

Georgia State University

ScholarWorks @ Georgia State University

Political Science Theses

Department of Political Science

Spring 5-13-2021

¿Qué, Diferencia? Application of Difference-in-Differences to Mexico's Drug War

Jared Greathouse

Follow this and additional works at: https://scholarworks.gsu.edu/political_science_theses

Recommended Citation

Greathouse, Jared, "¿Qué, Diferencia? Application of Difference-in-Differences to Mexico's Drug War." Thesis, Georgia State University, 2021.
doi: <https://doi.org/10.57709/22712815>

This Thesis is brought to you for free and open access by the Department of Political Science at ScholarWorks @ Georgia State University. It has been accepted for inclusion in Political Science Theses by an authorized administrator of ScholarWorks @ Georgia State University. For more information, please contact scholarworks@gsu.edu.

¿Qué diferencia? Application of Difference-in-Differences to Mexico's Drug War

by

Jared Greathouse

Under the Direction of Charles Hankla, PhD

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Arts

in the College of Arts and Sciences

Georgia State University

2021

ABSTRACT

I analyze publicly available data to estimate the impact of military interventions in Mexico's Drug War. An update to previous research, I collect a dataset using press sources and other public materials on Mexico's deployment of military force to fight drug traffickers in the country. I employ a newly developed difference-in-differences design to estimate the causal effects of the policy at the municipio-month level. The statistical analysis implies that Mexico's military interventions increased violence substantially, in both the overall population as well as the proxy I use for drug-trade related homicides.

INDEX WORDS: Regression, Causal, Econometrics, Difference-in-differences

Copyright by
Jared Amani Greathouse
2021

¿Qué diferencia? Application of Difference-in-Differences to Mexico's Drug War

by

Jared Greathouse

Committee Chair: Charles Hankla

Committee: Toby Bolsen

Eric Sevigny

Electronic Version Approved: 4/28/2021

Office of Graduate Services

College of Arts and Sciences

Georgia State University

May 2021

DEDICATION

I dedicate this research my family for being there for me always in my journey from the very beginning. I love you all so much. I also dedicate this research to the victims of the war on drugs.

ACKNOWLEDGEMENTS

There are many people to thank for the success of this project. Dr. Andrew Wedeman for reading the very first draft of this back when I was a senior. Brian J. Phillips, Diego Valle-Jones for comments on earlier drafts as well as substantive comments. Clement de Chaisemartin for guidance on how to use the command the estimation is based on. And of course, my thesis committee without whom this research wouldn't exist. However, all errors are my own, and this work was produced without any external funding or financial support.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	V
LIST OF FIGURES	VII
I. INTRODUCTION.....	1
II. THEORY	2
<i>A. Network Diffusion.....</i>	<i>2</i>
<i>B. Hobbes.....</i>	<i>2</i>
<i>C. Fragmentation</i>	<i>3</i>
III. DATA	4
<i>A. Outcome Data</i>	<i>4</i>
<i>B. Intervention Criteria.....</i>	<i>4</i>
1. Search Strategy	5
IV. DESIGN	6
<i>A. DD: Assumptions, Estimands and Interventions.....</i>	<i>6</i>
1. Parallel Trends Assumption	6
2. Econometric Strategy	8
V. ESTIMATION	9
<i>A. Assessing PTA, Graphical Tests.....</i>	<i>9</i>
<i>B. DD Estimation</i>	<i>10</i>
VI. CONCLUSION	13
APPENDIX.....	14
REFERENCES.....	36

LIST OF FIGURES

<i>Fig. V-1, Graphical PTA</i>	9
<i>Fig. V-2, DD: Overall Homicide</i>	10
<i>Fig. V-3 DTH Homicides</i>	11

I. INTRODUCTION

Do military interventions (MIs) against drug-trafficking organizations (DTOs) affect violence? The question is of considerable importance given the last 15 years in Mexico. For Mexico, violence has been particularly formidable. Two facts illustrate this point well: In recent years, homicide levels have partly caused a decrease in life expectancy for Mexicans.¹ Secondly, small-analyses of Mexico City data indicates that not even the lockdown policies related to the SARS-CoV-2 pandemic could slow the violence, with the homicide rate remaining relatively unchanged following non-pharmaceutical interventions.² The grim situation was described in a recent volume: “The enterprise of killing in Mexico’s drugs war is dizzying... Thousands are killed in the country’s gangland violence every year, making it one of the most violent landscapes in the world. Since 2007 over 100,000 people have lost their lives in narco-violence in the country. While not in a declared state of war, Mexico is now experiencing what one might call the *industrialization of death* [emphasis mine]”, where “killings take place on an industrial scale.”³

In 2006, Mexican President Felipe Calderon initiated war against drug traffickers, firstly deploying the military in his home state of Michoacán de Ocampo. The purpose of this, was for the military to be drug traffickers *peor pesadilla*, or their “worst nightmares”.⁴ Officially, these military was meant to reduce crime and violence related to organized crime in Mexico, as a mixture of sheer brawn and deterrence. These tactics expanded under Calderon’s successors too in various permutations. However, whether these interventions had any effect on homicides is an empirical question. This study examines the effect of MIs on homicides in Mexican municipalities from December 2006- December 2019.

¹ José Manuel Aburto et al., "Homicides In Mexico Reversed Life Expectancy Gains For Men And Slowed Them For Women, 2000–10," *Health Aff.* 35, no. 1 (January, 2016), DOI: 10.1377/hlthaff.2015.0068; Vladimir Canudas-Romo et al., "Mexico's epidemic of violence and its public health significance on average length of life," *J. Epidemiol. Community Health* 71, no. 2 (2017), DOI: 10.1136/jech-2015-207015; José Manuel Aburto and Hiram Beltrán-Sánchez, "Upsurge of Homicides and Its Impact on Life Expectancy and Life Span Inequality in Mexico, 2005–2015," *Am. J. Public Health* 109, no. 3 (2019), DOI: 10.2105/ajph.2018.304878.

² Jose Roberto Balmori de la Miyar, Lauren Hoehn-Velasco, and Adan Silverio-Murillo, "Druglords don't stay at home: COVID-19 pandemic and crime patterns in Mexico City," *Journal of Criminal Justice* 72 (January, 2021), DOI: <https://doi.org/10.1016/j.jcrimjus.2020.101745>.

³ Amalendu Misra, "Prologue: The Horror," in *Towards a Philosophy of Narco Violence in Mexico* (London, England: Palgrave Macmillan, 2018). DOI: 10.1057/978-1-137-52654-0_1.

⁴ Jorge Chabat, *Combating Drugs in Mexico Under Calderon: The Inevitable War*, 2010, Centro de Investigación y Docencia Económicas.

II. THEORY

A. *Network Diffusion*

There are three predominate explanations for why MIs against DTOs may increase violence. One such explanation is trafficking network diffusion. In an important study by Dell, regression discontinuity estimates find that enforcement by Partido Accion Nacional (PAN) mayors weakens other criminal organizations in the local area via their crackdowns against traffickers.⁵ That is to say, PAN mayors are more enforcement prone than members of Mexico's more liberal parties. These crackdowns make the municipio inhospitable for business. In this view, drug trafficking organizations (DTOs) are understood as companies which seek to outcompete other traffickers to expand market share relative to other groups and maintain the flow of drug across the border. Crackdowns heighten the cost of trafficking drugs through more militarized areas of Mexico. Practically this results in a diversion of the roads that drug mules need to take to get to the American border. This diversion of traffic has the propensity to cause a clash between competing traffickers who fight amongst each other to maintain control of the land they use to move product from Mexico to the United States.

B. *Hobbes*

MIs against DTOs also have the effect of decreasing the opportunity costs of other rival groups attacking their now weakened rivals. Analogies to companies are again useful here. Traditional companies don't want competition, they want to control as much of market share as they possibly can, without respect to legal, moral or ethical outcomes. In this view, DTOs compete with each other based on their opportunity to do so. Given that MIs against drug traffickers weaken their respective organizations (for the time being anyways), other groups are incentivized to attack while their enemies are weakest, sometimes phrased as a Hobbesian state of war.⁶ Other scholars have made similar arguments, with statistician and geographer

⁵ Melissa Dell, "Trafficking Networks and the Mexican Drug War," *Am Econ Rev* 105, no. 6 (June, 2015), DOI: 10.1257/aer.20121637.

⁶ Javier Osorio, "Las causas estructurales de la violencia: evaluación de algunas hipótesis," in *Las bases sociales del crimen organizado y la violencia en México*, ed. José Antonio Aguilar Rivera (México: Secretaría de Seguridad Pública Federal y Centro de Investigación y Estudios en Seguridad, 2012); Javier Osorio, "Hobbes on Drugs:

Diego Valle-Jones arguing that the Sinaloa Cartel, in the years following the first interventions, waited until their rivals were weak and then proceeded to take more control of the market.⁷

C. *Fragmentation*

Additional empirical findings also document the relationship between enforcement measures and violence, via what's generally called "fragmentation" or some variant. Mediation analyses by Atuesta and colleagues,⁸ investigated what happened to the number of criminal organizations when the government arrested or killed traffickers. The number of DTOs *increased* post-enforcement by creating smaller groups, which fought against each other and the state than before, consequentially increasing violence.

Additionally, fragmentation may have more local effects on homicide as opposed to simply changing market composition/structure: Calderon and colleagues write "Local criminal cells might find it too costly to continue to engage in long-distance drug trade— which requires coordinating a large criminal network—and might switch to other delinquent behaviors to extract resources",⁹ such as murder for hire. In this purview, these additional homicides would no longer be related to the drug trade since the homicides are being committed for money against other civilians instead of on the basis that the killers work for the drug traffickers.

Instead of testing these hypotheses, I want to test if this relationship exists to begin with before the literature tests specific hypotheses. This study uses an updated dataset on MIs exceeding what other published analyses have done (detailed below). I exploit a long time series of pre-policy data to better approximate causal relationships between the intervention and homicide, using some simple new techniques in causal inference to better approximate causal effects.

Understanding Drug Violence in Mexico" (Ph.D Doctoral Dissertation, University of Notre Dame, 2013) (3738644); Javier Osorio, "The Contagion of Drug Violence: Spatiotemporal Dynamics of the Mexican War on Drugs," Article, *J. Conf. Res.* 59, no. 8 (2015), DOI: 10.1177/0022002715587048.

⁷ "Statistical Analysis and Visualization of the Drug War in Mexico," 2010, <https://tinyurl.com/yzou7x32>.

⁸ Laura H. Atuesta and Aldo F. Ponce, "Meet the Narco: increased competition among criminal organisations and the explosion of violence in Mexico," *Global Crime* 18, no. 4 (2017), DOI: 10.1080/17440572.2017.1354520.

⁹ Gabriela Calderón et al., "The Beheading of Criminal Organizations and the Dynamics of Violence in Mexico," Article, *J. Conf. Res.* 59, no. 8 (2015), DOI: 10.1177/0022002715587053.

III. DATA

A. Outcome Data

I study 1) overall homicide rate in a municipio in a given month as well as 2) the drug trade homicide rate (DTH).¹⁰ The second outcome requires further description: of course, there is no updated public repository for DTHs. There *was* once a dataset the Mexican government published on DTHs, but had no data pre-2006, and was only updated until 2010. One attempt to circumnavigate this missing data was examining the mean squared error across a million regressions to determine what the best age-gender cohort was, comparing public data to the government's data on drug trade homicides. The best proxy was homicides of men aged 15-39, and it is the measure I use here.¹¹ Both outcomes range from January 1990-December 2019. I also gathered data on the population of each of the 2466 municipios from 1990-2019.¹² Municipios with no population data at all from 1990-2005 were dropped (24 in total). Given that population is observed quintennially, linear interpolation was used to calculate the population in quintennial gaps (e.g., 2005-2010). All of the above are taken from INEGI.

B. Intervention Criteria

One difficult aspect of estimating causality is defining an intervention. One definition Espinosa and Rubin (E&R) used was “a confrontation between army and organized crime that resulted in at least three civilian deaths (where civilian could refer to a member of a cartel)”. I agree that this serves as a good proxy for enforcement. E&R continue however, writing “Note that this definition of treatment is different from “sending military forces” to a municipality, which would be the ideal definition for this topic”. E&R don't use this definition because the official list is classified, suggesting that future work should conduct comprehensive bilingual American media searches to get a more comprehensive list of MIs.¹³

¹⁰ "Mortality," 2021, <https://tinyurl.com/y3dbxxre>.

¹¹ Calderón et al., "The Beheading of Criminal Organizations and the Dynamics of Violence in Mexico."

¹² "XI General Census of Population and Housing 1990-2020," 2021, <https://tinyurl.com/yfkoykaq>.

¹³ Valeria Espinosa and Donald B. Rubin, "Did the Military Interventions in the Mexican Drug War Increase Violence?," *Am. Stat.* 69, no. 1 (February, 2015), DOI: 10.1080/00031305.2014.965796.

1. Search Strategy

Using Google search capabilities, I conducted a fairly comprehensive search of American media in both English and Spanish.¹⁴ After adapting the MIs from E&R, I searched through the websites *Borderland Beat*, *El Universal*, *La Jornada*, *Milenio*, and *Proceso*.¹⁵ I also searched generically, using keywords such as “Chihuahua” army “deployed” ” for each state in Mexico. I also include cases where troops clashed with DTOs (where *any* civilian, not just three people died) OR where troops were deployed to the area. This EXCLUDES simple arrests of traffickers and seizures of drugs or other contraband. If no community, city, locality or similar aggregation is mentioned to infer the location where the of clash/deployment took place, the article is dropped from the analysis. In total, 519 individual interventions were identified, with 289 individual municipios receiving an intervention at any point within the time series.

¹⁴ The full list is included in Appendix A.

¹⁵ In the list, states are omitted which didn't give relevant results. Examples of search queries include “site:https://www.eluniversal.com.mx/ ejercito desplegar before:2020-01-01”, “site:http://www.borderlandbeat.com soldiers "chihuahua" troops”, “site:http://www.borderlandbeat.com deployed "military””, “site:https://www.milenio.com "operativos" desplegar municipios”. The full list, open to expansion or correction, will be made public upon completion of my thesis, along with code and raw data.

IV. DESIGN

Ideally we'd infer causality via randomized controlled trials. In social science however, we can't (and wouldn't want to) do this for many phenomena such as increases in wages, earthquakes and floods or electoral outcomes. Thus, researchers must employ scientific thinking and careful statistical practices to properly isolate causal impacts via adjusting for simultaneity and imbalance in background covariates.¹⁶ The identification strategy I use is a difference-in-differences design (DD).¹⁷

A. DD: Assumptions, Estimands and Interventions

1. Parallel Trends Assumption

Predating randomization by 80 years with its roots in epidemiology,¹⁸ DD designs rely on a fairly simple intuition: even if randomization is impossible, perhaps investigators can use panel data regression methods to compare a unit which received an intervention to a unit which didn't in a sort of before and after framework. The parallel trends assumption (PTA) is a form of strict exogeneity $E[\varepsilon | X] = 0$.¹⁹ In terms of conditional expectations, PTA posits $E(Y_1^0 | X = x, D = 1) - E(Y_0^0 | X = x, D = 1) = E(Y_1^0 | X = x, D = 0) - E(Y_0^0 | X = x, D = 0)$, or that treated units (Y_{it}^1) would've followed those of the untreated units (Y_{it}^0) had it not been for the intervention. If PTA can be justified empirically, DD identifies the causal effect.

PTA is a difficult assumption to test for, especially in the case of the Mexican Drug War. The original PTA was developed for the canonical DD estimator, where $i = 2$ and $t = 2$ where i is a unit $i \dots, N$

¹⁶ Jerzy Splawa-Neyman, D. M. Dabrowska, and T. P. Speed, "On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9," *Statist. Sci.* 5, no. 4 (1990), DOI: 10.1214/ss/1177012031; Donald B. Rubin, "For objective causal inference, design trumps analysis," *Ann. Appl. Stat.* 2, no. 3 (2008/09, 2008), DOI: 10.1214/08-AOAS187; C. Bind Marie-Abele and Donald B. Rubin, "Bridging observational studies and randomized experiments by embedding the former in the latter," *Stat. Methods Med. Res.* 28, no. 7 (2019), DOI: 10.1177/0962280217740609; Donald B. Rubin, "Essential concepts of causal inference: a remarkable history and an intriguing future," *BioStat Epidemiol* 3, no. 1 (January, 2019), DOI: 10.1080/24709360.2019.1670513.

¹⁷ Michael Lechner, "The Estimation of Causal Effects by Difference-in-Difference Methods," *Found. Trends Econom* 4, no. 3 (2011), DOI: 10.1561/0800000014.

¹⁸ Ellen C Caniglia and Eleanor J Murray, "Difference-in-Difference in the Time of Cholera: a Gentle Introduction for Epidemiologists," *Curr. Epidemiol. Rep.* (2020), DOI: 10.1007/s40471-020-00245-2.

¹⁹ Scott Cunningham, *Causal inference: The mixtape*, (New Haven, CT: Yale University Press, 2021).

and t is a time period $2, \dots, T$. In this case, verification of PTA is impossible. Some generalized DD estimators allow for $i \geq 2$ and $t \geq 2$. For example, some studies implement DD via the two-way fixed effects (TWFE) model.²⁰ Econometricians typically use staggered adoption event study estimators to estimate the validity of parallel trends.²¹ There are three central problems with this approach: Firstly, in the “staggered” setting, $D_{t-1} = 1$. This is not the case here because $\exists i_t \in N D_{t-1} \neq 1$. This means that PTA assumptions change as well, since we’d now need to adjust for the treatment turning on and off.²² Secondly, the TWFE estimator only gives weighted averages of estimates where some of the estimated weights may be negative even if the effect is positive. Thirdly, TWFE may not account for underlying unobservable heterogeneity.²³

Unit-specific trends, matching, synthetic controls or other methods are sometimes used to make PTA more plausible.²⁴ While matching and synthetic controls show promise, these methods are prohibitive due to software and time reasons. Unit specific trends also don’t seem well suited: while adding unit-specific trends in the pre-policy period is defensible in cases where $D_{t-1} = 1$, including them throughout the entire time series where the policy varies may introduce bias by capturing any effect *previous* interventions might have on these linear, unobservable variables.²⁵

²⁰ Eric L. Sevigny et al., "PROTOCOL: The effects of cannabis liberalization laws on health, safety, and socioeconomic outcomes: An evidence and gap map," *Campbell Syst. Rev.* 17 (2020), DOI: 10.1002/cl2.1137.

²¹ Brantly Callaway and Pedro H. C. Sant’Anna, "Difference-in-Differences with multiple time periods," *Journal of Econometrics* forthcoming (2020), DOI: 10.1016/j.jeconom.2020.12.001.

²² Ricardo Mora and Iliana Reggio, "Alternative diff-in-diffs estimators with several pretreatment periods," *Econom Rev* 38, no. 5 (May, 2019), DOI: 10.1080/07474938.2017.1348683; Michelle Marcus and Pedro H. C. Sant’Anna, "The Role of Parallel Trends in Event Study Settings: An Application to Environmental Economics," *J Assoc Environ Resour Econ* 8, no. 2 (2021), DOI: 10.1086/711509.

²³ Kosuke Imai and In Song Kim, "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data," *Political Analysis* (2020), DOI: 10.1017/pan.2020.33; Jonathan Kropko and Robert Kubinec, "Interpretation and identification of within-unit and cross-sectional variation in panel data models," *PLoS One* 15, no. 4 (2020), DOI: 10.1371/journal.pone.0231349; Marc K. Chan and Simon S. Kwok, "The PCDD Approach: Difference-in-Differences when Trends are Potentially Unparallel and Stochastic," *Journal of Business & Economic Statistics* (2021), DOI: 10.1080/07350015.2021.1914636.

²⁴ Andrew M. Ryan et al., "Now trending: Coping with non-parallel trends in difference-in-differences analysis," *Stat. Methods Med. Res.* 28, no. 12 (December, 2019), DOI: 10.1177/0962280218814570; Myoung-jae Lee and Yasuyuki Sawada, "Review on Difference in Differences," *Korean Economic Review* 36, no. 1 (Winter, 2020).

²⁵ Erin C. Strumpf, Sam Harper, and Jay S. Kaufman, "Fixed Effects and Difference-in-Differences," Chapter 14 in *Methods in Social Epidemiology*, 2nd ed., eds. J. Michael Oakes and Jay S. Kaufman, (San Francisco, CA: Jossey-Bass & Pfeiffer, 2017).

2. Econometric Strategy

Even without additional sophisticated methods, we can still exploit recent advances in the DD methods to test PTA in this instance. To evaluate PTA, I estimate the difference between the “joiners”, that is municipios switching from untreated to treated for the first time, and the “leavers”, the units switching from treated to not.²⁶ For simplicity, I presume the intervention only lasted for that month, although we know that in practice sometimes the troops are deployed for months on end. To make this process explicit, my long difference placebo estimator takes the form of

$$DD_{+,t,k}^{pl} = \sum_{i:D_i=t} \frac{N_{i,t}}{N_{t,0}^1} (Y_{i,t} - Y_{i,t-l-1}) - \sum_{i:D_{i,1}>t} \frac{N_{i,t}}{N_t^{nt}} (Y_{i,t-1} - Y_{i,t-l-1}),$$

$$DD_{-,t,k}^{pl} = \sum_{i:D_i=t} \frac{N_{i,t}}{N_{t,0}^0} (Y_{i,t-k} - Y_{i,t-l-1}) - \sum_{i:D_{i,0}>t} \frac{N_{i,t}}{N_t^{nt}} (Y_{i,t-k} - Y_{i,t-l-1}),$$

This long difference placebo DD estimator compares the evolution of the trends of the eventually treated groups vs units which aren't treated in the previous lead periods up until the contemporaneous effect, as well as any dynamic effects in the post policy periods. To attempt to model pre-intervention trends correctly, I use a lead of 2 years so as not to capture medium term fluctuations in violence, and a lag of three years to estimate post policy effects. The goal of the DD design is to estimate the average treatment effect on the treated (ATT). The estimator itself looks like

$$DD_{i,t} = Y_{i,t} - Y_{i,D_{i,1}-1} - \sum_{i:D_{i,0}>t} \frac{N_{i,t}}{N_t^{at}} (Y_{i,t-1} - Y_{i,t-l-1}),$$

Here, $D = 1$ if a municipio experienced an intervention in a given month. There are 519 individual interventions which occurred within the post-2006 period.

²⁶ For all the specifics behind this approach I adopt here and related approaches, see Clément de Chaisemartin and Xavier D'Haultfœuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *Am Econ Rev* 110, no. 9 (2020), DOI: 10.1257/aer.20181169; Clément de Chaisemartin and Xavier D'Haultfœuille, Difference-in-Differences Estimators of Intertemporal Treatment Effects, 2020. DOI: <https://tinyurl.com/yedcmrqq>.

V. ESTIMATION

A. Assessing PTA, Graphical Tests

The first two figures present an informal test of PTA.

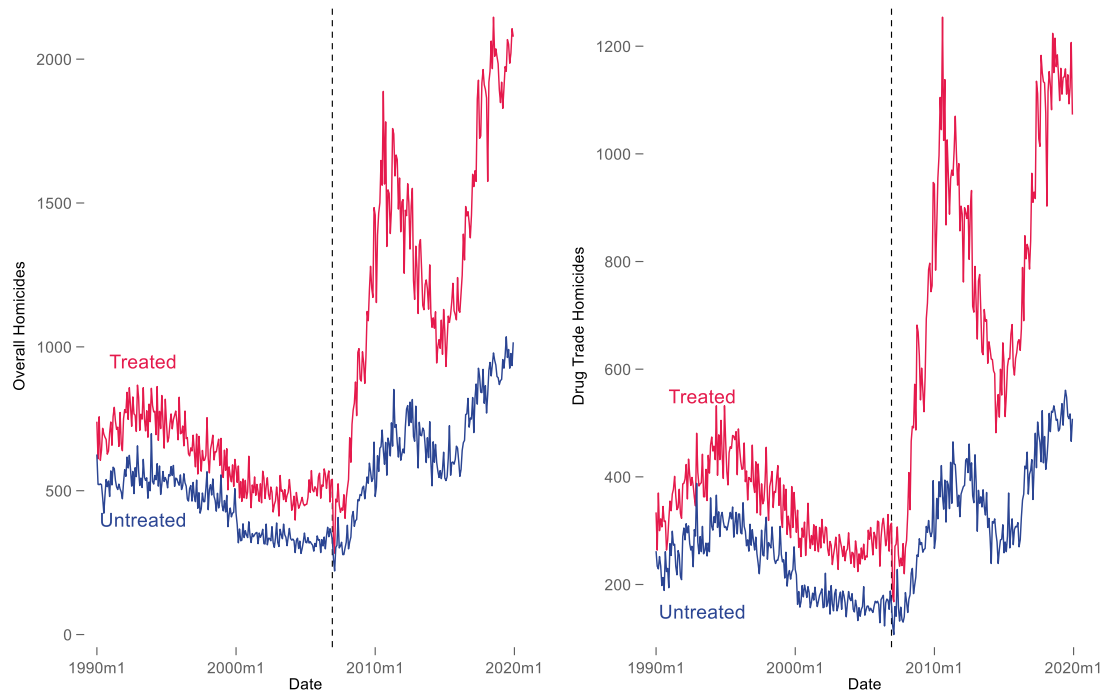


Fig. V-1, Graphical PTA

Evidence *against* PTA would be the trends in the intervention group increased before December 2006, and would imply that omitted variables are in fact causing the dramatic rise in homicides. Looking at the two figures, that isn't what we see. There at least some evidence for PTA based on the data presented. Binning each municipio into groups of ever versus never treated, we first see a slight rise in the number of homicides in both groups for both forms of homicide. Both groups of homicide see precipitous drops in homicide from the 1990s to the mid 2000s. After 2006 however, the homicides for both sets of units drastically increases in a relatively short timeframe, particularly in units which received the intervention. Below, we see the estimates for the pre-policy leads by 9 months. Models were only fit with unit-fixed

effects, since the negative binomial models would not converge with temporal indicators added. Figures 2 and 3 refer respectively to overall population and drug trade homicides.

B. DD Estimation

Now, we consider the formalized DD estimates. These estimates, as described above, use “clean” controls, that is, compare newly treated units to “clean” controls, to borrow the language from a recent paper using a similar method.²⁷ Bear in mind, this DD estimator relies on comparing newly treated units, the joiners, to units that have not been treated. In the traditional TWFE approach, this estimator doesn’t distinguish between units that have been treated yet or not. DD_L drops units that have been treated already from the control group for newly treated units, allowing for more valid comparisons. The results of the estimator are presented below.

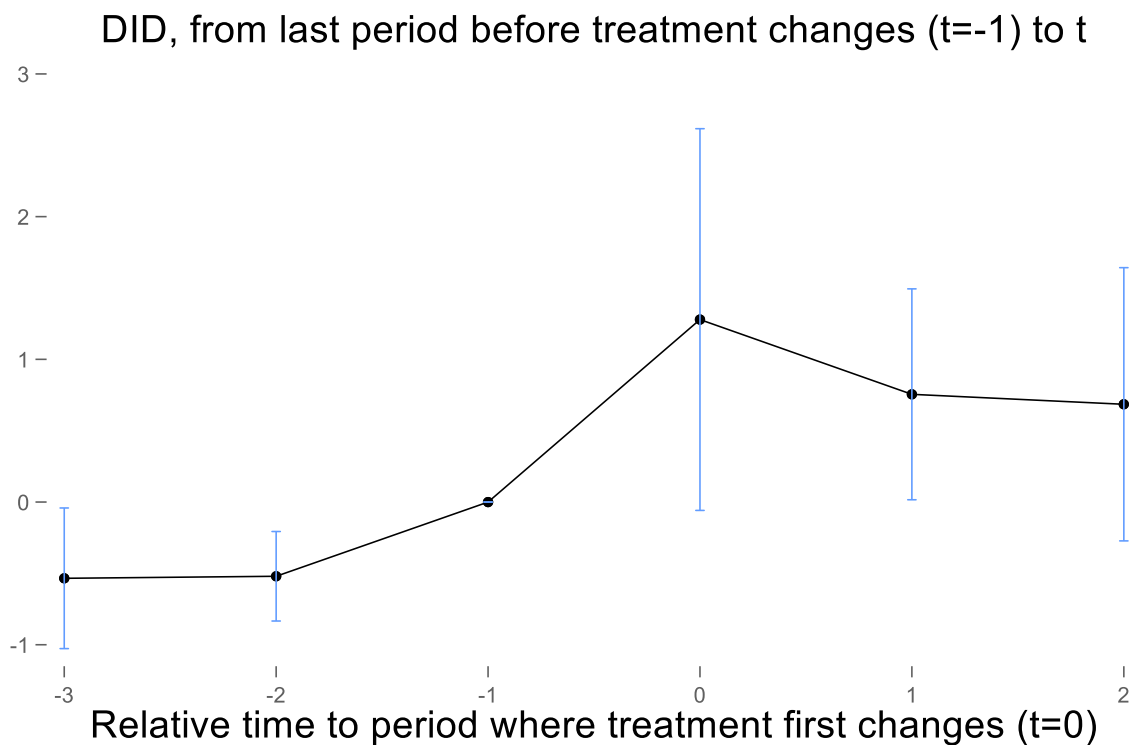


Fig. V-2, DD: Overall Homicide

²⁷ Doruk Cengiz et al., "The Effect of Minimum Wages on Low-Wage Jobs," *Quart. J. Econ.* 134, no. 3 (August, 2019), DOI: 10.1093/qje/qjz014.

The DD estimates indicate what the previous graphical analyses implied: there is no good evidence of a practically meaningful PTA violation. The point estimates for the contemporaneous effects imply that the weighted ATT of a military intervention increases the homicide rate per 100k in the general population relative to the first time the treatment changed by about 1.28 [95%: -.0585, 2.62] in the contemporary period, .755 in the year after [95%: .01600, 1.49], and .685 two years after an intervention [95%: .01600, 1.49]. To iterate why this is preferable to the TWFE approach, the TWFE approach doesn't distinguish between what constitutes a good control/comparison unit. The treated units are retained in the analysis as comparators. In the DD_L approach, we explicitly compare newly treated municipios only to the municipios which haven't received an intervention yet, also known as clean controls. I repeat this same exercise with the proxy for drug trafficking homicides below.

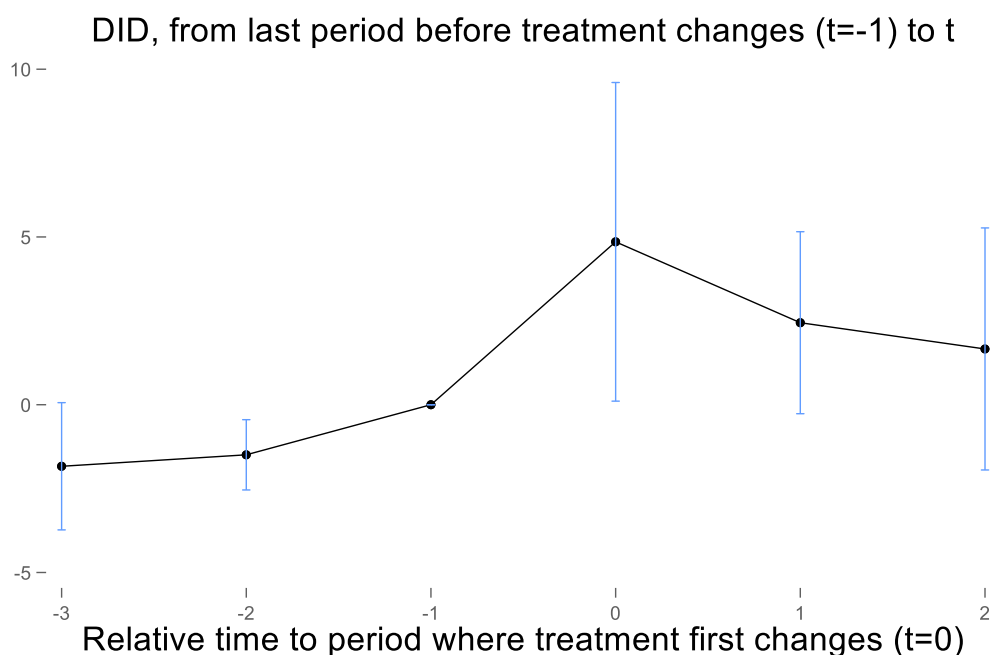


Fig. V-3 DTH Homicides

The DD estimates still indicate no violation of PTA. The point estimates for the contemporaneous effects imply that the weighted ATT of a military intervention increases the drug trade homicide rate per 100k by about 4.86 [95%: 0.107, 9.60] in the contemporary period, 2.44 in the year after [95%: -0.267,

5.16], and 1.66 two years after an intervention [95%: -1.94, 5.27] This still doesn't change the central conclusions of the analysis, namely that MI have increased homicides substantially relative to the year before the interventions occurred. The policies of the Mexican government seem to have produced increases in violence in the contemporary period, with this trend increasing since 2006.

VI. CONCLUSION

While I've extended previous works and applied new methods, there are multiple shortcomings to my analysis: Firstly, I could've done a more systematic search to get a list of interventions, using other publications or Lexis Nexis. Methodologically, I could've also improved my analysis in several ways: there are DD commands which allow for coarsened exact matching and other estimators which would be useful. While powerful, I thought it best to leave analyses of this and similar complexities for published work or a dissertation. These methods would go a long way in making sure that the intervention groups are as comparable as possible on pre-intervention trends.

Another methodological aspect I could improve, not explicitly discussed above, is accounting for spillover effects. It's perfectly possible that there are real spillover effects from interventions, which would dilute what we use as the control groups: in this case, units would switch in and out of the control groups not simply based on treatment status, but also based on geographic proximity to treated units. Of course, this is simply an ad-hoc approach, though: really addressing this question seriously would involve causal network methods, as was also suggested by E&R. Including other background covariates would also improve comparisons: however, due to time reasons, collecting such granular level data would've been quite difficult, but will be useful in the furthering of this work. Additionally, cartel information and other variables specific to the drug trade would've been useful in ensuring that units are being compared appropriately. For now, however, the main takeaway seems to be that military interventions in the Mexican Drug war likely increased homicides in the short and medium terms. Whether this causal evaluation holds true when evaluated with more granular covariates and more rigorous assessment of comparison units and additional adjustment techniques is left for future work.

APPENDIX

I. Aguascalientes

1. Rincon de Romos, Aguascalientes: August, 2008
2. Aguascalientes, Aguascalientes, Jan 2013
3. Aguascalientes, Aguascalientes, Dec 2018
4. Jesús María, Aguascalientes, July 2019

II. Baja California

1. Tijuana, April 18, 2007 (Hospital Shootout)
2. Tijuana, April 26, 2008
3. Tijuana, October, 2009
4. Tijuana, Jan 2010
5. Tijuana, Sep 2016
6. Tijuana, Feb 2019
7. Tijuana, Baja California
8. Ensenada, Baja California
9. San Quintín, Baja California (all here. Code SQ as Esenada, because at this time, July 2019, SQ wasn't officially a municipio yet, they must mean the city here.)

III. Baja California Sur

1. La Paz, February 2014
2. Los Cabos
3. La Paz, April 2017
4. Los Cabos, Jan 2018
5. La Paz, Jan 2018
6. La Paz, Baja California Sur
7. Comondú, Baja California Sur
8. Mulegé, Baja California Sur

9. Los Cabos, Baja California Sur (July 2019, all [here](#))

IV. Campeche

1. Ciudad del Carmen, Carmen, [Dec](#) 2007
2. Campeche capital, Campeche
3. Ciudad del Carmen, Campeche (July 2019, all [here](#))

V. Coahuila

1. Piedras Negras, [May](#) 2010
2. Saltillo, [March](#) 2011
3. Ciudad Acuna, [Dec](#) 2011
4. Ciudad Acuna, [Feb](#) 2012
5. Piedras Negras
6. Saltillo, [Sep](#) 2012
7. Ciudad Acuna, [Feb](#) 2013
8. Torreón Municipality
9. Matamoros Municipality
10. San Pedro Municipality
11. Francisco I. Madero Municipality
12. Viesca Municipality [Feb](#) 2013 (LS)
13. Monclava, [March](#) 2013
14. San Juan de Sabinas, [May](#) 2019
15. Torreón, Coahuila
16. Saltillo, Coahuila
17. Monclova, Coahuila
18. Cuatro Ciénegas, Coahuila (July 2019, all [here](#))

VI. Colima

1. Colima, [Dec](#) 2010

2. Tecoman, August 2017
3. Colima, Jan 2018
4. Tecomán
5. Manzanillo, Jan 2018
6. Colima, Feb 2018
7. Manzanillo, Colima, Feb 2019
8. Manzanillo, Colima, July, 2019

VII. Chiapas

1. Frontera Comalapa
2. Chicomuselo
3. Jiquipilas, April, 2008
4. Tuxtla Gutierrez, Feb 2010
5. ~~Tuxtla Gutierrez, Dec 2011 (Presumed) **This article isn't very specific. However, the original article mentions that this is part of Operativo Laguna Segura. Thus, we can assume at a conservative level that Torreón**~~
6. ~~Chiapas, Jan 2013. Upon further investigation, this refers to Terreon.~~
7. Comitán, Chiapas
8. Huehuetán, Chiapas
9. Las Margaritas, Chiapas
10. Ocosingo, Chiapas
11. Palenque, Chiapas
12. Tapachula, Chiapas
13. Tonalá, Chiapas
19. Tuxtla Gutiérrez, Chiapas (July 2019, all here)
20. Palenque, Dec 2019

VIII. Chihuahua

1. Ciudad Juarez, March 2008
2. Chihuahua City, March 2008 (ER)
3. Juarez, March 2009
4. Acension, June 2009
5. Chihuahua, August 2009
6. Buenaventura, Oct 2009
7. Juarez, April 2010
8. Juárez, August 2010
9. Guadalupe y Calvo, Chihuahua, December 2012
10. Guachochi, Chihuahua, Feb 2013
11. “[Hidalgo del] Parral June 2013
12. Jimenez, Chihuahua August 2017
13. Juarez, Jan 2018
14. Cd. Juárez
15. Chihuahua
16. Parral, Chihuahua, May, 2018
17. Juárez, Chihuahua, Feb 2019
18. Chihuahua, Chihuahua
19. Delicias, Chihuahua
20. Guachochi, Chihuahua
21. Ciudad Cuauhtémoc, Chihuahua
22. Ciudad Juárez, Chihuahua (July 2019, all here)

IX. CDMX

1. Tlahuac, May 2015
2. Iztapalapa
3. Gustavo A. Madero

4. Tlalpan
 5. Tláhuac
 6. Xochimilco, (July 2019, all [here](#))
 7. Cuauhtémoc, [Oct 2019](#)
- X. Durango
1. Gómez Palacio
 2. Lerdo, [August 2008](#)
 3. [Santiago Papasquiaro, August 2010](#)
 4. Gómez Palacio
 5. Lerdo, jan 2013 (OP LAG SEGUR)
 6. [Otaez, Durango, August 2013](#)
 7. Durango capital
 8. Gómez Palacios (July 2019, all [here](#))
- XI. Guanajuato
1. Irapuato
 2. Salamanca [August 2017](#)
 3. Celaya
 4. Apaseo el Grande
 5. León, [March 2018](#).
 6. León
 7. Irapuato
 8. Celaya
 9. Salamanca, Guanajuato, [Jan, 2019](#)
 10. San Miguel de Allende
 11. Apaseo el Alto

12. Apaseo el Grande
13. Celaya
14. Comonfort...
15. Irapuato
16. Pueblo Nuevo
17. Romita
18. Silao
19. Jaral del Progreso
20. Salamanca
21. Juventino Rosas
22. Valle de Santiago
23. Villagrán
24. Cortazar
25. Moroleón
26. Salvatierra
27. Santiago Maravatío
28. Uriangato
29. Yuriria, Guanajuato, Feb 2019
30. Irapuato
31. Celaya
32. Romita
33. Pueblo Nuevo
34. Silao...
35. Apaseo el Alto
36. Apaseo el Grande
37. Comonfort

38. San Miguel de Allende ...
39. Juventino Rosas
40. Villagrán
41. Jaral del Progreso
42. Valle de Santiago
43. Yuriria
44. Cortazar
45. Moroleón
46. Salvatierra
47. Santiago Maravatío, Guanajuato, March 2019
48. Irapuato, Guanajuato
49. Salamanca, Guanajuato
50. Uriangato, Guanajuato
51. Celaya, Guanajuato
52. San Francisco del Rincón, Guanajuato
53. Jerécuaro, Guanajuato
54. León, Guanajuato (July 2019, all here)
55. San Luis de la Paz, Guanajuato
56. Guanajuato, Guanajuato (July 2019, all here)
57. Celaya
58. Irapuato
59. León, Guanajuato, Nov 2019

XII. Guerrero

1. Acapulco
2. Zihuatanejo
3. Iguala

4. Chilpancingo
5. Zirandaro
6. Coyacua de Catalan
7. Pungarabato
8. Cutzamala de Pinzon Jan 2007.
9. Arcelia: Dec 2008 (ER)
10. Acapulco, June 2009
11. Acapulco, March 2010
12. Acapulco: April 2010
13. Taxco, 2010 June
14. Acapulco, Oct 2011
15. Zihuatanejo: May 2012
16. Tecpan de Galeana, September, 2012
17. Acapulco
18. Chilpancingo, GUR, Jan 2014
19. Acapulco
20. Iguala
21. Taxco
22. Teloloapan
23. Eduardo Neri
24. San Miguel Totolapan
25. Ajuchitlán del Progreso
26. Apaxtla de Castrejón
27. Pungarabato
28. Coyuca de Catalán
29. Tlalchapa

30. Buenavista de Cuellar
31. Zirándaro
32. Pedro Ascencio de Alquiciras
33. Pilcaya
34. Tlapehuala
35. Cuetzala
36. Cocula
37. General Canuto A. Neri
38. Ixcateopan
39. Cutzamala de Pinzón
40. Tetipac, (all [April 2014](#))
41. Acapulco, [March 2016](#)
42. Acapulco [September 2016](#)
43. Chilapa de Álvarez
44. Zitlala [March, 2017](#)
45. Acapulco: [February 2018](#)
46. Leonardo Bravo, [Nov 2018](#)
47. Acapulco
48. Chilpancingo
49. Zihuatanejo
50. Chilapa de Álvarez, (July, all [here](#))
51. Acapulco
52. Chilpancingo, GUR, [Feb 2019](#)
53. Acapulco, [May 2019](#)
54. Leonardo Bravo, [Sep 2019](#)
55. Iguala, [Oct 2019](#)

56. Acapulco: November 2019

XIII. Hidalgo

1. Pachuca, Hidalgo
2. Actopan, Hidalgo (July 2019, all [here](#))

XIV. Jalisco

1. Mexquitic, July 2011
2. San Sebastian del Oeste
3. Puerto Vallarta, April 2015
4. San José de Avila (Unión de Tula)
5. Villa Purificación, Jalisco: May 2015
6. Puerto Vallarta, Jalisco, September 2015
7. Tala, Jalisco, July 2017
8. Ocotlán, Jan 2018
9. San Julián, Jalisco, August 2018
10. Tlajomulco de Zúñiga
11. Guadalajara Feb 2019
12. Zapopan, June 2019
13. Guadalajara, Jalisco
14. Lagos de Moreno, Jalisco
15. Tlajomulco, Jalisco
16. Puerto Vallarta, Jalisco (July 2019, all [here](#))

XV. EDOMEX

1. Nezahualcoyotl, Sep 2012
2. August 28, 2014: EDOMEX, Valle de Bravo
3. Amatepec

4. Ixtapan de la Sal
5. Sultepec
6. Tejupilco
7. Tlatlaya
8. Tonicato
9. Zacualpan
10. Zumpahuacán (Dec 2014, all)
11. Chalco, May 2015
12. Tlalnepantla
13. Naucalpan
14. Tultitlán
15. Chimalhuacán
16. Ecatepec
17. Nezahualcóyotl
18. Tecámac
19. Valle de Chalco, EDOMEX, Sep 2016
20. Ecatepec de Morelos, Feb 2019
21. Ecatepec, Estado de México
22. Nezahualcóyotl, Estado de México
23. Atlacomulco, Estado de México
24. Nicolás Romero, Estado de México
25. Ixtapaluca, Estado de México
26. Tejupilco, Estado de México
27. Chalco, Estado de México
28. Chimalhuacán, Estado de México
29. Atizapán de Zaragoza, Estado de México

30. Coacalco, Estado de México
31. Cuautitlán, Estado de México
32. Cuautitlán Izcalli, Estado de México
33. Metepec, Estado de México
34. Huixquilucan, Estado de México
35. Teotihuacán, Estado de México
36. Tultitlán, Estado de México
37. Jilotepec , Estado de México
38. Valle de Chalco, Estado de México
39. Tecámac, Estado de México
40. Texcoco, Estado de México
41. Tultepec, Estado de México
42. La Paz, Estado de México
43. Toluca, Estado de México
44. Naucalpan, Estado de México
45. Tlalnepantla, Estado de México
46. Zumpango, Estado de México
47. Tenancingo, Estado de México all here, July 2019

XVI. Michoacan de Ocampo

1. Aguililla
2. Apatzingán
3. Coalcomán, Dec 2006
4. Apatznigan: May, 2007
5. Turicato
6. May 2007: Carácuaro
7. Apatzingan, June 2007

8. Parácuaro
9. Apatzingán
10. Nueva Italia
11. Aguililla
12. Buena Vista
13. Tepalcatepec
14. La Huacana
15. Arteaga, Feb 2008
16. Presume capital: July 2009
17. La Piedad, Jan 2010
18. Heroica Zitácuaro, June 2010
19. Morelia
20. Pátzcuaro Nov 2010
21. Dec 2010, Apatzingán, Michoacan
22. Tacámbaro, Michoacán, August 2011
23. Pátzcuaro
24. Quiroga
25. Erongarícuaro
26. Tzintzuntzan Oct 2011
27. Tancitaro, Michoacan, October 2011
28. Tiquicheo: March 2012
29. La Ruana (Buenavista), May 2013
30. Lázaro Cárdenas, Nov 2013
31. Múgica, Jan 2014
32. Buenavista
33. Apatzingán, March 2014

34. Huetamo
35. San Lucas, December 2014
36. La Piedad: October 2015
37. Buenavista, Michoacan March 2017
38. Buenavista, Michoacan, February 2019
39. Zamora: May 2019
40. Morelia, Michoacán
41. Uruapan, Michoacán
42. Lázaro Cárdenas, Michoacán
43. Apatzingán, Michoacán
44. Zamora, Michoacán
45. Huetamo, Michoacán
46. Los Reyes, Michoacán
47. Zacapu, Michoacán
48. Pátzcuaro, Michoacán (July 2019, all here)
49. Uruapan, Michoacán, August 2019
50. Tepalcatepec, Michoacan, Sep 2019
51. Aguililla, Michoacan: October 2019

XVII. Morelos

1. Cuernavaca
2. Temixco
3. Jiutepec
4. Yautepec
5. Cuautla
6. Emiliano Zapata
7. Xochitepec

8. Puente de Ixtla
9. Jojutla
10. Zacatepec, May 2012
11. Coatlán
12. Puente de Ixtla
13. Tetecala, Dec 2014
14. Jojutla, September 2015
15. Cuernavaca
16. Jiutepec, (July 2019, all here)

XVIII. Nayarit

1. Tepic, June 2010
2. Tepic, Nov 2010
3. Tepic, Feb, 2017
4. Tepic
5. Bahía de Banderas (July 2019, all here)

XIX. Nuevo Leon

1. Linares
2. Galeana
3. Monterrey, Feb 2007
4. Marin, April 2007
5. Cadeyereta, Dec 2007
6. Garcia, Nuevo Leon: November 2009
7. Los Ramones, Nuevo Leon: February 2010
8. San Nicolas de los Garza, April 2010
9. Monterry, Nuevo Leon: June 2010
10. General Treviño, Nuevo Leon Sep 2010

11. Garcia
 12. Cadereyta
 13. Escobedo
 14. General Teran, Jan 2011
 15. Escobedo, Nuevo Leon, May 2011
 16. Monterrey, Sep 2010
 17. Monterry, August 2011
 18. Cadereyta Jimenez, Nuevo Leon, March 2012
 19. Cerralvo, Nuevo Leon, April 2013
 20. Monterrey, Feb 2019
 21. Monterrey, Nuevo León
 22. García, Nuevo León
 23. Guadalupe Victoria, Nuevo León
 24. Sabinas Hidalgo, Nuevo León (July 2019, all [here](#))
- XX. Oaxaca
1. Juchitán de Zaragoza, April 2016
 2. Loma Bonita, Oct 2017
 3. Oaxaca capital, Oaxaca
 4. San Juan Baustista Tuxtepec, Oaxaca
 5. Salina Cruz, Oaxaca (July 2019, all [here](#))
- XXI. Puebla
1. Quecholac
 2. Palmar de Bravo
 3. Tepeaca
 4. Tecamachalco
 5. Acajete

6. Amozoc
7. Acatzingo, Puebla: [March 2018](#)
8. Tehuacán, Puebla
9. Puebla, Puebla (July 2019, all [here](#))

XXII. Queretato

1. Querétaro capital, Querétaro
2. San Juan del Río, Querétaro (July 2019, all [here](#))

XXIII. Quintana Roo

1. Cancun: [February 2009](#)
2. Cancun
3. Playa del Carmen, [April 2017](#)
4. Cancun, [January 2018](#)
5. [Cancun, October 2018](#)
6. Cancun, [Jan 2019](#)
7. Benito Juárez, [Feb 2019](#)
8. Benito Juárez
9. Cozumel
10. Solidaridad
11. Othon (July 2019, all [here](#))

XXIV. SLP

1. SLP City, [April 2011](#)
2. Río Verde
3. Santa María del Río
4. Matehuala
5. San Luis Potosí (July 2019, all [here](#))

XXV. Sinaloa

1. La Joya de los Martinez: June, 2007
2. Badriaguato,: March 2008
3. Navolato
4. Culiacan: May 2008
5. April 2009, Ahome
6. Badiraguato
7. Sinaloa de Leyva
8. Ahome
9. El Fuerte, June 2009
10. Choix, Sinaloa, April 2012
11. Choix, Sinaloa July, 2012
12. Culiacan, Sinaloa, August 2013
13. El Rosario, \Sinaloa, August 2015
14. Badiraguato: October 2016
15. Mazatlan: December 2016
16. Mazatlan, Sinaloa, July 2017
17. Culiacán, Feb 2019
18. Rosario, April 2019
19. Ahome
20. El Fuerte
21. Mazatlán
22. Culiacán (July 2019, all here)
23. Culiacan, October 2019

XXVI. Sonora

1. Cananea, May 2007
2. Nogales: October 2008 (ER)

3. Hermosillo
4. Cajeme
5. Guaymas
6. San Luis Río Colorado (July 2019, all [here](#))
7. Guaymas: [October 2019](#)

XXVII. Tabasco

1. Cárdenas, Tabasco
2. Villahermosa, Tabasco (July 2019, all [here](#))

XXVIII. Tamaulipas

1. [Ciudad Victoria, NL, Feb 2007](#)
2. Tampico, Tamaulipas: October, 2007
3. Reynosa
4. Nuevo Laredo
5. Río Brav
6. Valle Hermoso, [Jan](#) 2008
7. Matamoros, [March](#) 2008
8. Ciudad Mier, April, 2008
9. Reynosa
10. Miguel Alemán
11. Matamoros
12. Mier
13. Guerrero
14. Díaz Ordaz
15. Victoria
16. Tampico
17. Madero, [Feb](#) 2010

18. Camargo: April 2010
19. Ciudad Mier, September 2010
20. Nuevo Guerrero
21. Ciudad Mier
22. Miguel Aleman
23. Camargo
24. Diaz Ordaz Tamaulipas Nov 2010
25. Reynosa, Tamaulipas, Nov 2010
26. Mier, Tamaulipas April 2011
27. San Fernando, Tamaulipas: November 2011
28. Reynosa, Tamaulipas, April 2013
29. Mier Tamaulipas, April 2014
30. Altamira
31. Tampico, June 2014
32. Reynosa
33. Matamoros, Tamaulipas, Dec 2014
34. González
35. Aldama
36. Soto la Marina, Tamaulipas, Jan 2015
37. Nuevo Laredo, September 2016
38. Nuevo Laredo, Tamaulipas, October 2015
39. Matamoros, Tamaulipas, July 2017
40. Ciudad Mante, Tamaulipas, Dec 2017
41. Matamoros
42. Ciudad Madero
43. Soto la Marina

44. Nuevo Laredo

45. Reynosa (July 2019, all [here](#))

XXIX. Tlaxcala

46. Tlaxcala, Tlaxcala (July 2019, all [here](#))

XXX. Veracruz

1. [Panuco, Veracruz, September 2010](#)

2. Boca del Río, [May 2011](#)

3. Veracruz, [June 2011](#)

4. Coatzacoalcos, Veracruz, [Sep 2012](#)

5. Minatitlán, [April 2019](#)

6. Zongolica, Veracruz: [April 2019](#)

7. Minatitlán

8. Coatzacoalcos

9. Cosoleacaque

10. Acayucan

11. Tuxpan

12. Veracruz

13. Orizaba

14. Poza Rica

15. Xalapa

16. Cosamalopan

17. Córdoba

18. Martínez de la Torre (July 2019, all [here](#))

XXXI. Yucatan

1. Mérida, Yucatán

2. Progreso, Yucatán (July 2019, all [here](#))

XXXII. Zacatecas

1. Villa de Cos: May, 2008 (ER)
2. Villanueva and Luis Moya, September 2011
3. Fresnillo, October, 2012
4. CDO, Zacatecas, May 2012
5. Pinos and Villa González, August 2012
6. Río Grande, Zacatecas, Jan 2013
7. Sombrerete: July 2013
8. Jalpa
9. Fresnillo
10. Río Grande
11. Zacatecas (July 2019, all here)

REFERENCES

- Aburto, José Manuel, and Hiram Beltrán-Sánchez. "Upsurge of Homicides and Its Impact on Life Expectancy and Life Span Inequality in Mexico, 2005–2015." *Am. J. Public Health* 109, no. 3 (2019): 483-89. DOI: 10.2105/ajph.2018.304878.
- Aburto, José Manuel, Hiram Beltrán-Sánchez, Victor M. Garcia-Guerrero, and Vladimir Canudas-Romo. "Homicides in Mexico Reversed Life Expectancy Gains for Men and Slowed Them for Women, 2000–10." *Health Aff.* 35, no. 1 (January, 2016): 88-95. DOI: 10.1377/hlthaff.2015.0068.
- Atuesta, Laura H., and Aldo F. Ponce. "Meet the Narco: Increased Competition among Criminal Organisations and the Explosion of Violence in Mexico." *Global Crime* 18, no. 4 (2017): 375-402. DOI: 10.1080/17440572.2017.1354520.
- Balmori de la Miyar, Jose Roberto, Lauren Hoehn-Velasco, and Adan Silverio-Murillo. "Druglords Don't Stay at Home: Covid-19 Pandemic and Crime Patterns in Mexico City." *Journal of Criminal Justice* 72 (January, 2021): 101745. DOI: <https://doi.org/10.1016/j.jcrimjus.2020.101745>.
- Calderón, Gabriela, Gustavo Robles, Alberto Díaz-Cayeros, and Beatriz Magaloni. "The Beheading of Criminal Organizations and the Dynamics of Violence in Mexico." *Article. J. Conf. Res.* 59, no. 8 (2015): 1455-85. DOI: 10.1177/0022002715587053.
- Callaway, Brantly, and Pedro H. C. Sant'Anna. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics* forthcoming (2020). DOI: 10.1016/j.jeconom.2020.12.001.
- Caniglia, Ellen C, and Eleanor J Murray. "Difference-in-Difference in the Time of Cholera: A Gentle Introduction for Epidemiologists." *Curr. Epidemiol. Rep.* (2020): 1-9. DOI: 10.1007/s40471-020-00245-2.
- Canudas-Romo, Vladimir, José Manuel Aburto, Victor Manuel García-Guerrero, and Hiram Beltrán-Sánchez. "Mexico's Epidemic of Violence and Its Public Health Significance on Average Length

- of Life." *J. Epidemiol. Community Health* 71, no. 2 (2017): 188-93. DOI: 10.1136/jech-2015-207015.
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. "The Effect of Minimum Wages on Low-Wage Jobs." *Quart. J. Econ.* 134, no. 3 (August, 2019): 1405-54. DOI: 10.1093/qje/qjz014.
- Chabat, Jorge. *Combatting Drugs in Mexico under Calderon: The Inevitable War*. 2010. Centro de Investigación y Docencia Económicas.
- Chan, Marc K., and Simon S. Kwok. "The Pcdid Approach: Difference-in-Differences When Trends Are Potentially Unparallel and Stochastic." *Journal of Business & Economic Statistics* (2021): 1-43. DOI: 10.1080/07350015.2021.1914636.
- Cunningham, Scott. *Causal Inference: The Mixtape*. New Haven, CT: Yale University Press, 2021.
- de Chaisemartin, Clément, and Xavier D'Haultfœuille. *Difference-in-Differences Estimators of Intertemporal Treatment Effects*. 2020. DOI: <https://tinyurl.com/yedcmrqq>.
- . "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *Am Econ Rev* 110, no. 9 (2020): 2964-96. DOI: 10.1257/aer.20181169.
- Dell, Melissa. "Trafficking Networks and the Mexican Drug War." *Am Econ Rev* 105, no. 6 (June, 2015): 1739-79. DOI: 10.1257/aer.20121637.
- Espinosa, Valeria, and Donald B. Rubin. "Did the Military Interventions in the Mexican Drug War Increase Violence?". *Am. Stat.* 69, no. 1 (February, 2015): 17-27. DOI: 10.1080/00031305.2014.965796.
- Imai, Kosuke, and In Song Kim. "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis* (2020): 1-11. DOI: 10.1017/pan.2020.33.
- "Mortality." 2021, <https://tinyurl.com/y3dbxxre>.
- "Xi General Census of Population and Housing 1990-2020." 2021, <https://tinyurl.com/yfkoykaq>.
- Kropko, Jonathan, and Robert Kubinec. "Interpretation and Identification of within-Unit and Cross-Sectional Variation in Panel Data Models." *PLoS One* 15, no. 4 (2020): e0231349. DOI: 10.1371/journal.pone.0231349.

- Lechner, Michael. "The Estimation of Causal Effects by Difference-in-Difference Methods." *Found. Trends Econom* 4, no. 3 (2011): 165-224. DOI: 10.1561/08000000014.
- Lee, Myoung-jae, and Yasuyuki Sawada. "Review on Difference in Differences." *Korean Economic Review* 36, no. 1 (Winter, 2020): 135-73.
- Marcus, Michelle, and Pedro H. C. Sant'Anna. "The Role of Parallel Trends in Event Study Settings: An Application to Environmental Economics." *J Assoc Environ Resour Econ* 8, no. 2 (2021): 235-75. DOI: 10.1086/711509.
- Marie-Abele, C. Bind, and Donald B. Rubin. "Bridging Observational Studies and Randomized Experiments by Embedding the Former in the Latter." *Stat. Methods Med. Res.* 28, no. 7 (2019): 1958-78. DOI: 10.1177/0962280217740609.
- Misra, Amalendu. "Prologue: The Horror." Chap. 1 In *Towards a Philosophy of Narco Violence in Mexico*, 1-12. London, England: Palgrave Macmillan, 2018. DOI: 10.1057/978-1-137-52654-0_1.
- Mora, Ricardo, and Iliana Reggio. "Alternative Diff-in-Diffs Estimators with Several Pretreatment Periods." *Econom Rev* 38, no. 5 (May, 2019): 465-86. DOI: 10.1080/07474938.2017.1348683.
- Osorio, Javier. "The Contagion of Drug Violence: Spatiotemporal Dynamics of the Mexican War on Drugs." Article. *J. Conf. Res.* 59, no. 8 (2015): 1403-32. DOI: 10.1177/0022002715587048.
- . "Hobbes on Drugs: Understanding Drug Violence in Mexico." Ph.D Doctoral Dissertation, University of Notre Dame, 2013 (3738644).
- . "Las Causas Estructurales De La Violencia: Evaluación De Algunas Hipótesis." In *Las Bases Sociales Del Crimen Organizado Y La Violencia En México*, edited by José Antonio Aguilar Rivera, 73-132. México: Secretaría de Seguridad Pública Federal y Centro de Investigación y Estudios en Seguridad, 2012.
- Rubin, Donald B. "Essential Concepts of Causal Inference: A Remarkable History and an Intriguing Future." *Biostat Epidemiol* 3, no. 1 (January, 2019): 140-55. DOI: 10.1080/24709360.2019.1670513.

- . "For Objective Causal Inference, Design Trumps Analysis." [In en]. *Ann. Appl. Stat.* 2, no. 3 (2008/09, 2008): 808-40. DOI: 10.1214/08-AOAS187.
- Ryan, Andrew M., Evangelos Kontopantelis, Ariel Linden, and James F. Burgess. "Now Trending: Coping with Non-Parallel Trends in Difference-in-Differences Analysis." *Stat. Methods Med. Res.* 28, no. 12 (December, 2019): 3697-711. DOI: 10.1177/0962280218814570.
- Sevigny, Eric L., Rosalie Liccardo Pacula, Ariel M. Aloe, Danye N. Medhin, and Jared A. Greathouse. "Protocol: The Effects of Cannabis Liberalization Laws on Health, Safety, and Socioeconomic Outcomes: An Evidence and Gap Map." *Campbell Syst. Rev.* 17 (2020): e1137. DOI: 10.1002/cl2.1137.
- Splawa-Neyman, Jerzy, D. M. Dabrowska, and T. P. Speed. "On the Application of Probability Theory to Agricultural Experiments. Essay on Principles. Section 9." [In en]. *Statist. Sci.* 5, no. 4 (1990): 465-72. DOI: 10.1214/ss/1177012031.
- Strumpf, Erin C., Sam Harper, and Jay S. Kaufman. "Fixed Effects and Difference-in-Differences." Chap. 14 In *Methods in Social Epidemiology*, J. Michael Oakes and Jay S. Kaufman, eds., 341-68. San Francisco, CA: Jossey-Bass & Pfeiffer, 2017.
- "Statistical Analysis and Visualization of the Drug War in Mexico." 2010, <https://tinyurl.com/yzou7x32>.