The good, the bad and the ugly: The socio-economic impact of drug cartels and their violence*

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Abstract

This article assesses the impact of drug cartels in Mexico, a country that has witnessed an unprecedented expansion of cartels and wave of drug-related violence since mid-2000. Using the difference-in-difference kernel matching method, the article finds that the areas most plagued by drug-related violence suffered a steep decline in production, profits, salaries, the number of businesses and workers in manufacturing. Unemployment and poverty also rose in the most violent areas. The few areas where cartels managed to work free of drug-related killings failed to see a change in poverty or unemployment, contradicting anecdotal storytelling of cartels benefiting local economies.

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1. Introduction

Crime and violence are commonplace across many developing regions, particularly in Latin America currently holding the highest crime rate worldwide. In some instances, such as Bolivia, Colombia, Mexico, and Peru drug cartels have contributed to both the high crime and violence rates. Cartels, apart from using gross violence to intimidate and punish rivals, are known to also corrupt state institutions and directly commit crimes against civilians such as extortions and kidnappings among others. Nowadays, Mexico is amongst the worst affected by drug violence. Until mid-2000, cartels had operated fairly peacefully in the country. But since then, when the government started prosecuting cartels with military force, cartels have been fighting fiercely for territory resulting in over 63,000 drug-related homicides just between 2006 and 2012. Several Mexican cities have become prey to this wave of violence, and in some the overall death toll has been as high as in countries experiencing civil war (Molzahn et al., 2013). Despite the scale of the ongoing conflict, little is known about how families and businesses living in the crossfire have been affected.

The literature has thus far reported that crime, perceptions of safety and unemployment have worsened in areas where Mexican cartels have been fighting for turf (BenYishay and Pearlman, 2013; Robles et al., 2013; Calderón et al., 2015; Dell, 2015; Gutiérrez-Romero, 2016). Also, although the general migration from Mexico to the US has decreased, the opposite has been the case in border areas hit by drug violence (Ríos, 2014). Beyond these effects, not much is known about other important impacts that cartels have had. Another issue that remains largely unexplored is the potential benefit that cartels may bring; especially considering that cartels generate substantial profits, offer a broad range of jobs and do not always engage in battles for territory.

We contribute to the literature by analyzing the impact of Mexican drug cartels when they battle for territory and when they do not. Specifically, we examine the impact on industries where it is possible to identify, from economic census records, where production is taking place at small-area-level. In particular, we analyze manufacturing, one of the biggest industries in Mexico, accounting for 35% of Gross Domestic Product. We also estimate the broad impact of cartels on poverty, inequality, unemployment and migration within the country using population censuses.

We focus on assessing the impact on municipalities that experienced cartels or drug-related homicides for the first time in 2006 or afterward. Our chosen period of analysis is not arbitrary. Although drug cartels have worked in Mexico for over a century, they have never covered the entire territory (Ríos, 2012). According to our estimates, right before 2005 drug cartels operated in about 20% of the 2,456 municipalities in the country (roughly half of those affected areas also experienced some low-level of drug-related homicides). In 2006, soon after the country started prosecuting drug leaders, cartels began expanding to new areas that had not experienced cartels or drug killings before. By 2010, cartels were operating in about 40% of the municipalities (Coscia and Ríos, 2012; Molzahn et al., 2013; Reed, 2013). Thus, by estimating the impact in newly 'conquered' areas, one can gain valuable insights into the immediate effects of cartel presence and their violence.

We identify the municipalities where cartels have been active, with and without drug-related homicides, using the official records on the date, location and number of killings stemming from battles among cartels and with the state authority (SNSP, 2011). These records, also used by other recent studies, are unfortunately available only from December 2006 until September 2011 (Calderón et al., 2015; Dell, 2015; Gutiérrez-Romero, 2016). Thus, for earlier periods we identify where cartels have been active by extensively surveying government reports, specialized blogs, national and international media.

To estimate the impact of cartels we use the difference-in-difference kernel matching estimator as proposed by Heckman et al. (1998). Specifically, to evaluate the impact of drug cartels working 'peacefully,' we focus on municipalities that remained free of drug-related homicides during the period 2000-2010. Among these areas, we estimate the change in outcomes before they had any cartels (2000-2005) and after cartels settled (in 2006 or afterward). We then compare the change in these outcomes to the ones experienced by similar municipalities free of cartels and drug-related homicides, which serve as our control group.

Similarly, to assess the impact of drug-related homicides we focus on municipalities that remained free of cartels and drug-related homicides during 2000-2005. Among these areas, we estimate the change in outcomes before and after they experienced drug-related homicides for the first time in 2006 or afterward. We then compare that change in outcomes to the one experienced by areas free of cartels and drug-related homicides.

Treated and control municipalities are matched based on their similar characteristics and probability of experiencing cartels and drug-related homicides. To identify the factors increasing the likelihood of areas experiencing cartels we follow the recent literature. These factors, described in detail in the next section, refer to the stricter policies imposed against cartels, municipalities' socio-geographical characteristics and whether a municipality is ruled by a different political party than its state. This lack of political coordination has been found to be a decisive factor as to where cartels fight for territory (Castillo et al., 2012; Dell, 2015; Ríos, 2015).

We find neither poverty nor unemployment changed in areas where drug cartels worked 'peacefully,' that is free of drug-related homicides. Instead, there is plenty of evidence of the damaging effects of drug violence. For instance, areas with the highest rates of drug-related homicides experienced a decline in production, profits, salaries, number of establishments and workers in manufacturing, when compared to other similar areas yet not affected by the drug violence. The areas hardest hit by drug-related homicides also suffered an increase in poverty, unemployment, and changes in migration patterns, which suggests that people moved from more to less violent areas.

All the evidence mentioned above refers only to the municipalities that experienced cartels or drug-related homicides for the first time in 2006 or afterward. As a robustness test we also analyze the impact on municipalities that were free of cartels and drug-related homicides during 1990-2000, but that experienced drug-related homicides for the first time during 2001-2005. These areas suffered a decline in the number of workers in manufacturing and a rise in poverty rates, relative to similar areas used as a control group. Both these impacts worsened even further during the period 2006-2010 when drug-related homicides severely intensified.

The article continues as follows. Section 2 describes the causes of the Mexican war on drugs. Section 3 describes the econometric method and databases used. Section 4 estimates the impact of cartels and drug-related homicides on poverty, inequality, migration and unemployment. Section 5 assesses the impact on manufacturing. Section 6 shows the robustness checks, and Section 7 concludes.

2. The causes of Mexican drug violence

Since the 1970s, the US has spent more than a trillion dollars trying to dismantle drug cartels in Latin America, thus far with limited impact other than fueling violence in the region (Huey, 2014). For instance, during the 1980s the US focused on reducing coca production in Peru and Bolivia, back then the primary producers. The policy, although successful, displaced coca production to Colombia, which saw its worldwide coca production increasing from a mere 10% to 90%. The war on drugs then shifted to combating the Colombian cartels. These cartels were dismantled, but they got fragmented into various small organizations amid a 20-year wave of drug violence that claimed over 15,000 lives, many victims of narco-terrorism (Huey, 2014). Peru subsequently re-claimed its position as a global coca producer, while over 90% of the cocaine that enters the US does it now through Mexico, amid unprecedented levels of drug-related violence.

Mexico has trafficked illicit drugs, mostly to the USA, over the last century and without major episodes of violence until recently. The previous peaceful coexistence among cartels and the authorities was underpinned by the political system that prevailed in the country under the 70-year ruling of party the Institutional Revolutionary Party (PRI). Though elections were held regularly, the PRI kept the power across all spheres at federal, state and municipality level. This strong hegemony allowed cartels to establish broad agreements with state-member actors, and in exchange for bribes were allowed to work in certain areas and shipment routes, called *plazas*, while receiving protection from the army and police among others (Campbell, 2009).

By the beginning of the new millennium, municipalities started for the first time to have a different political party than that of the state or federal administration.[1] This lack of 'political coordination' made it more difficult for cartels to carry on working in their plazas and agreed shipment routes. Cartels then had to establish new agreements with the new political actors, who could no longer guarantee protection as before. Cartels then resorted to arming themselves in a bid to defend their plazas and secure new ones, and this is one of the main reasons why a few clustered areas experienced about 6680 killings between 2000 and 2005 (Ríos, 2015).

PRI's defeat in both the 2000 and 2006 presidential election to political party PAN was a major blow to the stabilizing and mediating role the state authority had played with organized crime. The victory of PAN's presidential candidate, Felipe Calderón, was marred

[1] Ríos (2012) explains that 2,162 out of the 2,475 municipalities were ruled by the same party across all levels in 1990. The number of municipalities sharing the same party across all government's levels declined to 1,654 in 1998 and to 1,433 in 2010.

by allegations of vote-rigging in 2006. To regain legitimacy, Calderón unexpectedly declared war on drug cartels and deployed the army into their hotspots (Ravelo, 2012). Soon after, an unprecedented wave of violence erupted. About 47,515 killings, mostly of cartel members, were officially attributed to the conflict among cartels and the state, just between December 2006 and September 2011. These casualties represented half of all national homicides (as seen in Fig. A.1 in Appendix A). During this period, cartels also trebled and spread to new areas, given that some fractured into two or more over leadership disputes as their leaders got arrested or killed (Calderón et al., 2015).

Several researchers argue that Calderón's war on drugs was mostly responsible for the increase in both the drug violence and the number of cartels in Mexico (Guerrero-Gutiérrez, 2011; Osorio, 2012; Dell, 2015; Shirk and Wallman, 2015).[2] Municipalities ruled by the political party PAN became among the worst affected by drug violence, as these areas were more likely to implement Calderon's policies against cartels (Dell, 2015). Dell estimates that cartel attempts to control new territories after the arrest or death of rival cartel leaders explain over 85% of the drug-related homicides. Because of these policies, cartels fragmented and spread to new territories, crucially to those which lacked political coordination –those municipalities ruled by a different political party than its state authority– (Ríos, 2015). The drug-related homicides also increased considerably in areas in close proximity to the USA border, the end point of the profitable drug market (Castillo et al., 2012).

[2] In 2006 Colombia also shifted its antidrug policy from attacking the drug production chain to seizing cocaine, intercepting drug shipments and destroying cocaine processing labs. This new Colombian strategy against cartels increased the price of cocaine in the USA, thus also contributing to some extent to the Mexican drug violence as cartels fought to secure the profitable market (Castillo et al., 2012).

2.1 Potential effects of drug cartels and drug violence

Beyond trafficking illicit drugs, cartels are involved in at least 25 other illegal activities ranging from kidnapping, extortions, car theft to charging forced 'security and toll' services (Ravelo, 2012). Gutiérrez-Romero (2016) using crime victimization surveys finds that households in the areas worst hit by drug violence spend 1,085 USD more on security than areas not affected by such violence. The rise in these expenses is likely to have affected local businesses. They might have reduced their production or eventually fled the area, destroying jobs as has happened in other countries hit by drug-related conflict and acts of terrorism (Abadie and Gardeazabal, 2003; Camacho and Rodriguez, 2013).

Although the literature has reported some of the adverse effects stemming from drug violence, it is less clear the overall impact that drug cartels might have on local economies, especially considering that they do not always battle for turf. Mexican cartels make about $6.6 billion in gross revenue just from exporting drugs to the US (Keefe, 2012). Although most of these profits remain in offshore bank accounts, Ríos (2008) broadly estimates the illicit drug industry employs 468,000 people in Mexico, making it the fourth largest employer among all the main industries in the country.

Anecdotal reports also suggest some areas have benefited from drug cartels. For instance, Marín (2002) recalls that he expected to find poverty and lack of infrastructure in his fieldwork in rural areas in Sinaloa, one of the Mexican states with the longest history in drug trafficking. He found the opposite. The farmers he interviewed recounted that, out of need, they chose to work for drug dealers as they pay in cash, and up to five years in advance. This evidence in Mexico matches to some extent the findings of Angrist and Kugler (2008) for Colombia. They report that coca production increases self-employment. Nonetheless, these apparent benefits are minor and offset by the violence associated with the coca production.

The recent expansion of cartels in Mexico provides a unique opportunity to estimate the immediate impact of cartels on local economies. To this end, we assess two types of impacts: of cartels working 'peacefully' free of drug-related homicides and of cartels fighting for turf with reported drug-related homicides. Specifically, we assess the effects that cartels and their associated violence have had on poverty, inequality, unemployment and migration within the country. To shed light on why these outcomes might have changed, we explore the impact on manufacturing, one of the biggest industries in the country. We also examine the impact on wholesale trade. Our main interest in examining this industry comes from the reports that suggest cartels are allegedly using legitimate wholesale trade businesses to legalize and send money from the US to Mexico. This is an apparent attempt to avoid using financial institutions that have been more severely scrutinized for money laundering (The Economist, 2014).[3]

3. Econometric method

Where cartels run their business 'peacefully' or fighting for territory is by no means random. Thus, to estimate the impact of drug cartels we cannot directly compare the outcomes of areas that have experienced drug cartels with those that have not. Such direct comparisons might be misleading because the areas exposed to drug trafficking or drug-related killings are likely to have different characteristics to areas not exposed to such 'treatments.' Instead, we estimate

[3] Drug cartels are allegedly hiring brokers in the black US-peso exchange market to contact wholesale trade businesses that import and export goods. If a legitimate importer in Mexico wants to buy US dollars to buy say merchandise in the US, these dollars could be bought at preferred financial institution and then wired to the seller. The importer could also buy dollars at a cheaper rate in the black market. If this second option is chosen, brokers in the black market inform drug cartels when to pay the bill, in dollars, for the merchandise to the wholesale retailer. Then the importer in Mexico pays the agreed amount in pesos to the broker who, after taking a cut, passes the rest of the payment to the cartel in pesos (Mozingo et al., 2014).

the impact of drug cartels by combining two evaluation methods widely used in non-randomized settings: propensity score matching with the difference-in-difference method. [4]

Propensity score matching serves two purposes. First, it helps to identify a suitable control group, in our case, areas that have not have experienced drug cartels or drug-related killing but with similar baseline characteristics to the areas affected. Second, once these control areas are identified, they are matched to areas affected by cartels, based on their likeness, to be able to make comparisons and estimate the average treatment effect. The unit of our analysis is at the municipality level, as we have information on where cartels have been active with and without killings at that small-area-level .

We identify the control group by estimating the likelihood, namely the propensity scores p_i, of a municipality i receiving treatment (D_i=1) -experiencing drug trafficking or drug-related killing- conditional on a set of observable baseline characteristics X_i, as shown in Eq.(1).

$$p_i = \mathrm{pr}(D_i = 1 \mid X_i) \tag{1}$$

Note that propensity score matching does not require everything in the information set X_i to be known. However, sufficient information is required to make the selection on observable assumption plausible (Todd, 2007). As just reviewed, previous literature has listed three key factors that make municipalities significantly more likely to experience drug cartels

[4] Dell (2015) instead uses regression discontinuity by comparing areas where PAN won and lost by a small margin. This method has the advantage of ensuring the areas compared are similar in terms of socio-demographic characteristics. However, it has the disadvantage of remaining with few observations, 152 areas in total (out of the 2,456 in the country). Moreover, many of these areas had experienced cartels and drug-related homicides before Calderón took office (32 areas according to our surveyed records). Besides, roughly half of the controls, where the PAN lost, experienced drug-related homicides after Calderón took office. Thus, although this method is useful to analyze to what extent violence increased once Calderón took office, it is not suitable to assess the impact of areas experiencing drug violence or cartels for the first time.

and associated killings, and we use these to estimate the propensity scores. These are: whether the municipality was ruled by PAN, whether it had a different ruling party at state level when Calderón took office in 2006 and its proximity to the US border. We also consider other municipality characteristics that might have made them more vulnerable due to their socio-economic setting. These are: population size; GDP per capita; percentage of people living in poverty; marginalization index[5]; percentage of children attending school; percentage of households receiving remittances; government subsidies received; whether urban, rural or mixed and past trends in overall homicide rates.

The estimated propensity scores, p_i, are then used to match treated areas to similar non-treated areas serving as controls. As standard in the literature, this matching is established by finding the region of common support. That is the region where the distributions of propensity scores for the treated and control areas overlap. Any areas whose propensity score fall outside of this region of overlap get deleted from the analysis as it is not possible to make inferences for treated areas that have no suitable controls. Besides determining the overlap region, we also ensure the propensity scores and the covariates used in X_i have a similar distribution in the treated and the control groups. This so-called balancing property is tested by splitting the areas into blocks according to their propensity score and checking the treatment and control areas have no statistically significant differences.

Rosenbaum and Rubin (1983) show that provided the treatment assignment strongly depends on observable baseline characteristics, denoted by X_i, and the balancing property is

[5] This index is composed by the percentage of population that cannot read or write, who are co-habiting in overcrowded conditions, living in a household without soil floor; living in areas of less than 5,000 inhabitants, earning up to two minimum salaries and who do not have complete primary, drainage, bathroom, electricity, or piped water.

satisfied, then the difference in responses between the matched treated and control areas provides an unbiased estimate of the average treatment effect.

All evaluation methods have risks for potential biases. In propensity score matching a concern is the possibility that systematic differences may remain between the matched treated and control areas. Such differences may arise if important unobserved characteristics influence selection into treatment. This potential bias could be lessened if the propensity score matching method is used in combination with other suitable observational methods (Gertler et al., 2011 p. 119).

Specifically, we use the difference-in-difference kernel matching estimator, proposed by Heckman et al. (1998). This estimator obtains the Average Treatment Effect (ATE) by comparing the change in outcomes of treated municipalities, before and after cartels moved into these areas, our defined treatment, to the weighted change in outcomes of the municipalities used as control group, as in Eq. (2). Since this estimator compares the changes experienced by the treated areas to the one experienced by controls, any time-invariant characteristic that might have affected selection into treatment, whether observable or unobservable, gets canceled out. Hence, this estimator has been argued to convincingly address concerns with time-invariant unobserved characteristics affecting selection into treatment (Gertler et al., 2011 p.120). [6]

$$ATE = \frac{1}{n_1}\sum_{i=1}^{n_1}\left[(Y_{1ti} - Y_{1t'i}) - \sum_{j=1}^{n_0} W(i,j)(Y_{0tj} - Y_{0t'j})\right] \tag{2}$$

where Y_1 and Y_0 are the outcomes of interest, such as poverty, for the treated i and control j areas. t' and t denote the pre- and post-treatment periods. n_1 and n_0 represent the size of the

[6] Similarly, Gutiérrez-Romero (2016) used the difference-in-difference method combined with instrumental variables. She used as an instrument whether the municipality and state shared the same political party, as a measure of political coordination. We include this variable in the estimation of the propensity score along other geographical and socio-economic characteristics.

treatment and control group, both in the region of common support. The kernel weighting function, $W(i, j)$ shown in Eq. (3), gives more weight to control municipalities that have propensity scores more similar to those of treated areas and down-weight more distant observations.[7]

$$W(i, j) = \frac{G\left[\dfrac{p_j - p_i}{a_n}\right]}{\sum_{k=1}^{n_0} G\left(\dfrac{p_k - p_i}{a_n}\right)} \tag{3}$$

where $G(\cdot)$ denotes the kernel function. a_n is a bandwidth parameter, and p_i is the propensity score of treated areas. p_j and p_k are the propensity scores of municipalities in the control group.

Note that in the difference-in-difference estimator the change that the control areas experienced (Y_{0tj} - $Y_{0t'j}$) is used as the counterfactual as to what would have happened to the treated areas had they not been affected by cartels. In practice, we cannot observe such counterfactual, but there are two ways to judge the validity of such a hypothetical scenario, as described next.

An underlying assumption of this counterfactual is that without the treatment, the changes experienced by the treated and control areas would have increased or decreased at the same rate. Hence, it is possible to assess the validity of this assumption, known as the parallel trend in the absence of treatment, by comparing if before the treatment began the treated and control areas experienced similar changes. As shown in the next section, the outcomes in the matched treated and control areas moved in tandem across various indicators before the treatment began. Thus, gaining confidence that the outcomes would have continued to move

[7] An advantage of kernel matching over other matching methods, such as nearest neighborhood or radius matching, is that it pairs each treated area to more than one control area, thereby using more observations and reducing the estimation's variance (Guo and Fraser, 2010, p. 245).

in parallel had the treatment not been implemented. The similarity found in past trends is perhaps not too surprising. The treated and control areas being compared have been matched on the basis of their similarity in baseline characteristics, thus yielding very similar parallel trends in outcomes before the treatment began.[8]

As in other evaluation methods, a tacit assumption in the difference-in-difference's counterfactual is that other than the treatment itself, there should be no other factors affecting the treatment and control groups differently. A violation of this assumption might occur if, for instance, families living in areas hit by the drug-related violence received extra financial support. To consider this possibility we estimate the kernel matching difference-in-difference estimator in two basic forms. In the first form, we do not control for any other covariate, as shown in Eq. (2). In the second, our preferred choice, we control for covariates that might have changed over time, r_{it}, and that as a result might have influenced outcomes. To add these time-varying covariates, r_{it}, we re-express the difference-in-difference kernel matching estimator in regression form, as shown in Eq. (4). This regression is estimated using a weighted panel fixed effects at the municipality level. Note that before running this regression, the propensity scores are estimated to determine the region of common support and test the balancing property. These propensity scores are then used in the panel fixed effects regression to weight the control municipalities using the kernel matching function $W(i, j)$ shown earlier in equation (3).

$$Y_{it} = \beta_1 Post_t + \beta_2 Treatment_i + \beta_3 (Post_t * Treatment_i) + \beta_4 r_{it} + \mu_i + \varepsilon_{it} \qquad (4)$$

[8] Comparing absolutely all treated and non-treated municipalities in the country using exclusively the difference-in-difference method is likely to yield biased estimates as these groups of areas exhibit quite different trajectories in past outcomes, such as poverty, deprivation and homicides. We only achieve parallel trends in these past outcomes between these groups if the difference-in-difference method is combined with propensity score matching, another advantage of combining these methods.

where Y_{it} is the outcome of interest for municipality i at time t (t=0 before, and t=1 after treatment). $Post_t$ is the post-treatment dummy variable. $Treatment_i$ is a dummy variable equal to 1 for treated and 0 for the control municipalities. Thus, the regression coefficient β_3 measures the average treatment effect, that is the difference-in-difference kernel matching impact. μ_i refers to the area (municipality) fixed effect and ε_{it} represent the residuals. Time-varying variables, r_{it}, include the growth in remittances and poverty-relief subsidies per capita, both at the municipality level. We also consider the regional labor market, using the unemployment rate. We use the unemployment at state and not municipality level as people living in municipalities affected by drug violence might still find jobs in nearby non-treated areas within the same state. To avoid endogeneity issues with the intensity of drug-related violence all variables in r_{it} are lagged by two years. It is worth noting that the estimated average treatment effects are reasonably consistent when estimated with and without the time-varying variables r_{it}. This suggests that the observed differences in outcomes after the treatment began are likely to stem mainly from the treatment received.

3.1 Data

We use the official statistics by the Mexican government on the casualties credited to the conflict among cartels and the state (SNSP, 2011). This dataset is available at small-area level (municipality) and only from December 2006 until September 2011. For earlier periods without such records, we identify which areas experienced cartels or drug-related homicides by searching online government bulletins, media reports and specialized blogs. Appendix B describes in detail how we searched extensively for these reports, as well as how our findings match those of other similar studies.

Appendix C describes all the indicators used to measure the impact on poverty, inequality, migration and unemployment rates at municipality level, which are derived from population censuses. To measure the impact on manufacturing and wholesale industry we use the available economic censuses where it is possible to assess where the production is taking place at municipality level.

3.2. Selection of treatment and control groups

3.2.1. Impact of drug-cartels: Treatment group

To measure the impact of drug cartels when working 'peacefully', we define the treatment group as follows. Areas free of drug-related homicides during 2000-2010, but where cartels moved into and did so for the first time between December 2006 and December 2010. We limit the analysis up until 2010 given that it is the latest year for which we have population census records publically available.

3.2.2. Impact of drug-homicides: Treatment group

To measure the impact of drug-related homicides, we redefine our treatment group. This consists of areas that were free of cartels and drug-related homicides during 2000-2005, but that suffered at least one drug-related homicide for the first time between December 2006 and December 2010, according to official records. During this period there were 34,612 drug-related homicides. This homicide rate per 100,000 inhabitants by municipalities ranged from as low as 0.080 to as high as 1,565 killings. That is a large variance in the intensity of killings. Thus, besides estimating the impact among all areas that experienced at least one drug-related homicide, we also estimate the impact of drug violence by splitting areas according to their level of violence. Specifically, we divide treated municipalities into quartiles, according to their drug-related homicides rates.[9]

[9] Given the regional differences in economic development and drug-related homicides we did various alternative sub-divisions. For instance, we also divided areas affected by drug related violence such that those located in the

3.2.3. Defining the control group

For each of the two treatment groups mentioned above, we draw their respective control group from the same pool of municipalities that remained free of cartels and drug-related homicides during 2000-2010. Although drawn from the same pool, each treatment group is matched to its respective control group based on propensity score matching. This ensures the matched areas have on average the same characteristics and propensity of being treated.

We cannot ignore that some areas in the control group are near to those experiencing drug violence. Such closeness could bias (downwards) our impact estimates. To lessen this potential bias, we exclude control areas located within 10 kilometers of the epicenter of areas that experienced drug-related homicides during 2000-2010. In this way, the remaining control areas are still near enough to the treated areas to serve as proxies of the labor market conditions of the affected areas; yet, far enough to avoid spill-over effects.[10]

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north were compared exclusively to controls also located in the north, and vice versa for those affected areas in the south. For instance, from the first, second and third quartiles of drug-related homicides and their respective control groups, we removed municipalities located in southern states (Campeche, Chiapas, Oaxaca, Quintana Roo, Tabasco, Yucatan). From the bottom quartile and its respective control group (mostly located in the south) we removed municipalities in northern states (Baja California, Baja California Sur, Chihuahua, Coahuila, Nuevo Leon, Sinaloa, Sonora and Tamaulipas). These alternative sub-divisions yield a much smaller number of treated and controls yet they produce remarkably similar results to those presented here, thus we omit them (but are available upon request).

[10] As a robustness check we also excluded buffer areas within 15, 20 and 30 kilometers, finding very similar results to those when removing buffer areas within a radius of 10 kilometers from the of the epicenter of areas affected by drug-related homicides. Given the consistency of results we only present the results of removing areas within 10 kilometers, given that removing areas within a wider radius quickly shrinks the size of the control group. For instance, removing buffer areas within a radius of 20 kilometers halves the number of control areas and removing those within a radius of 40 kilometers shrinks the control group by more than 90%.

3.3 Propensity score matching for 2006-2010 post-treatment

Table A.1 shows the probit regressions coefficients, as marginal effects, for the two types of treatments analyzed: areas with cartels working 'peacefully,' and those with drug-related homicides. We also run separate probit regressions for each of the quartiles affected by drug-related homicides (columns 3-6).[11] The bottom of Table A.1 shows the total number of areas considered in the treated and control groups and the number of areas that were actually matched as they remained in the region of common support. Given that we discard areas that fall outside that region of common support, as is standard in the literature, the size of the quartile affected by drug-related homicides differs slightly.

The distribution of estimated propensity scores for each of the treated and control groups considered overlap well (Fig. A.2). As shown in Fig. A.3. the top quartile has a much higher *average* drug-related homicide rate (154) than the rest of the areas put together (13.2).

Fig. 1 illustrates the 68 municipalities that experienced drug cartels yet remained free of drug-related homicides. It is worth noting, that the great majority of these areas have only one drug cartel, thus being free of rivals and avoiding confrontations. This figure also shows the 403 matched areas used as a control group, which are in the proximity of the treated areas.

Fig. 2 shows the 613 municipalities that experienced at least one drug-related homicide and the matched 553 control areas. Although the areas with the highest levels of drug-related killings tend to be located in the north, those in the centre and south have also been affected by such violence. This figure also shows that the controls used are well scattered around municipalities experiencing drug-related killings.

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[11] We used roughly the same set of covariates to estimate the propensity score for each of these quartiles. However, we varied it slightly to ensure the estimated scores satisfy the balancing property within the region of common support.

The matched treated and control areas have no significant differences in the variables used to estimate the propensity scores (Table A.2). The descriptive statistics for the matched treated and control municipalities are quite similar before treatment began, without having any statistically significant differences, as shown in Table A.3. This table also presents the difference-in-difference kernel matching estimator without controlling for any covariates as in Eq. (2). These results broadly agree with those estimated with controls as shown in Tables (1) and (2).

Having calculated the propensity scores, we compare the matched treated and control areas using the Epanechnikov kernel matching method, with a bandwidth of 0.06. As mentioned earlier, for the difference-in-difference's counterfactual to be reliable and yield an unbiased estimate of the treatment effect, it requires that the matched areas -treated and controls- to have parallel trends in outcomes before treatment began. Fig. A.4, A.5 and A.6, show the control and treated areas had similar trajectories in poverty levels, index of marginalization and overall homicides rates before 2006. However, after that, the tandem in trajectories starts falling apart. That is particularly evident for the homicide rates. Take for instance Fig. A.4, Panel B, which shows the homicide rates for the municipalities that experienced drug-related homicides for the first time in 2006 or afterward, and its respective controls. Before 2006, the treated and controls had parallel trajectories in overall homicide rates. This trajectory breaks down in 2006 with homicides rates spiking in the treated areas to levels not seen before, which contributed to the sharp increase in the national average homicide rates. The official rates for drug-related killings over 2006-2010, also shown in Fig. A.4 Panel B, suggest that the sharp increase in the national average homicides and in the treated areas is being driven by the drug-related killings.

4. Impact on local economy

Having checked the robustness of the matched treated and control areas, we move on to estimate the difference-in-difference kernel matching regression, as shown earlier in Eq. (4).

4.1 Impact on inequality and poverty

Comparing the mid-2005 census to the population census of 2010, we find that areas where cartels worked ‘peacefully,’ free of drug-related homicides, experienced a decline in inequality, measured by the Gini index, relative to their control group. Could this decrease in inequality be the result of some low-income families benefiting from drug cartels? It is unlikely, as these areas experienced no change in poverty rates (Table 1 Panel A, columns 1-4).

A different picture emerges for the areas affected by drug-related homicides (Table 1, Panel B). These areas experienced no change in inequality, relative to their control group. However, poverty increased in the areas with the highest rate of drug-related homicides, those in the top quartile. Specifically, food poverty -which measures the percentage of the population without enough income to buy a basic food basket- increased by 2.5 percentage points in these areas. Similarly, capability poverty, -which adds those who cannot cover their health and education needs- increased by 2.8 percentage points as a result of this drug violence.

4.2 Impact on migration and population size

Areas where drug cartels worked ‘peacefully,’ free of drug-related homicides, suffered no change in population size or migration patterns (Tables 1 and 2, Panel A). Once again, a different picture emerges for the areas affected by drug violence. The most violent areas, those in the top two quartiles, suffered a decline in the number of people who migrated from other Mexican states with higher homicide rates (Table 1 column 6, Panel B). In contrast, the total number of immigrants, increased in the areas with the least drug-related homicides, in the first quartile (Table 2, column 1). The large increase in immigrants in these areas helps to explain why their net population rose, relative to their control group (Table 1, column 5, Panel B).

Overall, these migration patterns suggest drug violence displaced people from more to less violent places. It is nonetheless unclear why people migrated in higher proportion to areas with low levels of drug-related homicides, instead of controls free of drug-related homicides. One possibility is that the controls, free of drug-related homicides, might be slightly more distant, thus proving problematic and more expensive to move to. Unfortunately, the population census does not provide information of the municipality where people were living previously. Thus it is impossible to measure the exact distance that people migrated. However, with the information available it is possible to establish that nearly 90% of people who migrated did so within the same state of current residency, so likely to nearby areas. Due to an array of issues, people might have preferred moving within the same state, rather than to other more distant spatial clusters. People might prefer to remain close to their families, having similar access to labor markets and schools. Overall, then, it might be more convenient, and cheaper, to migrate to nearby areas with low-intensity of drug violence, than to others free of drug killings that are more distant. We find some evidence that the cost of migration might have played a role. For instance, the least violent areas, the bottom quartile, overall attracted more immigrants with low-earnings than high-earnings (Table 2 columns 2 and 3, Panel B).

4.3 Impact on unemployment

To assess the impact on unemployment, unlike previous studies, we use population censuses instead of labor surveys, to ensure that the data are representative at municipality level, the focus of our analysis. Using census records, unfortunately, comes at a cost, as unemployment rates are unavailable for the 2005 mid-census. Thus, we look at changes in unemployment rates by comparing the population census of 2000 and 2010.

There is no evidence that unemployment rates changed in areas where cartels were active free of drug-related homicides (Table 2 columns 4-6, Panel A). In contrast, in the most violent areas, those in the top two quartiles, unemployment rates increased among people with high- and low-education attainment (Panel B).[12]

5. Impact of cartels on industries

This section evaluates the impact of cartels on manufacturing and wholesale trade. Using economic census data at municipality level, for each industry we examine the overall production, profits, salaries per worker, number of establishments and workers per 10,000 inhabitants.[13]

The economic censuses used were conducted between 1 January to 31 December of 2003 and 2008 respectively. These censuses were carried out in different years to the population ones used earlier, thus, we slightly redefine the post-treatment period, spanning now from December 2006 until December 2008. We focus on areas that experienced cartels or drug-related homicides for the first time in 2006 or until 2008. As before, we also split

[12] In these areas, we do not find a change in overall unemployment rates, nonetheless this might be because the overall unemployment rates also include the population of working age that did not state their educational background.

[13] We do not analyze other industries, such as construction and finance where cartels are rumored to launder their money, because the censuses do not distinguish in which areas their production took place.

these areas, but now according to their drug-related homicide rate during 2006-2008. Since we redefine the span of our post-treatment, we now use as controls those areas free of cartels and drug-related homicides during 2000-2008. We also exclude from this group areas within 10 kilometers of those that experienced at least one drug-related homicide during 2000-2008.

By shortening the period of analysis, we miss two years where drug violence was intense 2009-2010. However, analyzing the impact of cartels on industries until the end of 2008 offers an important advantage. That is, we avoid assessing these impacts during the whole duration of the US recession period, during which Mexican exports decreased.

5.1. Propensity score matching for 2006-2008 post-treatment

We re-estimate the propensity scores to redefine the period of post-treatment. Table A.4 shows the results of the probit regressions as marginal effects. All estimated scores satisfy the balancing property and their distributions overlap well between the treatment and control groups (as seen in Table A.5 and Fig. A.7). Table A.6 shows the broad descriptive for the matched areas, and the difference-in-difference kernel matching estimator obtained without controls.

After matching the treatment and control areas, we obtain the difference-in-difference kernel estimator using the panel fixed effects regression shown in Eq. (4).

5.2. Impact on manufacturing

Manufacturing was affected in areas that experienced drug-related homicides, and the impact was more extensive in areas with more drug killings (Table 3, Panel B, Columns 1-5). For instance, the areas in the first two quartiles experienced a decline in salaries per paid worker. Areas in the third quartile also experienced a decline in salaries, and a decline in profits, and the number of workers. The areas in the top quartile, besides their decline in salaries, profits and number of workers, also experienced a decrease in production and the number of establishments per 10,000 inhabitants.

In sum, although with some differences in magnitude, salaries declined in every single quartile of areas experiencing drug-related homicides. This evidence supports the findings of Velásquez (2014) who using a panel survey shows earnings fell in areas with the highest overall homicide rates in Mexico, ignoring whether the homicides were drug-related or not. Thus, violence is likely to have increased the costs of doing business, such as insurance premiums, as has happened in other countries experiencing prolonged waves of violence and terrorism (Sandler and Enders, 2008). Our evidence is also consistent with the findings of Collier and Duponchell (2013), who show firms located in areas experiencing conflict end up hiring fewer workers and paying lower salaries.

Another relevant finding is the decline in salaries in areas where drug cartels were active and free of drug-related homicides (Table 3, Panel A, column 4). These areas remained with an overall homicide rate below that of national average (Fig. A.4, Panel A). So, the mere presence of cartels seems to have increased business costs thereby affecting salaries. These extra costs might stem from the instances or expectation of kidnappings and extortions targeted at businesses (Ravelo, 2012).

5.3. Impact on wholesale trade

We move on to analyze the impact on wholesale trade. Across the five statistics analyzed, none were negatively affected by the presence of cartels or by drug-related homicides (Table 3 in columns 6 to 10).

It is unclear why the wholesale trade industry was left unaffected by cartels even in the areas severely affected by drug violence. One possibility, is that wholesale trade businesses strongly depend on local markets, so they might be unable to outsource production or sales to other areas as easily as manufacturing. Also, we cannot ignore that cartels are allegedly using businesses in this industry as a façade for money laundering and to distribute illicit drugs (Proceso, 2014). Thus, we can only speculate that this could be another reason why this industry remained unaffected.

6. Robustness tests

6.1. Placebo tests (using 1990-2000 as pre-treatment vs. 2001-2005 as post-treatment)

We use a series of placebo tests, as is commonly done in the evaluation literature, to rule out the possibility that the impacts reported thus far occurred by pure chance. These placebo tests assume that municipalities were affected by cartels or drug-related homicides earlier than they were. Specifically, we assume the pre-treatment period dates back to 1990-2000, and the post-treatment refers to 2001-2005 (instead of 2006 or afterward). For these placebo tests, we use as control group the same areas as in sections 4 and 5 respectively. We also use propensity score matching to ensure the matched control and placebo treatment areas have the same distribution of baseline characteristics.

Table A.7 shows the results of the placebo tests for the main statistics of poverty, inequality, and migration. In these placebo tests, we cannot compare the impact on changes in unemployment rate and some migration patterns as these statistics are not available in the mid-census of 2005. Nonetheless, from all the placebo difference-in-difference kernel matching estimates presented, none are statistically significant at the 10% significance level. Table A.8 shows the placebo estimates for the manufacturing and wholesale trade industries. From the 60 placebo difference-in-difference kernel matching estimates presented, only one is statistically significant at the 10% significance level.

In sum, the placebo tests suggest the impacts showed earlier are unlikely to be driven by chance or unobserved characteristics.

6.2. Impact on areas that experienced drug-related homicides since 2001

As mentioned earlier, there was some low-scale drug-related violence during 2001-2005. The areas affected by violence during this earlier period were dropped from the analysis presented thus far. Here, we focus on estimating the impact on these areas first affected by drug violence, which might provide additional evidence on how cartels affect local economies. To this end, we redefine our treatment group as areas that were free of cartels and drug-related homicides during 1990-2000, but that experienced drug-related homicides for the first time during 2001-2005. The control group is composed of areas that at no point experienced cartels or drug-related homicides during 1990-2010.

Once again, we identify the areas where cartels were active with and without drug-related homicides in this earlier period by surveying government bulletins and online media reports. There are no official records to determine the exact intensity of drug killings for this earlier period. Thus, when estimating the impact of drug-related homicides we analyze all these areas as one group, without subdividing them into quartiles according to their intensity of drug violence. Again we use the difference-in-difference kernel matching estimator. We use roughly the same covariates as before to estimate the propensity score, but now lagged for our new baseline period 2000.[1] In Fig. A.8 we show the matched treatment and control areas, which satisfy the region of common support. These matched areas had parallel trends in both homicides rates and poverty statistics before the violence erupted among cartels as seen in Fig. A.9.

Table 4 shows the areas first affected by drug-related homicides during 2001-2005 had an increase in the percentage of people living in food poverty, relative to their control group and the baseline year (2000). These areas affected by drug violence also experienced a decrease in the number of businesses and workers in manufacturing, relative to their control group. The impact on salaries among these areas has a negative sign, though not statistically significant (thus this finding is omitted). This lack of statistical significance might be because of the small sample and low intensity of drug-related homicides, as well as kidnappings, in this earlier period.

These areas also suffered an increase in poverty when the statistics for the year 2000 are compared against 2010. During that period, the number of workers in manufacturing also declined further. These impacts reflects that about 90% of the areas first affected by violence during 2001-2005 also experienced drug-related homicides in 2006 or after, when the number of drug killings considerably intensified.

7. Conclusion

This article estimated some of the impacts that drug cartels and their associated violence have had on local economies in Mexico. To this end, we used the difference-in-difference kernel matching method, finding that drug-related violence has displaced people from more to less violent areas. Areas with the highest levels of drug-related homicides experienced the biggest impact on poverty and overall changes in the manufacturing industry. The manufacturing industry in these areas suffered a sharp decline in production, profits, salaries, the number of establishments and workers (compared to other similar areas not affected by the violence). While uncovering some of the negative sides of the drug violence, we found no major benefits in areas where drug cartels operated 'peacefully', that is, free of drug-related homicides. In these areas, we found no major impacts from cartels other than also experiencing a decline in salaries in manufacturing. This suggests that the mere presence of cartels increases businesses costs, perhaps as a result of an (expected) rise in cartels' extortions.

Our findings then contradict anecdotal storytelling of cartels benefiting the local economies where they operate. In contrast, the evidence presented suggests that cartels presence whenever associated with a steep increase of drug related violence affects severely municipalities' socio-economic life. Overall these findings deepen our understanding of the effects that drug cartels have on development when engaging in violence and not, hence have important implications for policy making. Although this evidence refers only to Mexico, the findings may well be relevant to other similar countries at risk of falling prey to the ever-expanding drug cartels.

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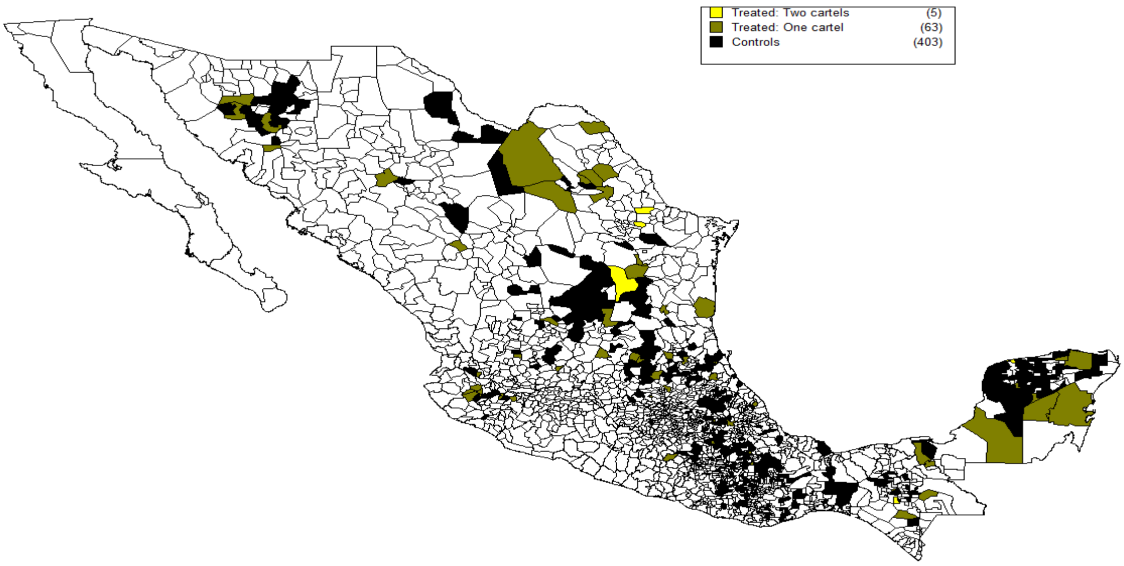


Fig. 1 Municipalities where cartels started operating for the first time in 2006 or after without drug-related homicides vs. controls in region of common support

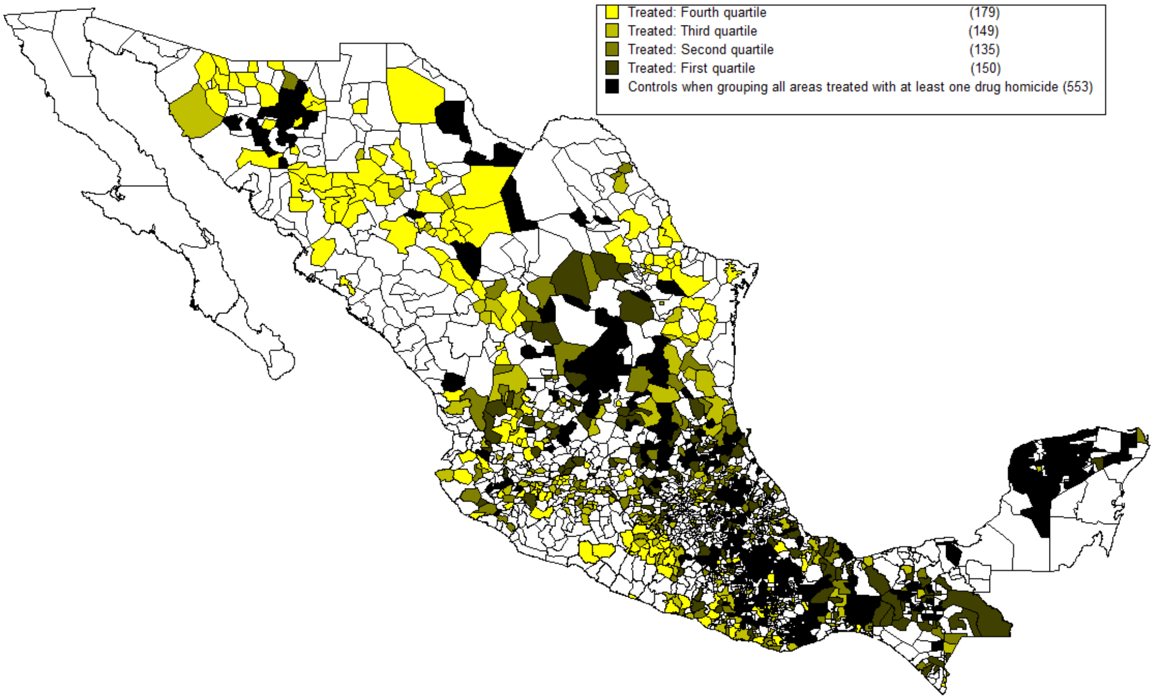


Fig. 2 Municipalities that experienced at least one drug-related homicides for the first time in 2006 after vs. controls in region of common support

Table 1
Impact of cartels and drug-related homicides on poverty, inequality and migration

	(1)	(2)	(3)	(4)	(5)	(6)
	Food poverty %	Capability poverty %	Patrimony poverty %	Gini	Total population	Number of people that resided in another state with more homicides 5 years ago per 10,000 inhabitants
Panel A: Since 2006 cartels moved into area without experiencing drug related homicides						
Areas experienced peaceful cartels						
Difference-in-difference	-3.573	-3.644	-2.829	-1.681***	-650.494	2.288
	(2.812)	(2.949)	(2.665)	(0.607)	(523.516)	(5.097)
Observations	942	942	942	942	942	942
Panel B: Since 2006 cartels moved into area experiencing drug related homicides						
All areas that experienced at least one drug related homicide						
Difference-in-difference	-0.536	-0.476	-0.204	0.367	883.434	-9.577***
	(0.985)	(1.084)	(1.174)	(0.385)	(560.685)	(3.127)
Observations	2,486	2,486	2,486	2,482	2,486	2,486
Fourth quartile (with most drug-related homicides)						
Difference-in-difference	2.549*	2.780*	2.632	0.161	214.832	-29.887***
	(1.365)	(1.534)	(1.692)	(0.517)	(364.681)	(6.206)
Observations	1,426	1,426	1,426	1,424	1,426	1,426
Third quartile						
Difference-in-difference	-0.954	-1.064	-1.082	-0.004	113.734	-11.133**
	(1.305)	(1.433)	(1.500)	(0.514)	(448.762)	(4.595)
Observations	1252	1252	1252	1252	1252	1252
Second quartile						
Difference-in-difference	-1.711	-1.401	-0.157	0.116	544.284	-3.464
	(1.529)	(1.654)	(1.711)	(0.524)	(664.601)	(4.789)
Observations	1,076	1,076	1,076	1,076	1,076	1,076
First quartile						
Difference-in-difference	2.307	2.559	2.400	-0.250	4,363.480**	0.437
	(1.970)	(2.044)	(1.867)	(0.622)	(2,028.167)	(4.196)
Observations	574	574	574	574	574	574

*The difference-in-difference kernel matching estimator compares each treated group to its respective matched control group using the panel fixed regression shown in Eq.(4). Controls used in all specifications: poverty-relief subsidies per capita, growth in annual remittances and state's unemployment rate. Robust standard errors in parentheses clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.10 Food poverty measures the percentage of the population without enough income to buy a basic food basket. Capability poverty, adds those who cannot cover their health and education needs. Patrimony poverty, adds those who cannot cover clothing, housing and public transport needs. Sources: Poverty and Gini estimated by CONEVAL, population census and controls INEGI.*

Table 2
Impact of cartels and drug-related homicides on migration and unemployment

	(1) Total number of migrants that moved into 2000 vs 2010[a]	(2) Number of people that moved in and had less earning income than non-migrant population 2000 vs 2010[a]	(3) Number of people that moved in and had more earning income than non-migrant population 2000 vs 2010[a]	(4) Unemployment rate 2000 vs 2010	(5) Unemployment rate low educated 2000 vs 2010[a]	(6) Unemployment rate high school plus 2000 vs 2010[a]
Panel A: Since 2006 cartels moved into area without experiencing drug related homicides						
Areas experienced peaceful cartels						
Difference-in-difference	-47.297	-50.370	4.477	-0.287	0.325	0.394
	(48.825)	(46.871)	(6.467)	(0.435)	(0.545)	(0.393)
Observations	923	921	497	934	934	934
Panel B: Since 2006 cartels moved into area experiencing drug related homicides						
All areas that experienced at least one drug related homicide						
Difference-in-difference	114.040*	99.154*	18.397**	-0.230	0.239	0.669**
	(63.106)	(57.051)	(8.624)	(0.295)	(0.332)	(0.283)
Observations	2,441	2,439	1,601	2,470	2,470	2,470
Fourth quartile (with most drug-related homicides)						
Difference-in-difference	-1.795	-3.777	-1.093	0.500	1.032**	1.282***
	(19.303)	(18.234)	(3.593)	(0.381)	(0.482)	(0.387)
Observations	1,387	1,385	749	1,418	1,418	1,418
Third quartile						
Difference-in-difference	27.497	25.568	2.472	0.021	0.937*	0.770**
	(41.135)	(38.797)	(6.219)	(0.383)	(0.548)	(0.306)
Observations	1,224	1,222	702	1,245	1,245	1,245
Second quartile						
Difference-in-difference	57.791	42.028	13.096	-0.567	-0.045	0.434
	(46.533)	(42.296)	(8.875)	(0.404)	(0.440)	(0.354)
Observations	1,059	1,057	635	1,068	1,068	1,068
First quartile						
Difference-in-difference	485.239*	419.622*	76.804**	-0.515	-0.298	0.431
	(279.017)	(248.957)	(37.033)	(0.414)	(0.556)	(0.393)
Observations	557	557	425	562	562	562

*The difference-in-difference kernel matching estimator compares each treated group to its respective matched control group using the panel fixed regression shown in Eq.(4). Controls used in all specifications: poverty-relief subsidies per capita and state's unemployment rate. Robust standard errors in parentheses clustered at municipality level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$ Sources: [a] Own estimates using the micro-data population sample from census records, provided by INEGI and Minnesota Population Center (2014). Unemployment rates taken from population census and controls by INEGI.*

Table 3
Impact of drug cartels and drug-related homicides on manufacturing and wholesale trade

	Manufacturing					Wholesale Trade				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	production thousand USD	profit thousand USD	workers per 10,000 inhabitants	salaries per worker thousand USD	establisments per 10,000 inhabitants	production thousand USD	profit thousand USD	workers per 10,000 inhabitants	salaries per worker thousand USD	establisments per 10,000 inhabitants
Panel A: Since 2006 cartels moved into area without experiencing drug related homicides										
Areas experienced peaceful cartels										
Difference-in-difference	-1,363.312	-5,823.237	-52.038	-0.560**	1.073	1,748.436	982.308	3.067	0.327	0.203
	(29,712.821)	(8,814.123)	(41.796)	(0.219)	(3.460)	(1,422.953)	(902.455)	(7.853)	(0.586)	(0.768)
Observations	996	996	996	996	996	996	996	996	996	996
Panel B: Since 2006 cartels moved into area experiencing drug related homicides										
All areas that experienced at least one drug related homicide	-24,388.032*	-10,031.096*	-34.889**	-0.468**	-0.912	1.853	69.978	-4.001	0.085	-0.290
Difference-in-difference	(14,328.420)	(5,446.402)	(15.929)	(0.226)	(1.774)	(450.237)	(388.513)	(2.627)	(0.334)	(0.354)
	2,562	2,562	2,562	2,562	2,562	2,562	2,562	2,562	2,562	2,562
Observations										
Fourth quartile (with most drug-related homicides)										
Difference-in-difference	-25,696.772*	-6,053.516**	-62.342**	-0.645*	-8.714**	-90.601	15.728	2.309	0.789	-0.623
	(13,132.072)	(3,082.142)	(26.530)	(0.338)	(3.512)	(304.897)	(302.451)	(3.528)	(0.614)	(0.701)
Observations	1,820	1,820	1,820	1,820	1,820	1,820	1,820	1,820	1,820	1,820
Third quartile										
Difference-in-difference	-3,885.785	-9,448.145***	-34.794**	-0.429**	2.261	-525.280	-830.298	-0.554	-0.055	0.275
	(17,877.384)	(3,542.147)	(16.474)	(0.217)	(3.003)	(955.819)	(863.292)	(3.225)	(0.348)	(0.677)
Observations	1,884	1,884	1,884	1,884	1,884	1,884	1,884	1,884	1,884	1,884
Second quartile										
Difference-in-difference	-35,082.980	-5,468.287	-15.147	-0.629*	1.491	1,960.185	2,082.901*	-6.954	-0.137	-0.599
	(32,717.286)	(11,584.091)	(24.320)	(0.335)	(2.523)	(1,600.229)	(1,205.671)	(4.419)	(0.337)	(0.488)
Observations	1,010	1,010	1,010	1,010	1,010	1,010	1,010	1,010	1,010	1,010
First quartile										
Difference-in-difference	10,607.423	2,272.004	-51.304	-0.623*	3.257	799.861	-938.371	-7.308	0.984	0.488
	(69,131.916)	(24,039.135)	(41.592)	(0.345)	(3.395)	(2,168.080)	(2,333.690)	(5.069)	(0.619)	(0.642)
Observations	384	384	384	384	384	384	384	384	384	384

*The difference-in-difference kernel matching estimator compares each treated group to its respective matched control group using the panel fixed regression shown in Eq.(4). Controls used in all specifications: Poverty-relief subsidies per capita, growth in annual remittances and state's unemployment rate, all lagged for two years. Robust standard errors in parentheses clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.10 Source: economic census and controls used INEGI.*

Table 4
Impact on municipalities that experienced drug-related homicides during 2001-2010

	Changes 2000 vs. 2005							Changes 2000 vs. 2010						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Food poverty %	Capability poverty %	Patrimony poverty %	Gini	Total population	Workers per 10,000 inhabitants	establisments per 10,000 inhabitants	Food poverty %	Capability poverty %	Patrimony poverty %	Gini	Total population	Workers per 10,000 inhabitants	establisments per 10,000 inhabitants
Difference-in-difference	3.369*	2.694	0.999	-0.00777	19.940	-72.348*	-5.951**	2.983**	2.934**	2.286*	-0.00227	201.2	-57.563**	-0.00628
	(0.0956)	(0.187)	(0.594)	(0.357)	(0.972)	(42.429)	(2.837)	(0.0340)	(0.0305)	(0.0745)	(0.773)	(0.860)	(28.740)	(0.991)
Observations	624	624	624	624	624	624	624	624	624	624	624	624	624	624

*The difference-in-difference kernel matching estimator compares each treated group to its respective matched control group using the panel fixed regression shown in Eq.(4). Controls used in all specifications: poverty-relief subsidies per capita, and state's unemployment rate, all lagged for 1998 and 2002. Robust standard errors in parentheses clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.10 Food poverty measures the percentage of the population without enough income to buy a basic food basket. Capability poverty, adds those who cannot cover their health and education needs. Patrimony poverty, adds those who cannot cover clothing, housing and public transport needs. Sources: Poverty and Gini estimated by CONEVAL, population census and controls INEGI.*

Appendices

Appendix A

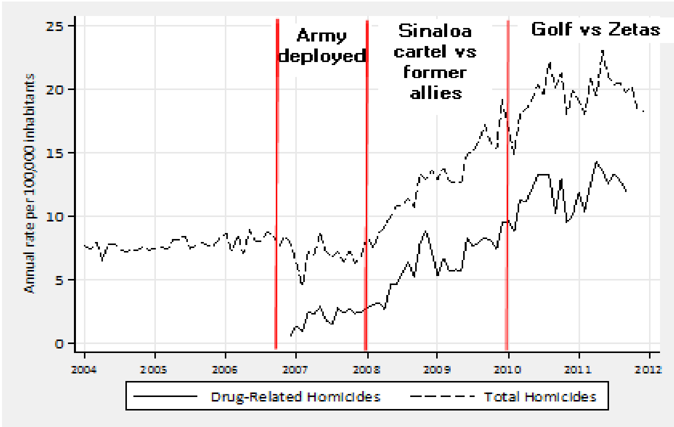


Fig. A.1 Homicide rates in Mexico 2004-2012

Table A.1
Probit marginal effects: Propensity scores used to evaluate impact on welfare statistics

			Drug-related homicides by sub-groups			
	Cartels but no drug-related homicides	At least one drug-related homicide	4th Quartile	3rd Quartile	2nd Quartile	1st Quartile
	(1)	(2)	(3)	(4)	(5)	(6)
Index of marginalization 2000	-0.000	-0.001	-0.002	-0.002	-0.000	-0.000
	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.000)
Capability poverty 2000	-0.011**	-0.027***	-0.030***	-0.005	0.001	-0.000
	(0.005)	(0.009)	(0.009)	(0.006)	(0.004)	(0.000)
Food poverty 2000	0.009**	0.020**	0.026***	0.002	-0.004	-0.000
	(0.005)	(0.009)	(0.009)	(0.006)	(0.004)	(0.000)
Parties uncoordinated at municipality and state level	-0.050**	0.069*	0.159**	0.096*	0.064	0.000
	(0.025)	(0.039)	(0.068)	(0.056)	(0.043)	(0.000)
Mixed type municipality (urban/rural)	-0.060***	-0.061	-0.105**	0.001	-0.004	-0.000
	(0.017)	(0.056)	(0.044)	(0.044)	(0.026)	(0.000)
Mixed type*Uncoordinated	0.035		0.187*	0.107	0.083	0.001
	(0.062)		(0.107)	(0.081)	(0.068)	(0.002)
Rural*Distance to north border	-0.000	0.000	-0.000	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population 2005	0.045	-0.017	-0.097	0.328**	0.409***	0.002
	(0.095)	(0.177)	(0.148)	(0.167)	(0.151)	(0.006)
Squared log population	-0.000	0.015	0.009	-0.012	-0.016**	-0.000
	(0.005)	(0.010)	(0.008)	(0.009)	(0.007)	(0.000)
Log GDP per capita 2005	0.022	0.175**	0.155**	0.117*	-0.001	0.000
	(0.038)	(0.078)	(0.071)	(0.065)	(0.035)	(0.000)
%Children school attendance 2005	-0.001	-0.007**	-0.009***	-0.005**	-0.000	-0.000
	(0.001)	(0.003)	(0.003)	(0.002)	(0.001)	(0.000)
Remmittances	0.002	0.011***	0.022***	0.019***	0.011**	0.000
	(0.002)	(0.002)	(0.005)	(0.006)	(0.005)	(0.000)
Squared remmitances	-0.000		-0.000***	-0.000**	-0.000*	-0.000
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Municipality ruled by PAN only	-0.003	-0.114**	-0.036	-0.062**	-0.042*	-0.000
	(0.022)	(0.050)	(0.043)	(0.030)	(0.023)	(0.000)
Municipality ruled by PRI only	-0.028	-0.010	0.033	-0.046	-0.013	-0.000
	(0.022)	(0.048)	(0.050)	(0.034)	(0.020)	(0.000)
Total homicide rate 2004	0.000		0.007***	0.005***	0.002**	0.000
	(0.000)		(0.002)	(0.002)	(0.001)	(0.000)
Squared Homicide rate 2004			-0.002	-0.002	-0.001	0.000
			(0.002)	(0.002)	(0.002)	(0.000)
Uncoordinated*Homicide rate 2004	0.000		-0.000**	-0.000	-0.000	-0.000
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Uncoordinated*Minimum distance to border	-0.000		-0.001**	-0.001**	-0.000**	-0.000
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R2	0.26	0.40	0.38	0.42	0.51	0.65
Available treated	74	811	202	203	203	203
Available controls	581	581	581	581	581	581
Total municipalities considered in probit	655	1392	783	784	784	784
Treated remaining in region of common support	68	690	179	149	135	150
Controls remaining in region of common support	403	553	534	477	403	137
Total matched municipalities in region in common support	471	1243	713	626	538	287

*Marginal effects of experiencing drug trafficking or drug-related homicides using probit regression shown in Eq.(1). (*) dF/dx is for discrete change of dummy variable from 0 to 1, z and P>|z| correspond to the test of the underlying coefficient being 0. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10*

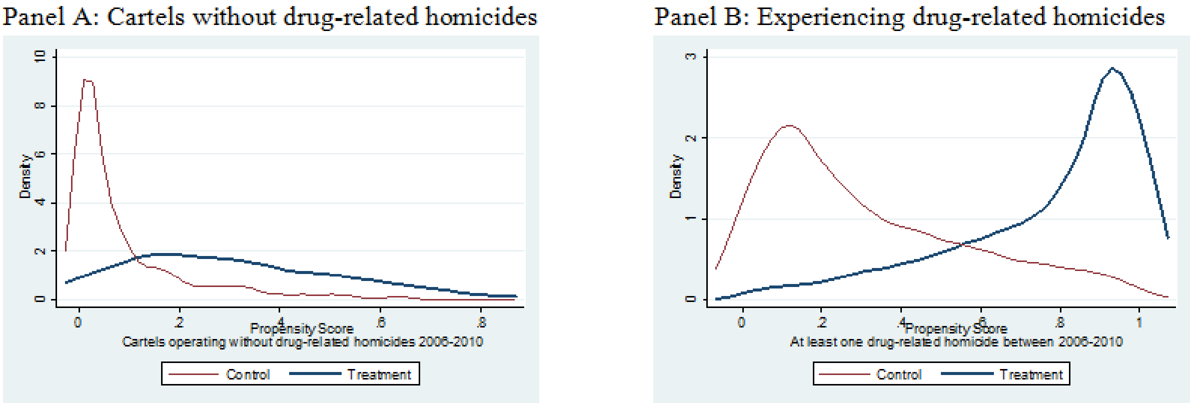


Fig. A.2 Distribution of propensity scores between treatment and control groups

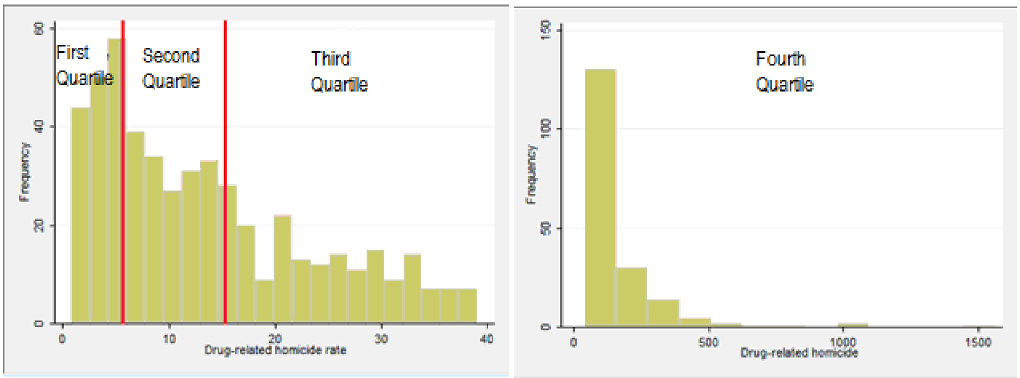


Fig. A.3 Rate of drug-related homicides per 100,000 inhabitants by quartiles in region of common support

Table A.2
Balancing test for covariates used to estimate propensity score to assess the impact on welfare statistics

	Panel A: Cartels without drug-related homicides			All that experienced at least one drug-related homicide			Panel B: Drug-related homicides 4th Quartile			3rd Quartile			2nd Quartile			1st Quartile		
	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff
Index of marginalization 2000	38.31	39.01	0.64	36.19	36.85	0.56	35.94	36.04	0.94	36.96	36.68	0.84	37.97	38.38	0.78	37.67	39.00	0.42
Capability poverty 2000	47.92	50.44	0.46	45.10	45.22	0.95	41.35	39.38	0.50	46.27	44.79	0.57	48.62	48.56	0.98	51.70	54.12	0.32
Food poverty 2000	40.93	43.41	0.46	37.87	38.17	0.88	34.85	33.03	0.51	39.03	37.84	0.63	41.10	41.07	0.99	43.83	46.16	0.35
Political parties uncoordinated	0.37	0.36	0.90	0.47	0.50	0.58	0.51	0.50	0.85	0.45	0.45	0.98	0.46	0.43	0.65	0.45	0.53	0.34
Mixed type municipality (urban/rural)	0.26	0.26	0.94	0.33	0.32	0.84	0.28	0.26	0.62	0.35	0.40	0.44	0.33	0.30	0.71	0.29	0.24	0.48
Mixed type*Uncoordinated	0.06	0.04	0.65	383.10	381.88	0.97	0.11	0.07	0.16	0.11	0.13	0.66	0.13	0.10	0.51	0.11	0.13	0.79
Rural*Distance to north border	380.20	398.24	0.74				365.52	378.67	0.77	419.07	363.33	0.25	429.24	421.67	0.89	377.62	424.06	0.47
Log Population 2005	9.23	9.28	0.72	9.69	9.62	0.48	8.93	8.74	0.20	9.47	9.44	0.79	9.76	9.83	0.51	10.46	10.48	0.85
Squared log population	86.36	87.43	0.72	95.04	93.65	0.48	81.18	77.75	0.18	90.42	89.97	0.81	95.77	97.22	0.49	109.78	110.03	0.90
Log GDP per capita 2005	10.80	10.78	0.69	10.84	10.85	0.71	10.89	10.89	0.92	10.81	10.86	0.31	10.78	10.78	0.91	10.76	10.72	0.42
Children school attendance 2005	64.17	63.92	0.72	63.60	63.21	0.45	63.04	63.14	0.91	63.48	63.49	0.98	64.61	63.76	0.24	63.48	62.75	0.37
Remmitances	7.89	7.47	0.76	8.47	8.49	0.98	10.64	11.02	0.74	9.14	8.54	0.58	6.87	6.97	0.91	5.87	5.28	0.55
Squared remmittances	151.04	141.78	0.84				199.02	200.13	0.97	154.71	138.56	0.57	100.19	98.70	0.95	93.29	65.41	0.25
Municipality ruled by PAN only	0.37	0.38	0.84	0.26	0.28	0.78	0.23	0.23	0.93	0.26	0.29	0.59	0.22	0.26	0.56	0.35	0.39	0.62
Municipality ruled by PRI only	0.43	0.42	0.88	0.49	0.52	0.47	0.52	0.53	0.88	0.49	0.46	0.67	0.48	0.51	0.65	0.47	0.47	1.00
Homicide rate 2004	3.82	3.74	0.93				15.79	15.00	0.81	9.57	9.39	0.90	9.26	8.19	0.44	6.53	6.85	0.76
Squared homicide rate 2004							868.43	877.73	0.98	263.51	246.41	0.80	248.55	198.64	0.49	82.16	85.72	0.88
Homicide rate 2004*uncoordinated	2.63	2.60	0.98				9.31	9.25	0.99	4.05	4.00	0.96	4.64	3.55	0.35	2.82	3.47	0.49
Uncoordinated*Main entrance to border							83.55	78.54	0.70	67.62	70.46	0.83	64.97	64.56	0.98	69.63	91.28	0.29

Sources: Parties uncoordinated at municipality and state level own estimates using official electoral results. Data on distances own estimates using geo-coding provided by INEGI. Rest of indicators from INEGI.

Table A.3
Descriptive statistics of welfare statistics across matched areas that fall in the region of common support

	Panel A: Cartels no drug-related homicides					Panel B: Drug-related homicides									
						At least one drug-related homicide					4th Quartile				
	2005		2010			2005		2010			2005		2010		
	Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)
Food poverty %	32.12	35.32	30.02	30.14	-3.1	29.55	29.50	27.05	26.74	-0.3	29.40	26.08	23.73	24.54	4.1**
	(16.56)	(19.53)	(18.22)	(19.51)	(2.8)	(15.03)	(16.30)	(16.69)	(16.17)	(1.0)	(15.66)	(15.85)	(16.85)	(16.70)	(2.0)
Capability poverty %	40.45	43.37	39.03	38.85	-3.1	37.72	37.53	35.81	35.41	-0.2	37.28	33.53	31.86	32.66	4.5**
	(17.60)	(20.26)	(20.01)	(21.07)	(3.0)	(16.14)	(17.22)	(18.52)	(17.83)	(1.1)	(16.97)	(16.99)	(19.30)	(18.61)	(2.3)
Patrimony poverty %	62.31	64.05	63.05	62.48	-2.3	59.84	59.47	60.11	59.68	-0.1	58.76	55.16	55.65	56.36	4.3*
	(16.98)	(18.10)	(20.06)	(19.82)	(2.7)	(15.99)	(16.52)	(19.32)	(17.94)	(1.2)	(16.73)	(16.79)	(21.21)	(19.05)	(2.4)
Gini	42.32	43.22	41.76	41.18	-1.5**	42.88	43.35	41.03	42.07	0.6	42.52	43.42	40.58	41.78	0.3
	(3.901)	(3.830)	(3.917)	(4.424)	(0.6)	(3.658)	(4.206)	(3.884)	(4.010)	(0.4)	(4.002)	(4.463)	(3.696)	(4.027)	(0.6)
Total population	17840.2	17225.2	18752.6	17344.5	-793.1	23027.7	25292.7	24578.9	27648.8	805.0	11368.1	14503.2	12002.1	15313.0	175.8
	(17032.7)	(17228.0)	(18599.5)	(17227.0)	(556.7)	(19719.4)	(23535.4)	(21908.2)	(26980.8)	(567.9)	(13406.1)	(18749.5)	(14758.0)	(20271.7)	(379.3)
Number of people that resided in another state with more homicides 5 years ago per 10,000 inhabitants	72.84	70.30	78.25	78.06	2.3	65.52	57.21	74.92	56.72	-9.9***	52.47	46.95	70.87	35.69	-29.7***
	(35.08)	(34.71)	(31.60)	(33.92)	(5.5)	(34.50)	(39.13)	(30.78)	(37.63)	(3.2)	(41.01)	(41.18)	(36.32)	(37.93)	(6.4)
Total number of migrants that moved into 2000 vs 2010[a]	218.2	327.6	276.6	290.6	-92.2	277.5	430.7	319.4	585.4	110.9*	153.9	233.7	167.8	244.3	-4.9
	(268.2)	(502.3)	(386.6)	(429.6)	(71.5)	(270.5)	(655.9)	(349.8)	(1632.2)	(61.7)	(196.8)	(402.6)	(225.4)	(359.9)	(19.9)
Number of people that moved in and had less earning income than non-migrant population 2000 vs 2010[a]	205.7	311.8	255.7	265.2	-93.8	260.6	403.1	291.0	530.8	95.7*	143.7	216.1	152.5	219.9	-6.6
	(255.9)	(485.5)	(372.0)	(390.2)	(68.9)	(257.5)	(625.5)	(326.9)	(1474.6)	(56.0)	(186.7)	(375.7)	(209.6)	(327.4)	(18.9)
Number of people that moved in and had more earning income than non-migrant population 2000 vs 2010[a]	18.46	21.28	22.67	30.35	5.0	22.24	32.98	31.10	56.86	18.9**	14.14	21.82	18.44	25.93	-1.1
	(19.65)	(24.38)	(27.85)	(45.40)	(6.7)	(20.00)	(42.29)	(32.44)	(167.4)	(8.3)	(16.02)	(34.57)	(23.04)	(39.43)	(3.6)
Unemployment rate 2000 vs 2010	0.802	0.837	4.399	4.127	-0.3	0.904	1.059	4.726	4.682	-0.2	0.860	1.032	4.406	5.175	0.6
	(0.541)	(0.598)	(3.472)	(3.098)	(0.4)	(0.521)	(0.759)	(3.294)	(2.942)	(0.3)	(0.583)	(0.773)	(3.303)	(3.986)	(0.4)
Unemployment rate low educated 2000 vs 2010[a]	0.944	1.007	4.792	5.073	0.2	1.084	1.174	5.023	5.278	0.2	0.975	1.197	4.728	6.082	1.1**
	(1.139)	(0.878)	(3.984)	(3.927)	(0.5)	(1.209)	(1.376)	(3.630)	(3.993)	(0.3)	(0.965)	(1.326)	(3.896)	(5.034)	(0.5)
Unemployment rate high school plus 2000 vs 2010[a]	0.983	0.819	3.371	3.583	0.4	0.855	0.823	3.294	3.779	0.5	0.742	0.436	3.091	4.116	1.3***
	(1.880)	(1.098)	(2.749)	(2.710)	(0.4)	(1.383)	(2.991)	(2.496)	(2.784)	(0.3)	(1.275)	(0.841)	(2.904)	(3.599)	(0.4)
Number of municipalities	403	68				553	690				534	179			

Table A.3 (*continuation*)

	Panel B: Drug-related homicides														
	3rd Quartile					2nd Quartile					1st Quartile				
	2005		2010			2005		2010			2005		2010		
	Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)
Food poverty %	29.36	30.25	26.49	25.85	-0.977	32.52	33.01	29.54	28.15	-1.458	33.96	31.44	31.91	31.82	2.539
	(13.91)	(15.86)	(15.65)	(15.64)	(0.441)	(14.94)	(16.79)	(16.10)	(15.84)	(0.331)	(13.50)	(16.19)	(14.33)	(16.70)	(0.195)
Capability poverty %	37.61	38.29	35.35	34.48	-0.953	41.12	41.07	38.71	37.02	-1.172	43.18	40.02	41.71	41.25	2.745
	(15.04)	(16.86)	(17.51)	(17.39)	(0.494)	(15.77)	(18.01)	(17.66)	(17.61)	(0.465)	(13.69)	(16.69)	(14.97)	(17.69)	(0.176)
Patrimony poverty %	59.99	60.06	60.07	58.88	-0.660	63.48	61.90	63.25	61.16	-0.0863	66.49	62.82	67.02	65.87	2.393
	(14.85)	(16.36)	(18.26)	(17.82)	(0.660)	(14.88)	(18.17)	(17.78)	(18.22)	(0.958)	(11.85)	(14.82)	(13.14)	(16.02)	(0.198)
Gini	42.90	43.04	41.37	41.67	0.128	43.06	43.61	41.92	42.39	0.165	43.04	43.48	42.38	42.61	-0.0878
	(3.778)	(3.918)	(3.821)	(3.806)	(0.805)	(3.599)	(4.094)	(3.781)	(4.185)	(0.762)	(3.389)	(3.773)	(4.223)	(3.972)	(0.893)
Total population	18487.8	18370.7	19359.9	19604.4	-8.888	23847.9	23956.5	25507.0	26526.9	340.9	41992.5	47962.0	44941.2	54037.8	4,124**
	(16505.8)	(15856.4)	(18064.8)	(17064.6)	(0.985)	(17710.7)	(24317.7)	(19469.1)	(27930.9)	(0.620)	(19697.9)	(60999.8)	(21766.0)	(67682.8)	(0.0410)
Number of people that resided in another state with more homicides 5 years ago per 10,000 inhabitants	61.87	55.01	73.06	54.12	-12.68***	63.83	60.45	75.29	62.94	-4.153	70.02	69.01	77.42	76.00	-0.0968
	(36.57)	(40.61)	(34.00)	(35.71)	(0.00913)	(35.88)	(38.62)	(30.90)	(35.52)	(0.389)	(28.77)	(33.81)	(23.98)	(30.76)	(0.980)
Total number of migrants that moved into 2000 vs 2010[a]	232.2	330.5	267.9	392.2	24.27	307.5	371.5	344.4	613.7	64.80	453.7	828.0	593.3	1353.2	487.8*
	(242.8)	(501.4)	(320.1)	(599.0)	(0.564)	(300.1)	(417.9)	(323.2)	(1349.4)	(0.182)	(319.5)	(2234.0)	(438.9)	(3821.5)	(0.0699)
Number of people that moved in and had less earning income than non-migrant population 2000 vs 2010[a]	217.2	306.5	246.3	353.1	22.96	288.3	346.9	314.5	559.9	47.46	425.2	775.5	541.3	1221.1	421.9*
	(231.2)	(471.1)	(303.6)	(544.4)	(0.562)	(287.7)	(391.4)	(300.6)	(1267.7)	(0.281)	(303.3)	(2074.5)	(410.6)	(3422.6)	(0.0788)
Number of people that moved in and had more earning income than non-migrant population 2000 vs 2010[a]	19.64	29.27	24.53	41.20	1.841	24.39	31.41	32.49	54.61	15.60*	35.54	58.95	53.13	138.0	77.47**
	(18.93)	(41.74)	(26.38)	(65.68)	(0.749)	(21.00)	(35.32)	(33.17)	(100.3)	(0.0900)	(24.84)	(170.9)	(42.88)	(412.4)	(0.0324)
Unemployment rate 2000 vs 2010	0.877	1.109	4.426	4.757	-0.0291	0.937	1.045	4.802	4.464	-0.421	0.935	1.099	5.005	4.454	-0.633
	(0.543)	(0.708)	(3.072)	(2.854)	(0.936)	(0.621)	(0.756)	(3.438)	(2.499)	(0.250)	(0.468)	(0.907)	(3.050)	(2.255)	(0.132)
Unemployment rate low educated 2000 vs 2010[a]	1.037	1.286	4.841	5.760	0.721	1.061	1.210	4.705	4.898	-0.0851	0.952	1.054	5.059	4.550	-0.429
	(0.963)	(1.425)	(3.638)	(4.585)	(0.182)	(1.065)	(1.934)	(3.385)	(3.259)	(0.845)	(0.862)	(1.004)	(3.047)	(2.694)	(0.373)
Unemployment rate high school plus 2000 vs 2010[a]	0.955	0.708	3.164	3.634	0.812**	0.920	0.975	3.283	3.884	0.410	0.885	1.241	3.407	3.649	-0.105
	(1.479)	(1.168)	(2.421)	(2.684)	(0.0193)	(1.502)	(1.563)	(2.191)	(2.664)	(0.249)	(1.184)	(5.750)	(1.803)	(2.125)	(0.861)
Number of municipalities	477	149				403	135				137	150			

*DID stands for difference-in-difference kernel matching, which is estimated by comparing each treated group to its respective matched control group using the Eq.(2). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10 Sources: [a] Own estimates using the micro-data population sample from census records, provided by INEGI and Minnesota Population Center (2014). All other statistics INEGI.*

Panel A: Cartels without drug-related homicides | Panel B: Experiencing drug-related homicides

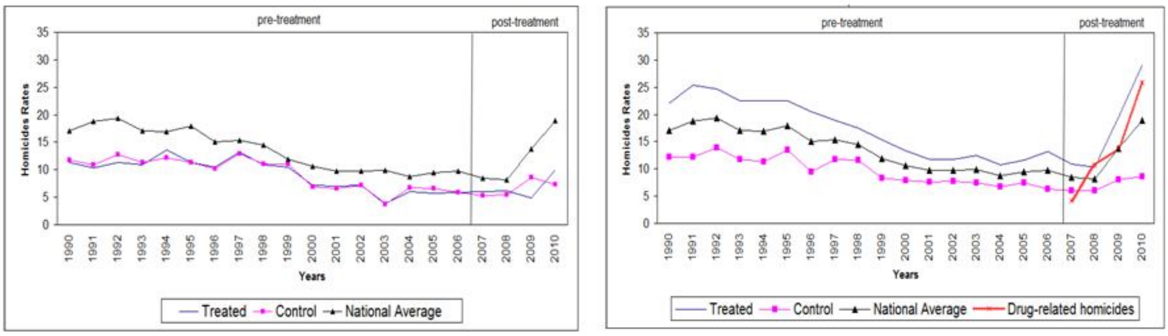


Fig. A.4 Trends in homicides rates between treatment and controls after kernel matching

Panel A: Cartels without drug-related homicides | Panel B: Experiencing drug-related homicides

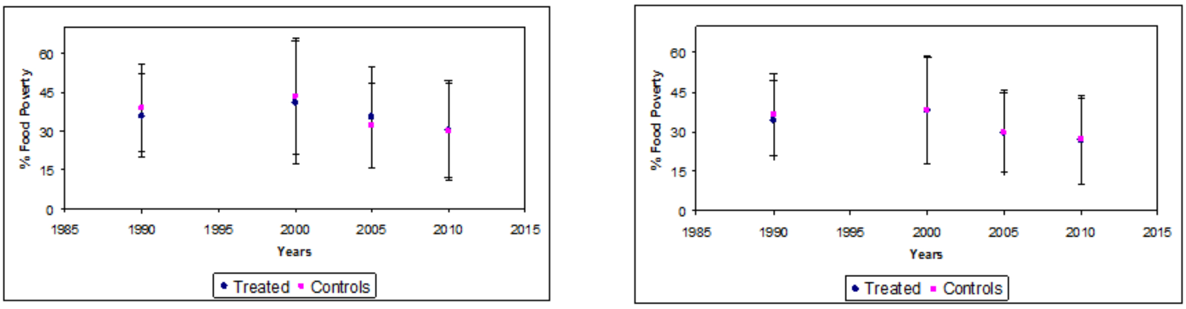


Fig. A.5 Trends in food poverty between treatment and controls after kernel matching

Panel A: Cartels without drug-related homicides | Panel B: Experiencing drug-related homicides

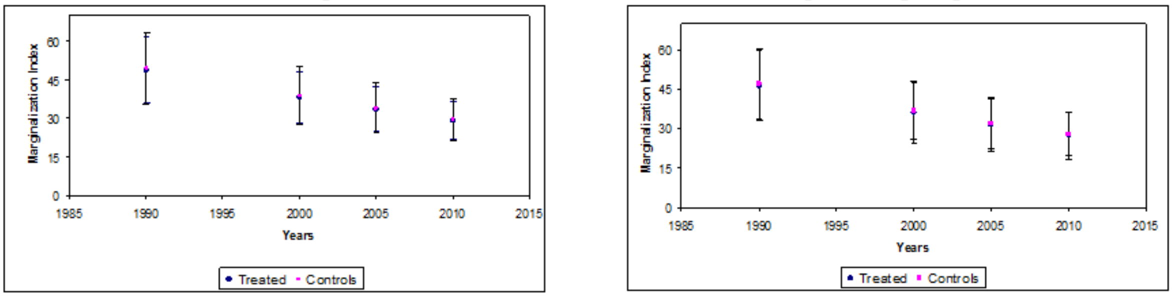


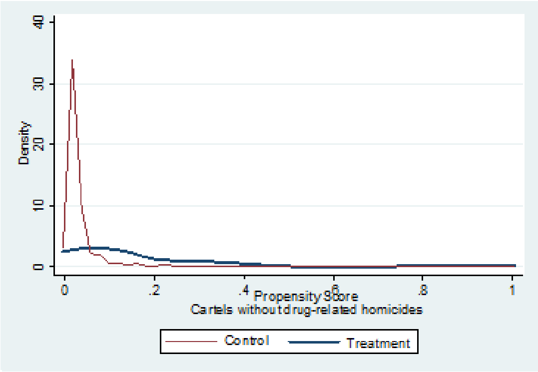
Fig. A.6 Trends in marginalization index between treatment and controls after kernel matching

Table A.4
Probit marginal effects: Propensity scores used to match areas and evaluate impact on industries

	Cartels but no drug-related homicides	At least one drug-related homicide	Drug-related homicides by sub-groups: 4th Quartile	3rd Quartile	2nd Quartile	1st Quartile
	(1)	(2)	(3)	(4)	(5)	(6)
Index of marginalization 2000	0.000		-0.003**	0.000	-0.000	0.000
	(0.001)		(0.001)	(0.000)	(0.000)	(0.000)
Capability poverty 2000	-0.001	-0.002**	-0.008*	-0.001	0.000	0.000
	(0.002)	(0.001)	(0.004)	(0.001)	(0.000)	(0.000)
Food poverty 2000	0.000		0.008*	0.000	-0.000	-0.000
	(0.002)		(0.004)	(0.001)	(0.000)	(0.000)
Parties uncoordinated at municipality and state level	-0.004	0.117***	0.073***	0.006	-0.002	0.000
	(0.011)	(0.029)	(0.023)	(0.009)	(0.002)	(0.000)
Mixed type municipality (urban/rural)	-0.011		-0.046**	0.004	-0.000	-0.000
	(0.007)		(0.021)	(0.007)	(0.002)	(0.000)
Mixed type*Uncoordinated	0.012		0.045	0.000*	0.002	-0.000
	(0.024)		(0.051)	(0.000)	(0.004)	(0.000)
Rural*Distance to north border	-0.000	0.000*	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Population 2005	-0.043	0.211***	0.240**	0.010	0.040	0.000***
	(0.038)	(0.013)	(0.098)	(0.010)	(0.028)	(0.000)
Squared log population	0.003		-0.012**	0.000*	-0.002	-0.000***
	(0.002)		(0.006)	(0.000)	(0.001)	(0.000)
Log GDP per capita 2005	0.020	0.350***	0.103***	0.139	0.007	0.000
	(0.015)	(0.065)	(0.036)	(0.207)	(0.007)	(0.000)
%Children school attendance 2005	0.000	-0.002	-0.004***	0.000	0.000	-0.000
	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Remmittances	0.002	0.006***	0.005**	0.000	0.000	0.000
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Squared remmitances	-0.000		-0.000	0.000*	-0.000	0.000
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Municipality ruled by PAN only	0.005	-0.078***	0.006	-0.002	-0.001	0.000
	(0.010)	(0.030)	(0.022)	(0.004)	(0.002)	(0.000)
Municipality ruled by PRI only	-0.003		0.024	0.002	0.001	0.000
	(0.008)		(0.023)	(0.004)	(0.002)	(0.000)
Total homicide rate 2004	0.000*		0.003***	0.001	0.000*	0.000*
	(0.000)		(0.001)	(0.001)	(0.000)	(0.000)
Squared homicide rate 2004	0.000*	-0.000	-0.000	-0.000*	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Homicide rate 2004*Uncoordinated	-0.000	-0.000	-0.001	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Minimum distance to border	-0.000		-19.275*	-0.000	-0.100	-0.000
	(0.000)		(11.512)	(0.000)	(0.674)	(0.000)
Pseudo R2	0.31	0.34	0.22	0.33	0.47	0.74
Available treated	46	485	121	121	121	122
Available controls	929	933	933	933	933	933
Total municipalities considered in probit	975	1418	1054	1054	1054	1055
Treated remaining in region of common support	40	403	115	107	109	82
Controls remaining in region of common support	458	878	795	835	396	111
Total matched municipalities in region in common support	498	1281	910	942	505	193

*Marginal effects of experiencing drug trafficking or drug-related homicides using probit regression shown in Eq.(1). (*) dF/dx is for discrete change of dummy variable from 0 to 1, z and P>|z| correspond to the test of the underlying coefficient being 0. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10*

Panel A: Cartels without drug-related homicides



Panel B: Experiencing drug-related homicides

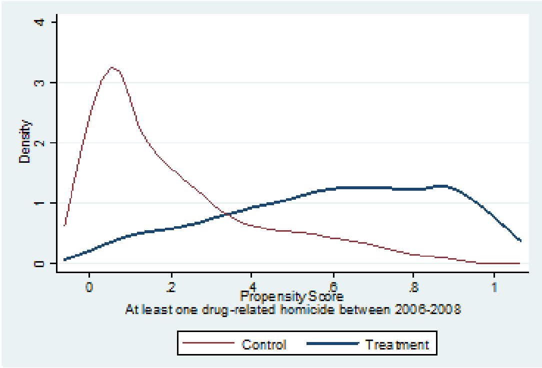


Fig. A.7 Distribution of propensity scores between treatment and control groups

Table A.5
Balancing test for covariates used to estimate propensity score to assess the impact on industries

	Panel A: Cartels without drug-related homicides			Panel B: Drug-related homicides														
				All that experienced at least one-drug related homicide			4th Quartile			3rd Quartile			2nd Quartile			1st Quartile		
	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff	Mean treated	Mean controls	p-value for diff
Index of marginalization 2000	33.98	34.7	0.735				35.8	35.94	0.916	35.39	35.85	0.694	32.66	32.41	0.879	34.04	32.87	0.638
Capability poverty 2000	43.44	43.22	0.952	44.49	43.84	0.684	41.94	41.99	0.986	44.47	45.25	0.723	42.53	42.56	0.992	46.46	44.47	0.615
Food poverty 2000	36.09	35.95	0.969				35.54	35.63	0.971	37.26	38.08	0.7	34.81	34.97	0.951	38.48	36.5	0.604
Uncoordinated	0.4	0.3	0.243	0.49	0.52	0.516	0.63	0.6	0.574	0.48	0.48	0.915	0.37	0.35	0.795	0.5	0.51	0.95
Mixed type municipality (urban/rural)	0.23	0.26	0.609				0.23	0.23	0.875	0.41	0.41	0.99	0.29	0.32	0.714	0.29	0.24	0.587
Mixed type*Uncoordinated	0.07	0.09	0.816				0.12	0.11	0.711				0.12	0.15	0.652	0.13	0.13	0.938
Rural*Distance to north border	361.17	348.78	0.864	358.26	359.79	0.961	407	416.78	0.826	364.73	366.65	0.969	304.94	301.61	0.95	302.61	290.64	0.872
Log Population 2005	10.01	9.91	0.575	9.86	9.79	0.423	8.97	8.87	0.368	9.79	9.78	0.975	10.35	10.28	0.47	10.88	10.86	0.829
Squared log population	101.19	99.26	0.588				81.54	79.73	0.386	118.23	117.88	0.654	107.67	106.09	0.429	118.69	118.16	0.789
Log GDP per capita 2005	10.91	10.89	0.831	10.87	10.88	0.732	10.89	10.89	0.898	10.87	10.85	0.637	10.94	10.93	0.803	10.87	10.88	0.908
Children school attendance 2005	64.37	64.11	0.764	63.67	63.53	0.739	62.76	62.8	0.945	64.54	64.29	0.625	64.06	64.17	0.871	63.91	64.24	0.773
Remmittances	7.73	7.65	0.955	8.37	8.32	0.94	9.79	9.98	0.851	8.76	8.95	0.85	8.49	7.93	0.591	5.15	4.87	0.792
Squared remmitances	116.93	117.96	0.973				176.83	180.9	0.893				125.43	115.54	0.69	64.85	50.27	0.462
Municipality ruled by PAN only	0.35	0.35	0.979	0.27	0.24	0.455	0.26	0.25	0.774	0.24	0.23	0.729	0.25	0.2	0.363	0.32	0.32	0.97
Municipality ruled by PRI only	0.4	0.44	0.679				0.49	0.47	0.705	0.49	0.48	0.903	0.5	0.5	0.982	0.45	0.45	0.956
Minimum distance to border	0	0	0.536				0	0	0.65	0.15815	0.15776	0.000974	0	0	0.364	0	0	0.654
Homicide rate 2004	6.18	5.88	0.81				15.89	15.86	0.991	9.78	8.91	0.465	10.06	9.53	0.73	6.25	5.7	0.661
Squared homicide rate 2004	85.11	82.47	0.925	415.96	374.86	0.734	938.45	890.3	0.893	208.43	172.16	0.381	231.66	200.85	0.69	69.17	61.1	0.726
Homicide rate 2004*uncoordinated	1.54	1.1	0.368	5.81	5.07	0.442	9.98	9.92	0.982	4.24	3.8	0.622	4.36	3.44	0.411	3.29	3.36	0.953

Table A.6
Descriptive statistics of industries across matched areas that fall in the region of common support

		Panel A: Cartels without drug-related homicides					Panel B: Drug-related homicides									
							At least one drug-related homicides					4th Quartile				
		2005		2010			2005		2010			2005		2010		
		Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)
Manufactures	production thousand USD	36060.8	73859.6	77460.2	115538.2	279.2	33845.3	69196.8	62825.7	76868.2	-21,309.1	18277.6	7286.1	39533.3	5548.9	-22,993.0**
		(110103.7)	(323470.7)	(250822.0)	-501193	(37,931.5)	(131290.5)	(468507.9)	(232892.9)	(445651.1)	(13,801.7)	(104165.7)	(25238.7)	(193417.5)	(17758.9)	(11,283.6)
	profit thousand USD	11968.5	10032.5	26186.3	17671.1	-6,579.2	10753.7	19639.9	20923.8	20697.8	-9,112.3*	5215.8	3339.4	10067.5	2385.5	-5,805.6**
		(34396.8)	(26939.9)	(85171.5)	-62000.1	(10,753.9)	(40227.0)	(117908.2)	(76861.7)	(95270.6)	(4,919.1)	(29771.9)	(11846.0)	(58149.0)	(7977.2)	(2,735.9)
	workers per 10,000 inhabitants	235.7	161.5	290.6	168.5	-47.9	219.0	208.2	270.1	221.4	-37.8**	170.4	224.1	217.0	195.5	-75.2**
		(332.5)	(239.1)	(388.8)	-206	(35.2)	(325.5)	(368.4)	(355.1)	(319.3)	(16.3)	(291.3)	(491.3)	(366.5)	(272.9)	(36.5)
	salaries per worker thousand USD	3.971	4.364	4.273	4.144	-0.5**	4.026	4.152	4.246	3.940	-0.4**	3.278	3.296	3.537	2.903	-0.7*
		(2.705)	(4.270)	(3.441)	-4.469	(0.2)	(3.132)	(3.542)	(4.099)	(3.310)	(0.2)	(3.103)	(3.008)	(4.174)	(2.144)	(0.3)
	establisments per 10,000 inhabitants	31.03	24.24	42.29	34.47	-1.0	33.03	32.40	46.05	44.23	-1.2	30.48	35.18	47.37	43.04	-9.0***
		(33.31)	(19.99)	(46.45)	-34.73	(3.2)	(64.15)	(55.83)	(92.24)	(62.41)	(1.8)	(89.06)	(90.62)	(136.1)	(86.46)	(3.3)
Wholesale trade	production thousand USD	4298.3	4178.7	3749.2	5114.4	1,484.9	2848.7	4582.6	2891.8	4663.9	38.3	955.1	2328.3	1075.4	2441.4	-7.2
		(6618.5)	(6433.6)	(5453.7)	-8747.5	(1,163.2)	(4907.3)	(10957.6)	(5492.9)	(13237.8)	(435.1)	(2648.6)	(7670.4)	(3401.9)	(9558.0)	(297.9)
	profit thousand USD	2634.3	2681.8	2447.6	3271.7	776.6	1923.8	2757.6	1960.3	2884.7	90.5	642.4	1470.2	747.0	1679.7	104.8
		(4044.9)	(4051.1)	(4014.7)	-5297.8	(744.6)	(3424.2)	(6168.9)	(4477.8)	(7505.8)	(374.1)	(1822.2)	(4534.3)	(2806.6)	(6897.1)	(314.7)
	workers per 10,000 inhabitants	39.28	43.33	43.09	47.58	0.4	33.82	40.26	37.28	40.32	-3.4	22.27	26.66	24.60	30.75	1.8
		(33.67)	(36.98)	(38.79)	-53.53	(6.7)	(29.87)	(50.02)	(39.07)	(50.89)	(2.5)	(26.52)	(36.13)	(32.04)	(47.08)	(3.2)
	salaries per worker thousand USD	4.821	5.386	4.800	5.381	0.0	4.639	4.721	4.595	4.726	0.1	3.337	3.304	2.947	3.589	0.7
		(3.080)	(3.100)	(3.147)	-3.351	(0.5)	(3.546)	(3.318)	(3.407)	(3.779)	(0.3)	(3.944)	(3.294)	(3.183)	(4.943)	(0.6)
	establisments per 10,000 inhabitants	6.900	7.484	7.079	7.855	0.2	6.545	6.845	6.766	6.831	-0.2	5.281	5.833	5.858	5.863	-0.5
		(4.443)	(5.377)	(4.920)	-5.915	(0.8)	(4.619)	(5.329)	(5.026)	(5.339)	(0.3)	(5.097)	(5.846)	(5.848)	(6.021)	(0.6)
Number of municipalities		458	40				878	403				795	115			

Table A.6 (*continuation*)

		Panel B: Drug-related homicides														
		3rd Quartile					2nd Quartile					1st Quartile				
		2005		2010			2005		2010			2005		2010		
		Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)	Control	Treated	Control	Treated	DID (no controls)
Manufactures	production thousand USD	28391.5	55095.7	51823.9	78988.0	459.9	54055.7	149207.1	104300.6	172860.5	-26,591.6	65765.1	219953.3	152108.6	324591.6	18,294.7
		(126152.6)	(387467.6)	(209724.3)	(575492.5)	(19,770.0)	(159995.9)	(586758.3)	(304135.1)	(629013.5)	(32,834.5)	(146610.7)	(856091.1)	(344874.9)	(1270168.6)	(73,496.2)
	profit thousand USD	9254.6	15622.4	16914.0	14597.7	-8,684.0**	18172.8	40345.2	35303.9	53920.2	-3,556.0	22076.6	75510.7	52502.5	111346.1	5,409.6
		(41064.6)	(96476.1)	(68255.8)	(80300.9)	(3,393.8)	(52485.1)	(143698.1)	(101911.6)	(198850.1)	(11,261.0)	(48852.8)	(271972.8)	(118000.7)	(404886.3)	(25,466.3)
	workers per 10,000 inhabitants	197.7	185.2	248.6	205.6	-30.5**	280.1	238.2	327.6	273.0	-12.6	279.3	321.5	371.5	367.4	-46.2
		(295.7)	(263.7)	(319.9)	(244.8)	(15.1)	(361.8)	(324.3)	(393.8)	(365.1)	(22.4)	(352.2)	(542.9)	(462.6)	(659.0)	(44.5)
	salaries per worker thousand USD	3.838	3.983	3.992	3.818	-0.3	4.500	4.714	5.014	4.638	-0.6*	4.484	5.336	5.141	5.479	-0.5
		(2.887)	(3.879)	(3.742)	(3.906)	(0.2)	(2.736)	(3.335)	(3.855)	(3.362)	(0.3)	(2.031)	(3.574)	(2.973)	(3.981)	(0.4)
	establisments per 10,000 inhabitants	35.17	33.78	49.98	50.87	2.3	32.25	32.73	41.78	43.67	1.4	30.07	29.84	39.97	42.63	2.9
		(68.57)	(39.82)	(98.76)	(60.29)	(3.3)	(26.75)	(30.88)	(37.86)	(48.37)	(2.5)	(22.82)	(29.31)	(32.88)	(39.72)	(3.3)
Wholesale trade	production thousand USD	2664.8	2883.0	3512.6	3459.2	-271.6	5234.1	12272.7	4611.3	14284.5	2,634.6	8932.9	18714.8	7345.6	18385.4	1,257.9
		(4524.3)	(7112.6)	(7463.2)	(10831.3)	(885.2)	(7069.8)	(31247.6)	(6414.5)	(44187.6)	(1,993.6)	(7983.5)	(97407.7)	(5856.5)	(86598.3)	(1,814.8)
	profit thousand USD	1819.6	1818.9	2630.5	1976.8	-653.1	3438.4	7330.2	2996.6	9414.6	2,526.1*	5692.5	12408.1	4557.7	10915.4	-357.9
		(3258.4)	(4259.9)	(6635.4)	(5060.2)	(733.2)	(4834.9)	(20053.8)	(5050.6)	(29489.8)	(1,494.4)	(5201.4)	(67341.5)	(3854.4)	(52612.8)	(1,872.6)
	workers per 10,000 inhabitants	36.07	37.71	37.53	40.02	0.8	44.64	57.80	48.92	56.39	-5.7	48.68	50.75	53.72	49.20	-6.6
		(30.33)	(55.46)	(37.02)	(51.04)	(3.2)	(32.42)	(61.16)	(41.23)	(65.59)	(4.6)	(29.50)	(40.34)	(36.11)	(41.32)	(5.3)
	salaries per worker thousand USD	4.728	4.987	4.570	4.683	-0.1	5.486	5.625	5.567	5.531	-0.2	6.249	5.844	5.638	6.144	0.9
		(3.332)	(3.264)	(3.198)	(2.766)	(0.4)	(2.799)	(3.233)	(3.056)	(3.355)	(0.3)	(2.720)	(2.748)	(2.341)	(3.452)	(0.6)
	establisments per 10,000 inhabitants	6.965	6.964	7.090	7.418	0.3	7.490	7.985	7.563	7.536	-0.5	7.459	7.158	7.333	7.374	0.3
		(4.711)	(6.252)	(5.207)	(5.892)	(0.7)	(4.022)	(4.905)	(4.371)	(4.862)	(0.5)	(3.634)	(3.667)	(3.784)	(4.129)	(0.7)
Number municipalities		835	107				396	109				111	82			

*DID stands for difference-in-difference kernel matching, which is estimated by comparing each treated group to its respective matched control group using the Eq.(2). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10 Source: INEGI, economic census.*

Table A.7
Placebo test on welfare indicators using 1990-2000 as pre-treatment and 2001-2005 as post-treatment

	(1) Food poverty %	(2) Capability poverty %	(3) Patrimony poverty %	(4) Gini	(5) Total population	(6) Resided in another state 5 years ago
Panel A: Placebo treatment assuming cartels moved into area without experiencing drug-related homicides in 2001 instead of 2006						
Difference-in-difference	3.955	3.881	3.070	0.00429	-179.2	-38.62
	(0.162)	(0.178)	(0.238)	(0.601)	(0.553)	(0.326)
Observations	905	905	905	905	905	905
Panel B: Placebo treatment assuming cartels moved into area experiencing drug-related homicides in 2001 instead of 2006						
All areas that are assumed to have experienced at least one drug-related homicide						
Difference-in-difference	0.926	0.581	-0.211	-0.00357	123.6	-2.499
	(0.530)	(0.708)	(0.892)	(0.513)	(0.709)	(0.938)
Observations	2,357	2,357	2,357	2,357	2,357	2,357
Fourth quartile (with most drug-related homicides)						
Difference-in-difference	0.879	0.718	0.405	0.0136	-289.8	9.967
	(0.578)	(0.663)	(0.803)	(0.107)	(0.541)	(0.744)
Observations	1,204	1,204	1,204	1,204	1,204	1,204
Third quartile						
Difference-in-difference	-0.410	-0.568	-0.831	-0.00576	-351.5	19.66
	(0.792)	(0.728)	(0.609)	(0.409)	(0.268)	(0.421)
Observations	1,312	1,312	1,312	1,312	1,312	1,312
Second quartile						
Difference-in-difference	1.159	0.751	-0.685	0.00789	88.63	41.25
	(0.542)	(0.707)	(0.732)	(0.277)	(0.838)	(0.231)
Observations	1,156	1,156	1,156	1,156	1,156	1,156
First quartile						
Difference-in-difference	2.532	2.055	0.816	-0.00420	-52.88	-21.95
	(0.254)	(0.375)	(0.714)	(0.552)	(0.928)	(0.593)
Observations	510	510	510	510	510	510

*The difference-in-difference kernel matching estimator compares each placebo treated group to its respective matched control group using the panel fixed regression shown in Eq.(4). Controls used in all specifications: Poverty-relief subsidies per capita and state's unemployment rate, all lagged for two years. Robust standard errors in parentheses clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.10 Source: economic census and controls used INEGI.*

Table A.8
Placebo test on manufacture and wholesale trade using 1990-2000 as pre-treatment and 2001-2005 as post-treatment

	Manufactures					Wholesale Trade				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	production thousand USD	profit thousand USD	workers per 10,000 inhabitants	salaries per worker thousand USD	establisments per 10,000 inhabitants	production thousand USD	profit thousand USD	workers per 10,000 inhabitants	salaries per worker thousand USD	establisments per 10,000 inhabitants
Panel A: Placebo treatment assuming cartels moved into area without experiencing drug-related homicides in 2001 instead of 2006										
Difference-in-difference	-40,851.694	-21,945.778	-23.391	-0.660	0.848	952.732	809.351	-2.543	0.204	0.089
	(27,502.002)	(17,561.034)	(31.028)	(0.637)	(5.572)	(718.142)	(681.971)	(3.595)	(0.334)	(0.545)
Observations	869	869	869	868	869	680	680	680	680	680
Panel B: Placebo treatment assuming cartels moved into area experiencing drug-related homicides in 2001 instead of 2006										
All areas that are assumed to have experienced at least one drug-related homicide										
Difference-in-difference	-28,903.811	-22,146.064	-25.141	-0.730	0.021	23.186	-134.522	-0.889	-0.115	-0.820*
	(28,892.661)	(18,447.494)	(25.246)	(0.633)	(3.193)	(382.194)	(276.202)	(3.419)	(0.314)	(0.491)
Observations	2,279	2,279	2,279	2,278	2,279	1,839	1,839	1,839	1,839	1,839
Fourth quartile (with most drug-related homicides)										
Difference-in-difference	-38,410.084	-18,713.283	-38.430	-0.748	2.028	-400.818	-357.706	-2.136	-0.075	-0.501
	(24,888.372)	(15,560.391)	(31.181)	(0.584)	(7.738)	(364.369)	(250.906)	(4.999)	(0.341)	(0.702)
Observations	1,139	1,139	1,139	1,138	1,139	776	776	776	776	776
Third quartile										
Difference-in-difference	-20,867.581	-11,916.734	8.117	-0.085	5.671	-440.678	-34.902	-7.248	0.484	-0.947
	(16,423.030)	(10,557.327)	(23.886)	(0.442)	(4.525)	(534.634)	(363.365)	(6.399)	(0.487)	(0.774)
Observations	1,246	1,246	1,246	1,245	1,246	902	902	902	902	902
Second quartile										
Difference-in-difference	-28,310.031	-17,382.017	-32.611	-0.857	-2.151	729.053	389.344	0.432	0.220	-1.033
	(23,218.878)	(14,995.864)	(21.147)	(0.562)	(2.588)	(691.555)	(516.252)	(4.774)	(0.545)	(0.713)
Observations	1,116	1,116	1,116	1,115	1,116	862	862	862	862	862
First quartile										
Difference-in-difference	-1,269.478	-17,933.842	-4.126	-0.626	1.901	183.664	62.928	2.904	0.469	-0.631
	(34,846.455)	(16,124.433)	(26.943)	(0.582)	(5.439)	(902.239)	(705.204)	(6.420)	(0.751)	(0.552)
Observations	507	507	507	507	507	484	484	484	484	484

*The difference-in-difference kernel matching estimator compares each placebo treated group to its respective matched control group using the panel fixed regression shown in Eq.(4). Controls used in all specifications: Poverty-relief subsidies per capita and state's unemployment rate, all lagged for two years. Robust standard errors in parentheses clustered at municipality level. *** p<0.01, ** p<0.05, * p<0.10 Source: economic census and controls used INEGI.*

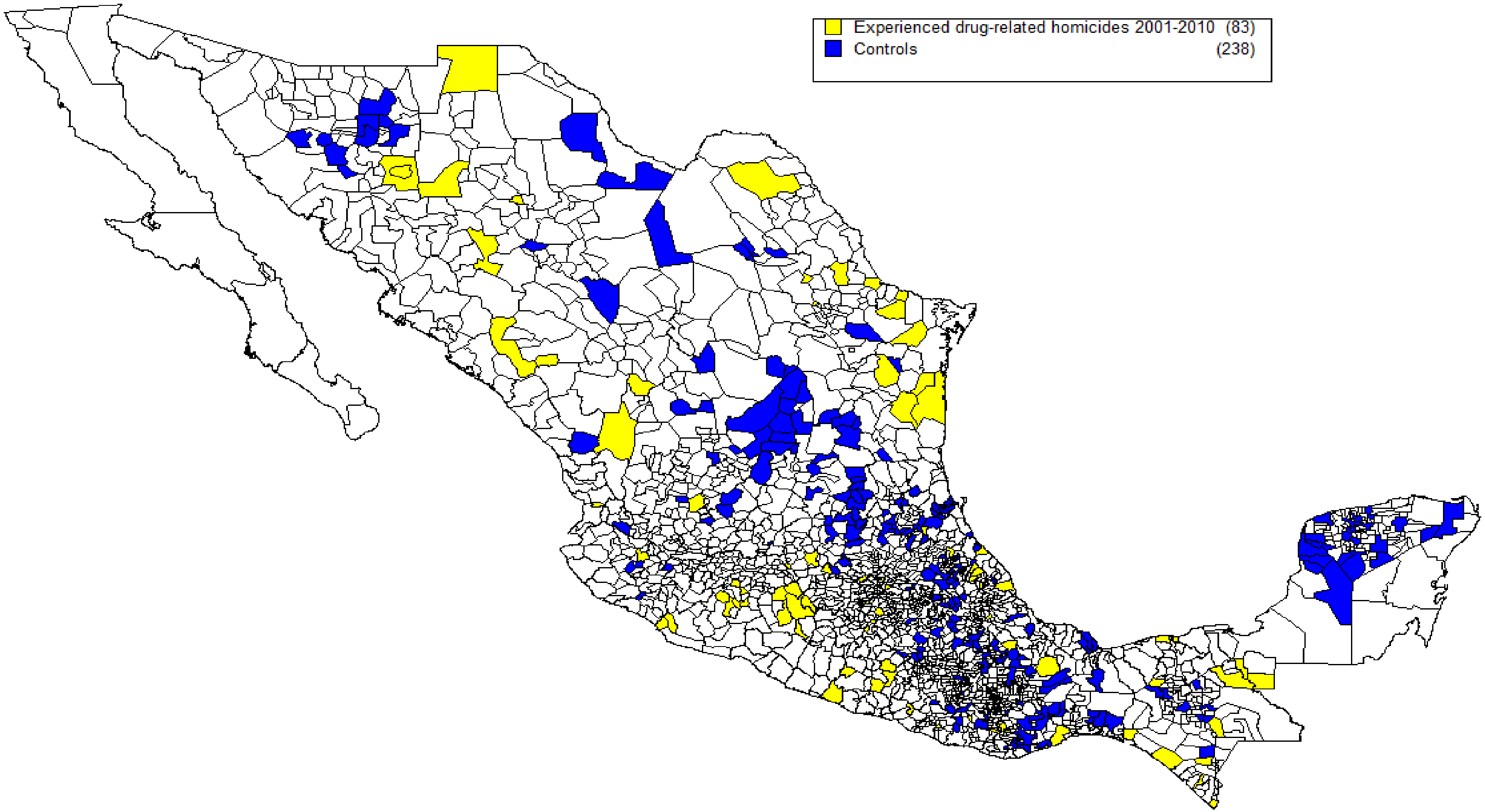
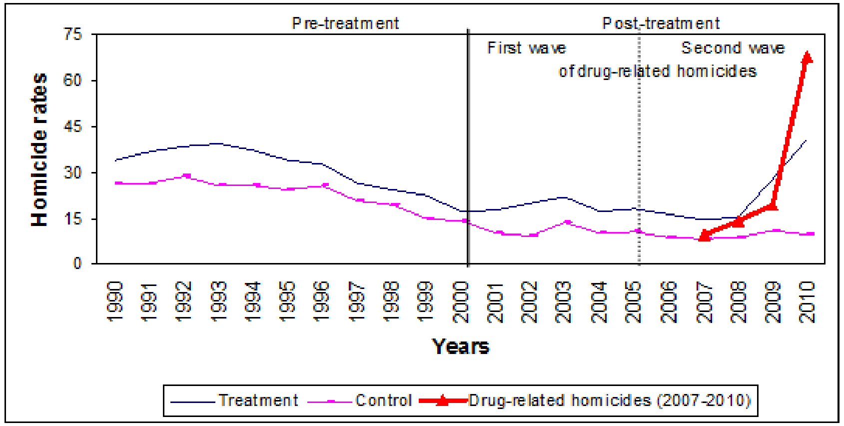


Fig. A.8 Municipalities that experienced drug-related homicides for the first time in 2001 or after vs. controls in region of common support

Panel A



Panel B

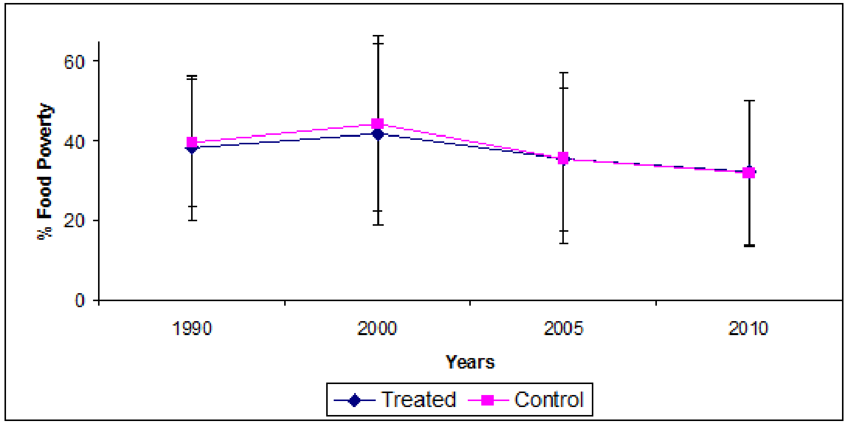


Fig. A.9 Homicide rates and food poverty in municipalities that experienced drug-related homicides for the first time in 2001 or after vs. controls in region of common support

Appendix B: Using Google to Identify Cartels' presence

We use the official records to identify which municipalities suffered drug-related homicides stemming from battles among cartels and with the state authority (SNSP, 2011). These official records, available from December 2006 until September 2011, have been used in previous studies to analyze the impact of drug-related violence (BenYishay and Pearlman, 2013; Robles et al., 2013; Calderón et al., 2015; Dell, 2015; Gutiérrez-Romero, 2016). In parallel to this official information, we also identify the municipalities where cartels operate with and without drug-related homicides using the Google search engine. Below we describe the six steps followed in this search.

1. First, we selected Google search Mexico, https://www.google.com.mx, as our exploratory analysis suggested more hits were found in this way rather than using the default Google search engine of other countries. Nonetheless, we kept our search wide open. That is we did not limit the search to a specific source, country or language. The exact list of sources where we found reports of municipalities being affected by drug cartels or drug-related homicides is listed in Table B.1.

2. In the 'Tools of Search,' we selected the corresponding period to search. As we analyze the impact of cartels for various periods, we split our search into different periods 1990-2000, 2001-2005, 2006-2008 and 2006-2010. For instance, if searching for 2000-2005, we selected 1 January 2000 until 31 December 2005. Note that our search was not made on a yearly basis.

Table B.1
Sources used to identify Mexican municipalities affected by drug cartels and drug-related homicides

Mexican newspapers and magazines		Mexican government sources	TV clips and other videos	Blogs	International sources
Agencia de Servicios Informativos de Chiapas	Informador	Informe de gobierno	TU TV México	Bloggeando desde Zacatecas	El diario (Spain)
Alcolor Político	La crónica	Procuraduría General de la Republica (PGR)	Grupo Reforma online videos	Cannabis café forum	El nuevo herald (USA)
Álvaro Sánchez Noticias	La Insignia	Procuraduría Agraria (PA)	Mashpedia videos	Defensa México	El Transnational Institute (Netherlands)
Centro de estudios para la transición democrática	La jornada	Secretaria de la Defensa Nacional (SEDENA)	Noticias y más vlog	El blog del narco	Foreign Military Studies Office (USA)
Centro de Periodistas de Investigación	La jornada de oriente		Noticiero e-consulta videos	En guerra contra el narco	Hechos de hoy (Spain)
Chiapas contralinea	La jornada Morelos		Puebla online TV videos	En medio	Univisión noticias (USA)
Chompipe periódico	La policiaca		TV Maya	Narco news	Carlos Resa Nestares (Spain). Data on erradicated illegal drug crop at Mexican municipality level, based on Mexican official data
CNN México	La política mx			Narcotráfico en México	
Contralínea	Las noticias México			Noticias del narco	
Contralínea Michoacán	Letras libres			Observatorio ciudadano	
Contralínea Sonora	Linderonote			Puro narco	
Crónica Oaxaca	México denuncia			The narco news bulletin	
Diario cambio	México informado			Tu aregnoticias	
Diario critica	Milenio				
Diario de colima	Mural				
Dossier político	Nexos				
Drogas México Org	Noticias Nayarit				
El economista	Noticias y actualidad				
El imparcial	NTR Zacatecas				
El imperial	Nvinoticias.com				
El matutino virtual	Off News info.				
El nauzonteco de Puebla	Orizaba en red				
El norte	Orizaba en red				
El nuevo diario	Periódico el Sur				
El occidental	Periodistas en Línea				
El orbe	Poblanerias				
El país	Puebla online				
El porvenir	Punto por punto				
El regional	Radio motul				
El siglo de Durango	Reforma				
El siglo de Torreón	Revista proceso				
El suracapulco	Reynosa libre				
El universal	Seminario Nuestro Tiempo				
El zenzontle	Sipse				
Es más noticias (Televisa)	Status Puebla				
Estrella roja	Tabasco Hoy				
Excélsior	Terra noticias				
Expansión	The Narco News Bulletin Chiapas				
Fronteriza Chiapas	Una Fuente				
IB times México	Vanguardia				
Imagen del golfo	Villaflores Times				
	Voltaire Net				
	Yucatán Ahora				
	Zeta Tijuana				

3. Then, for each of the 2,456 municipalities in the country we searched for incidences of drug-related homicide as a direct result of inter- or intra- cartels battles or with the authority. To this end, we searched the combination of name of the municipality and the word *narco*, a commonly used word to refer to drug cartels - *narco homicidios, narco violencia, asesinatos, drug-related homicides, narco fighting, narco-fosas* (where cartels dump bodies).

If this initial search proved successful, meaning Google suggested some hints, we proceeded to read the links provided. We made sure that the report suggested that the homicides were derived from battles amongst cartels and the state. Drug-related homicides tend to be extremely gruesome. Mutilations, people found dissolving in tanks full of acid or hanging from public bridges with messages. These are the tell-tell signs that lead journalists or authorities to suggest the assassinations or bodies found were derived from the cartels' conflicts and not from other types of opportunistic crime that went wrong. In other instances, although assassinations are less brutal there are also signs of their being drug-related, as they are committed in illicit drug labs, in clandestine airports of drug leaders or by people related to known drug lords.

Identifying relevant reports for each municipality

In our search, we also made sure the reports referred to the exact municipality analyzed, and not to the state or an area under the same name but in another country.

In some instances, we did not find a single hit when searching for the combination of municipality name and the above keywords of drug-related homicides. In these cases, we proceeded to check for the name of the municipality, its state and the keyword for drug-related homicides.

We also searched for the common names of municipalities, as some are abbreviated. For instance, the state commonly referred as Mexico, is officially known as the Estado de

Mexico. In a few cases the municipality has the same name as the state, such as Aguascalientes, the municipality, who is also in the state called Aguascalientes. In these instances, we specified in our Google search that our search was related to the municipality by searching for its commonly referred name, such as 'Ciudad de Aguascalientes.'

If the municipality's name is composed of two or more words, then we searched by its official name and also by its commonly shorted name. For instance, for the municipality officially called 'Valle de Chalco', we searched for both its official name and as its commonly known as 'Chalco.'

4. In case we failed to find evidence of drug-related homicides, we proceeded to search for other tell-tell signs of a cartel's presence. Primarily, we look for a combination of area (municipality, state) and the cartel's presence for a particular period.

To this end, we searched the combination of name of the municipality and the word *narco*. If this initial search proved successful, we made sure that the mentioned area indeed corresponded to the municipality analyzed, and that the event suggested was indeed relevant to infer the cartels' presence. If the initial combination of municipality and the word *narco* yielded no reports, or no relevant ones, we proceeded to search for combinations of the name of the municipality with the word *drug cartel*. If our search was unlucky, we then searched by the exact *name of drug cartels*. If that yielded unsuccessful results, we then searched directly for a combination of municipalities and the *name or alias of the cartel's leader.*

Identifying name of cartels and their leaders

We took the reports of Guerrero-Gutiérrez (2011), Ravalo (2012), Coscia & Ríos (2012) and various online bulletins issued by Stratford as guidelines of the names of cartels and their leaders. So for instance, when searching for the combination of the municipality and the

Sinaloa cartel, we searched as a keyword *Sinaloa cartel*, as well as its known drug leaders such as Joaquín Guzmán Loera, “El Chapo, el chapo Guzman”, Ismael Zambada, “El Mayo”, Juan José Esparragoza Moreno and “El Azul”.

5. If searching for specific drug cartels or drug leaders also proved unsuccessful, we then searched for specific cartel’s activities including *drug trafficking*, *drug cultivation*, *drug seizing*, *arrests of cartel’s members*, *narco mantas* (cartels’ messages displayed in bed-sheets), *narco politicians* (politicians associated with cartels), *narco-police, army or gangs*, and *narco airports.*

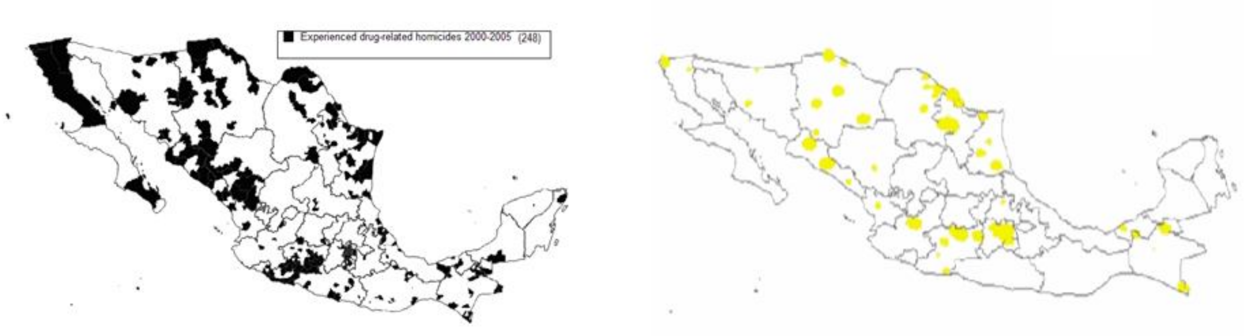
6. After finding and reading a report where it was possible to infer cartels’ presence or drug-related homicides, we copied *at least one* of the relevant links on to an Excel spread sheet. In cases where we found several links suggesting the presence of cartels in a particular municipality, we gave preferences to keeping at least one record of the links found in the following order of priority.

- newspapers and specialized magazines,
- online government reports,
- links to videos, from TV-news
- specialized blogs on drug-related themes
- YouTube videos talking about presence of cartels from locals’ vlogs.

Drug-related homicides 2000-2005

According to our online search, 248 municipalities experienced drug-related homicides between January 2000 and December 2005, the period for where there are no official records on such homicides. As showed in Fig. B.1, most of these areas Osorio (2012) also identified as affected by drug violence during the same period.[14] This reassures us that even though we did our online search manually and used different online sources, we found a similar geographical pattern as to where drug violence was reported. Ninety percent of the areas first affected by drug violence experienced again drug-related homicides between December 2006 and September 2011 if triangulating with official records for that period.

Panel A **Panel B**



Source: Authors own estimates from surveying media, specialized blogs and official records.

Source: Osorio (2012). Note: Map displayed in 3-dimension with kernel distributions to depict intensity of drug-related homicides.

Fig. B.1 Municipalities experiencing drug-related homicides during 2000-2005

Drug-related homicides 2006-2010

The detection of which municipalities have experienced drug-related homicides has been greatly facilitated by the recently released official records (SNSP, 2011). According to these records, 1,137 municipalities had at least one drug-related homicide during 2006-2010, the main period of our analysis.

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[14] Osorio (2012) monitored 11 national newspapers; 47 local newspapers; and press releases from the army, navy, federal police and the Attorney General's Office.

There were only 63 municipalities that according to our media search experienced drug-related homicides, but that do not appear in the official statistics of drug-related homicides. Since it is impossible to know the reason of discrepancy, we eliminate these 63 areas with conflicting information from our analysis. We do so to minimize a potential contamination of our control groups and to keep a consistent definition of what is referred to drug-related homicides according to official records during 2006-2010.[15]

Data on areas where cartels worked free of drug-related homicides

To identify the areas where cartels have been active without instances of drug-related homicides we also surveyed online reports. We found 243 areas where cartels were active without instances of drug-related homicides between January 2000 and December 2005.[16] We found another 145 areas had cartels working without instances of drug-related homicides from January 2006 until December 2010. According to our records, more than 90% of the areas where cartels operated free of drug-related homicides held the full monopoly of the plaza where they operated, as no other cartel was reported in the online records monitored. The correlation between having the monopoly of a plaza and not suffering from drug-related homicides has also been noted by other researchers (Castillo et al., 2012). In contrast, in areas experiencing drug-related homicides, we found two or more cartels battling for territory against other cartels or the state.

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[15] If we had included these 63 areas as treated areas by drug-related homicides our analysis would have offered same results as those presented, possible because most of these areas suffered quite low levels of drug-related homicides.

[16] This offers a similar number of areas affected by cartels to the one found by Coscia and Ríos (2012).

Appendix C: Data sources for socio-economic indicators

Data on poverty, inequality, migration, unemployment, and industries

We use Mexico's official statistics on poverty, all available at the municipality level. Food poverty measures the percentage of the population that cannot buy a basic food basket. Capability poverty adds those who cannot cover health and education needs, while patrimony poverty adds those who cannot cover clothing, housing, and public transport needs. CONEVAL, an autonomous agency, estimated all these indicators by combining household surveys (Encuesta Nacional de Ingreso y Gasto) with the Mexican Population Census using small-area statistics.[17]

Population censuses are used to explore changes in migration patterns, changes in the total population, and the number of people who lived in another state five years ago. To have a sense whether migrants are running away from drug violence we estimate whether people migrated from a state that had an overall higher homicides rate than the one into which they migrated.

We explore further internal migration patterns and profile of people that over previous five years relocated within the country using the 16% micro-census sample data of the 2005 and 2010 censuses (since these indicators and profile were not publicly released).[18] Specifically, we assess the earning income of immigrants, whether higher or lower than the inhabitants of the area they moved into in the country.

To measure changes in unemployment rates, we use population censuses of 2000 and 2010, since this statistic is not available for 2005. To have a sense of which groups have been

[17] Consejo Nacional de Evaluación de la Política de Desarrollo Social (CONEVAL) is in charge of evaluating indicators in Mexico to improve public policy in the country.

[18] This micro-data set is a sample of 16% of all records in the census, provided by INEGI in collaboration with the Minnesota Population Centre (2014).

most affected by unemployment, we also look at the unemployment rates according to people's education attainment the 16% weighted sample of the 2000 and 2010 censuses.

We also assess changes in the activity of two leading industries: manufacturing and wholesale trade drawing data from the economic censuses. Specifically, we look at what happened, in net terms, to the overall production, profits, salaries per worker, number of workers, and establishments per 10,000 inhabitants. We do not analyze other industries, such as construction and finance where cartels are also rumored to use for money laundry, because the censuses do not distinguish in which areas their production took place.