | 8 |
| Quintana Roo | 7.5 | 15.2 | 104 |
| San Luis Potosí | 6.2 | 11.6 | 87 |
| Sinaloa | 10.4 | 17.9 | 72 |
| Sonora | 5.6 | 8.5 | 51 |
| Tabasco | 3.8 | 14.6 | 281 |
| Tamaulipas | 4.9 | 17.9 | 263 |
| Tlaxcala | 27.8 | 3.1 | -89 |
| Veracruz | 4.8 | 9.0 | 87 |
| Yucatán | 1.5 | 2.9 | 101 |
| Zacatecas | 3.0 | 10.2 | 243 |

**Notes.** Column (a) shows the average annualized murder rate before the War on Drugs, and (b) after the war. Column (c) calculates the percentage change. The Mexican War on Drugs resulted in different effects across states. Although the murder rate increased in the majority of states, caution should be exercised on the interpretation. For example, although Yucatán's murder rate almost doubled, both rates are meager. In contrast, Morelos' rate increased 71%, but it went from a high rate of 17 to an even higher one of 29.
*Source*: Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública.

Table 2: Organized-crime Index. Principal Component Analysis

| Component | Eigenvalue | Proportion | Cumulative |
|---|---|---|---|
| Component 1 | 1.38 | 0.46 | 0.46 |
| Component 2 | 0.87 | 0.29 | 0.75 |
| Component 3 | 0.75 | 0.25 | 1.00 |
| | Eigenvectors | | |
| Variable | Component 1 | Component 2 | Component 3 |
| Murder rate | 0.62 | -0.28 | -0.73 |
| Extortion rate | 0.51 | 0.86 | 0.09 |
| Kidnapping rate | 0.60 | -0.43 | 0.67 |

**Notes**. The table shows the variables used for the construction of the organized-crime index with principal component analysis, the eigenvalues, and the proportion of explained variance. I use the murder, extortion, and kidnapping rates for all the 32 Mexican states. The indexes are comparable between time and space. I keep only the first component to build the index since all variables are estimated with a positive sign—that is, increases in murder, extortion, and kidnapping increase organized crime. The first component explains 46 percent of the data variance.
*Source*. Own estimations using sources from INEGI and Mexico's Ministry of Interior.

Table 3: State weights

| State | Weight | State | Weight |
|---|---|---|---|
| Aguascalientes | 0.057 | Nayarit | 0.000 |
| Baja California Sur | 0.000 | Oaxaca | 0.000 |
| Campeche | 0.000 | Puebla | 0.000 |
| Coahuila | 0.000 | Querétaro | 0.000 |
| Colima | 0.000 | Quintana Roo | 0.000 |
| Chiapas | 0.000 | San Luis Potosí | 0.000 |
| CDMX (Mexico City) | 0.250 | Sonora | 0.000 |
| Guanajuato | 0.317 | Tabasco | 0.000 |
| Hidalgo | 0.000 | Tlaxcala | 0.000 |
| Jalisco | 0.001 | Yucatán | 0.375 |
| Mexico State | 0.000 | Zacatecas | 0.000 |

**Notes**. The table displays the weights of the states used on the estimation of Chihuahua's synthetic control. I excluded states that had significant increases in their organized-crime indexes during the estimation period. *Source*: Own estimations using data from INEGI, the Secretary of the Interior of Mexico and Banxico (Mexican Central Bank)

Table 4: Predictor balance of Chihuahua and its Synthetic Control

| Variable | Treated | Synthetic | Average |
|---|---|---|---|
| Industrial production | 84.13 | 86.98 | 96.91 |
| Workers (permanent) | 19.04 | 14.70 | 12.25 |
| Workers (temporal) | 1.16 | 1.43 | 1.89 |
| Labor force participation rate | 41.83 | 42.98 | 43.26 |
| Unemployment rate | 2.93 | 3.71 | 4.22 |
| GDP per capita (2003q1) | 11.65 | 11.64 | 11.65 |
| GDP per capita (2004q3) | 11.67 | 11.68 | 11.69 |
| GDP per capita (2007q1) | 11.74 | 11.75 | 11.74 |
| GDP per capita (2008q1) | 11.77 | 11.77 | 11.75 |
| Government spending per capita | 62,747.71 | 65,739.97 | 87,594 |
| Remittances per capita | 51,520.85 | 84,685.41 | 90,790 |

**Notes**. The table displays the averages of the variables used for estimation for Chihuahua, its synthetic control, and the donor pool.
*Source*: Own estimations using data from INEGI and Banxico.

Table 5: Empirical targets: Model and data

| Category | Description | Moments | |
|---|---|---|---|
| | | Model | Data |
| Non-target moments | Informality share | 0.444 | 0.447 |
| | Average size (workers) | 5.865 | 5.460 |
| | Share. 100+ workers | 0.292 | 0.298 |
| | Capital output ratio | 2.016 | 2.000 |
| | Average size. 100+ workers | 380.033 | 359.970 |
| Target moments | Crime loss / output (%) | 0.451 | 0.481 |
| | Security / output (%) | 0.497 | 0.379 |
| | (crime + sec.)/ output (%). 100- workers | 0.675 | 0.725 |
| | Prevalence of crime (%) | 0.234 | 0.337 |
| | Profits of drug cartels (% of GDP) | 2.076 | 2.100 |
| | Labor in drug trafficking (% labor force) | 0.310 | 0.310 |
| | Labor producing drugs (% labor force) | 0.560 | 0.560 |
| | Revenues (% of GDP) of drug producers | 0.501 | 0.400 |
| | Percentage of seized drugs | 75.900 | 55.000 |
| | Number of drug cartels | 37.000 | 37.000 |

**Notes**. The target moments related to the distribution of establishments are from Ordóñez (2014). I calculate the moments related to property crimes using the business victimization survey *Encuesta Nacional de Victimizacion de Empresas 2018* from INEGI (2018). The drug trafficking moments are taken from Rios and Sabet (2008), Coscia and Rios (2012), and different official sources. The model moments are obtained by solving the model for all equilibrium values and finding a set of parameters that minimizes the squared difference between the target and the model moments.

Table 6: Calibrated parameters

| Category | Description | Parameter | Value | Source |
|---|---|---|---|---|
| Establishments | Income share of capital | $\alpha_k$ | 0.330 | Ordóñez (2014) |
| | Capital depreciation rate | $\delta$ | 0.050 | |
| | Income tax rate | $\tau_y$ | 0.250 | |
| | Min value of talent distribution | $s_{\min}$ | 1.000 | |
| | Discount rate | $\beta$ | 0.943 | |
| | Income share of labor | $\alpha_n$ | 0.446 | |
| | Maximum capital of informals | $k_{caught}$ | 10.500 | |
| | Maximum value of talent | $s_{\max}$ | 13.500 | |
| | Shape of distribution | shape | 4.250 | |
| Property crimes | Scale of security cost | $b$ | 7.422 | Ranasinghe and Restuccia (2018) |
| | Scale extortion cost | $a$ | 19.350 | |
| | Elasticity term of security cost | $\psi$ | 0.817 | Joint calibration |
| | Elasticity term of extortion cost | $\rho$ | 2.485 | |
| | Returns to spending on protection | $\lambda_z$ | 0.043 | |
| | Rule of law | $\lambda_R$ | 0.499 | |
| Drug markets | Elasticity of drugs | $B$ | 0.610 | Bussink et al. (2016) |
| | Interdiction | $e$ | 5.171 | Joint calibration |
| | Elasticity of labor to routes | $\alpha_h$ | 0.074 | |
| | Level demand for drugs | $A$ | 0.075 | |
| | Level for producing drugs | $A_x$ | 5.465 | |
| | Returns to scale for prod. drugs | $\alpha_x$ | 0.407 | |
| | Determines dist of fixed costs | $c_f^{\max}$ | 0.001 | |

**Notes**. This table displays the calibrated parameters. I take the first 9 moments from Ordóñez (2014). The parameters related to the scale of the crime technology are from Ranasinghe and Restuccia (2018), which the authors calibrated for Colombia. I assume that the level of crime technology between Colombia and Mexico is the same, but the returns in Mexico are different. For the elasticity of drugs, I use estimations from the Bussink et al. (2016). I jointly estimate the rest of the parameters by minimizing the distance between the sample and data moments.

Table 7: Percentage change w.r.t. calibrated economy (keeping tax rate constant)

| **Variable** | **Drug trafficking** | **Crime** | **Informality** | **All illegality** |
|---|---|---|---|---|
| Capital | 0.54 | 5.70 | 20.29 | 28.21 |
| Labor | -0.14 | 0.79 | 12.92 | 13.15 |
| Output | 0.51 | 2.58 | 11.94 | 14.84 |
| Entrepreneurship | 0.68 | -3.65 | -56.55 | -58.21 |
| Informality | 0.93 | -6.40 | -100.00 | -100.00 |
| Wage rate | -0.21 | 4.50 | -12.69 | -7.92 |
| Security spending | 1.93 | -100.00 | 42.67 | -100.0 |
| Output stolen | 1.94 | -100.00 | 142.86 | -100.0 |
| Drug profits | -100.00 | -0.74 | -10.30 | -100.0 |

**Note**s. This table displays the percentage change of some aggregate variables with respect to the calibrated economy by shutting down drug trafficking (second column), crime against businesses (third column), informality (fourth column), and all illegality (last column). The comparison is between steady states. Shutting down drug trafficking involves setting the parameter of interdiction to a large value. Shutting down crime against businesses results from setting full protection of property rights. Shutting down informality results from setting the probability that the government catches and punishes informal entrepreneurs to one. Shutting down informality results from including all the previously mentioned mechanisms.
The estimations of this table result from keeping the tax rate fixed at 0.25.

Table 8: Percentage change w.r.t. calibrated economy (keeping tax revenue constant)

| **Variable** | **Drug trafficking** | **Crime** | **Informality** | **All illegality** |
|---|---|---|---|---|
| Capital | 1.87 | 30.83 | 53.14 | 63.47 |
| Labor | 0.15 | 5.74 | 13.24 | 13.75 |
| Output | 1.16 | 13.05 | 21.43 | 24.74 |
| Entrepreneurship | -0.68 | -23.65 | -56.91 | -57.97 |
| Informality | -1.53 | -41.40 | -100.00 | -100.00 |
| Wage rate | 0.24 | 13.04 | 10.68 | 16.81 |
| Security spending | 0.74 | -100.00 | 57.67 | -100.00 |
| Output stolen | 0.99 | -100.00 | 124.21 | -100.00 |
| Drug profits | -100.00 | -9.77 | -16.04 | -100.00 |
| Tax rate | -1.60 | -30.88 | -51.02 | -52.17 |

**Note**s. This table displays the percentage change of some aggregate variables with respect to the calibrated economy by shutting down drug trafficking (second column), crime against businesses (third column), informality (fourth column) and all illegality (last column). The comparison is between steady states. Shutting down drug trafficking involves setting the parameter of interdiction to a large value. Shutting down crime against businesses results from setting full protection of property rights. Shutting down informality results from setting the probability that the government catches and punishes informal entrepreneurs to one. Shutting down informality results from including all the previously mentioned mechanisms.
The estimations of this table result from keeping the tax revenue constant.

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