Increasing Intergovernmental Coordination to Fight Crime: Evidence from Mexico

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Abstract

Latin America is the most violent region in the world, with many countries also suffering from high levels of criminality, including the presence of powerful criminal organizations. Identifying government responses that improve citizen security is imperative. Existing research argues that improving intergovernmental coordination helps the state combat criminality, but has limited its analysis to political factors that affect coordination. I study the impact of increasing intergovernmental coordination between law enforcement agencies on crime, violence, and organized crime. Using the generalized synthetic control method, original data on the staggered implementation of a police reform that increased intergovernmental police coordination and detailed data on criminal organizations and criminality in the Mexican state of Guanajuato, I find that the reform weakened criminal organizations and reduced violent crime, but increased violence.

Keywords: Intergovernmental coordination, police, crime, violence, organized crime, Mexico

*I thank Megan Erickson, Hannah Barron, Omar García-Ponce, and the participants of the 2023 Public Choice Society conference panel on Crime, Conflict, and Policing.

1 Introduction

Latin America is the most violent region in the world (Roser and Ritchie 2022) and suffers from high levels of crime, in large part driven by powerful criminal organizations (Global Initiative Against Transnational Organized Crime 2021). In response, governments across the region are increasingly turning to tough-on-crime enforcement policies (Flores-Macías and Zarkin 2021). Yet, these policies have generally backfired and exacerbated violence, displaced crime, and triggered criminal wars (Dell 2015; Lessing 2017; Osorio 2015; Calderón et al. 2015; Ríos 2013; Durán-Martínez 2015; Alcocer 2022). Identifying government responses that improve citizen security is therefore imperative.

A leading argument is that increasing intergovernmental coordination helps the state combat violence, crime, and criminal organizations (Rios 2015; Trejo and Ley 2016; Durán-Martínez 2015, 2017; Alberti et al. 2022). These scholars generally argue that intergovernmental coordination on security issues improves with vertical political alignment, which results in better security outcomes in politically aligned municipalities (Rios 2015; Durán-Martínez 2015, 2017; Trejo and Ley 2016; González and Cáceres 2019; Alberti et al. 2022). Alternatively, other scholars have found that this vertical alignment and coordination on security policy can *increase* violence (Dell 2015).

Yet, existing studies have limited their focus to party politics and overlooked other factors that increase intergovernmental coordination on security issues. Moreover, due to data constraints, they have yet to empirically test whether and how it impacts organized crime. This article contributes to the literature by analyzing whether improving intergovernmental coordination through policies that increase coordination between enforcement agencies also helps the state combat criminality and organized crime. This article follows the theoretical insights of Durán-Martínez (2015, 2017), who argues that a state's "[e]nforcement efficacy depends on the ability to coordinate enforcement actions and thus should increase as power within the security apparatus is more cohesive" (Durán-Martínez 2015, 1382). However, while Durán-Martínez (2015, 2017) focuses on a multi-pronged concept of state coordination that includes enforcement and political factors, this study focuses specifically on the role of coordination between enforcement agencies.

Empirically, this study looks at Mexico, a country where levels of criminality are particularly high and where powerful criminal organizations operate. I leverage original data on the staggered implementation of a police reform that increased coordination between local and state police agencies in order to counteract organized crime and reduce high-impact crimes in the state of Guanajuato, detailed panel data on cartel activity in the state between 2000 and 2021, and monthly crime and violence data. Using the generalized synthetic control (GSC) method (Xu 2017), I find that increasing intergovernmental police coordination weakens cartel presence, reduces the number of cartels, and curtails cartel wars. I also find that it reduces violent theft rates, but simultaneously increases both overall homicide and cartel-related homicide rates.

This paper makes three main contributions. Substantively, it extends the argument that intergovernmental coordination can help address criminality by moving beyond political alignment and investigating coordination between enforcement agencies. Data-wise, it provides detailed cartel data and transparent procedures on how to measure organized crime that other scholars can replicate or build on. Methodologically, this is the first study investigating the effect of intergovernmental coordination using quantitative data on organized crime and the GSC method.

2 Context

Mexico is a federal system with three levels of government (federal, state, and municipal), each with its own police forces. Through the early 2000s, violence by criminal organizations, known as "cartels" in Mexico, began to rise. In response, the newly-elected president declared war against cartels in December 2006 and deployed thousands of federal troops throughout the country, which significantly increased crime, violence, and cartel wars (e.g., Ríos 2013; Osorio 2015; Lessing 2017; Trejo and Ley 2020; Calderón et al. 2015; Dell 2015; Castillo and Kronick 2020; Alcocer 2022),

This raised serious concerns about the effectiveness of local police, heterogeneity of local policing practices, and poor intergovernmental coordination between police departments (Domínguez Ramos 2018) In response, between 2010 and 2014, two police reforms aiming to increase coordination between local and state police to counteract organized crime and reduce high-impact crimes were proposed and rejected in the national congress (Instituto Belisario Domínguez 2015).[1] These reforms were over 90% of crimes committed fell within the jurisdiction of state and local police (e.g., property theft, homicide, kidnapping, extortion, etc.) (de los Reyes 2010).

Despite the police reforms not being adopted at the federal level, they served as a template for various states and municipalities that independently decided to implement them. By the 2018, 71.5% of Mexico's 2,457 municipalities had implemented some version of the police reform (López 2018). However, the lack of a federal mandate has meant that its implementation has been decentralized and uneven geographically, temporally, and in kind, and consequently, no dataset exists identifying where, when, or how the police reform has been implemented.

3 Case and data

This paper focuses on the state of Guanajuato, a state in central Mexico with historically low levels of criminality and no significant cartel presence before 2008. Starting in 2008, however, cartels began entering the state, causing crime and violence to increase substantially. In response, starting in 2014, some municipalities began to adopt police reforms to increase intergovernmental police coordination. Since then, 21 of its 46 municipalities adopted some form of the reform.[2] Six municipalities implemented Unique State Command (Mando Unico Estatal or MUE), where local police were disbanded and the state police took over local policing, and are therefore excluded from the analysis.

The reform analyzed here is named Unique Police Command (Mando Unico Policial or MUP) and was explicitly intended to improve coordination between state and local police forces. The reform entails local governments continuing to hold administrative and financial power over local police but handing operational command to state police through the appointment of a member of the state police as police chief. This allows these organizations to better coordinate by, among others, sharing and integrating information, processes, operations, responses, protocols, guidelines, and standards. For example, when describing the reform implementation process, a local mayor stated that "[t]here was a meeting between local police, transit police, state police, the Red Cross, and firefighters precisely to talk about the topic of coordination... this has allowed us to ensure that

[1]See the Appendix for a detailed discussion of these proposed reforms.
[2]A map of these municipalities are shown in Appendix Figure A1.

MUP has optimal communication and coordination to attend reports together with the emergency agencies" (Redacción 2022).

Below I introduce the data used in the analysis. Descriptive statistics for all variables are shown in Table 1.

Table 1: Summary statistics for variables in analysis.

	n	mean	sd	min	max
Effect on Cartels (Municipality-year)					
MUP	726	0.088	0.284	0	1
Cartel presence strength	726	1.110	1.186	0	3
Number of cartels	726	0.908	1.115	0	5
Cartel war	726	0.275	0.447	0	1
Log population	726	11.078	0.919	8.805	13.293
Log economically inactive pop.	726	10.095	0.935	7.565	12.545
Governor from rival party	726	0.430	0.495	0	1
President from rival party	726	0.534	0.499	0	1
Governor and president from rival party	726	0.295	0.456	0	1
Individuals in local public security	726	174.843	185.047	0	1,280
Effect on Crime and Violence (Municipality-month)					
MUP	8,712	0.092	0.288	0	1
Violent theft rate	4,356	1.573	2.865	0	32.233
Non-violent theft rate	4,356	10.119	9.369	0	89.955
Homicide rate	8,316	1.713	4.272	0	104.948
Cartel-related homicide rate	8,316	0.753	2.315	0	59.970
Number of cartel cells	8,712	0.197	0.477	0	3
Number of weak cartels	8,712	0.556	0.790	0	4
Number of strong cartels	8,712	0.154	0.376	0	2
Cartel war	8,712	0.275	0.447	0	1
Log population	8,712	11.078	0.919	8.805	13.293
Log economically inactive pop.	8,712	10.095	0.934	7.565	12.545
Governor from rival party	8,712	0.430	0.495	0	1
President from rival party	8,712	0.534	0.499	0	1
Governor and president from rival party	8,712	0.295	0.456	0	1
Individuals in local public security	8,712	174.843	184.930	0	1,280

3.1 Treatment: police reform increasing intergovernmental coordination

Data on which municipalities have implemented the reform, how, and the timing of its adoption does not exist. Due to this data constraint, this article focuses on the central state of Guanajuato. Through in-depth qualitative research on each of Guanajuato's 46 municipalities, I create a hand-coded dataset identifying the municipalities that adopted MUP and the timing of the implementation. I draw on data from municipal and state government official documents, statements by government officials reported in media outlets, journalistic reports, and news articles. For each municipality, I identify (1) whether they adopted MUP or MUE at any point before December 2021, (2) if they did, the month and year that they implemented them, (3) if they rescinded MUP or MUE, the month and year they did so, (4) if they re-implemented MUP or MUE, the month and year they did so, and (5) if they changed from MUP to MUE or the inverse, the month and year they did so. The resulting data is a municipality-month panel dataset identifying the months, if any, that each municipality had MUP or MUE. In this study I focus on MUP and exclude the municipalities that implemented MUE since it does not entail intergovernmental coordination. For the analysis on the effect of MUP on cartel activity, which is measured at the municipality-year level, this dataset is also aggregated to the municipality-year level.[3]

3.2 Dependent variable: criminal governance

To analyze whether MUP impacted cartels, I use detailed data on the population of cartels in Guanajuato by Alcocer (2023). This dataset collects detailed information on the population of cartels operating in Guanajuato between January 2000 and December 2021, including the municipalities they operated in, how well established they were in a municipality, and the relationships between them (rivals, allies, neutral). This data was created using extensive qualitative research and fieldwork and measures various aspects of cartel dynamics in the state of Guanajuato.[4]

For this study, I rely on three measures from this dataset: (1) how well established cartels are in a municipality (or cartel strength), (2) the number of cartels operating in a municipality, and (3) whether two or more cartels are actively contesting a municipality. For the first variable, I use the measure of how well established each cartel is in a given municipality per year (no presence < cell presence < weak presence < strong presence) to identify the strongest presence in each municipality-year. For the second variable, I use a simple count of the total number of cartels operating in a municipality per year. Finally, using the group-dyad and geographic presence data, I identify municipality-years where cartels are actively fighting over a municipality.[5]

3.3 Dependent variable: crime and violence

To analyze the effect of MUP on crime, I use official data on two of the most prevalent types of crimes in Mexico: theft and homicides. First, I use data on the monthly incidences of crime per municipality from the National Public Security System (SESNSP) and on population from the 2010 census (INEGI) to create two variables: (1) monthly rates of violent theft per 100,000 inhabitants, and (2) monthly rates of nonviolent theft per 100,000 inhabitants. Data for these crimes is available from January 2011 to December 2021.

Second, I use monthly mortality data from Mexico's Statistical Agency (INEGI) to measure homicide prevalence in two ways. First, I use all homicides to calculate the monthly homicide rate for each municipality from January 2000 to December 2020. Second, Calderón et al. (2015) show that homicides of young men (males between the ages of 15-39) correlate highly, temporally and geographically, with homicides perpetrated by cartels. I therefore use the homicide rate of young men for each municipality from January 2000 to December 2020 to measure cartel-related homicides.

[3]To determine the start year, I adopt the following procedure: (1) if MUP was implemented by July in year t, the start year is set as t, (2) if MUP was implemented in August or later in year t, the start year is set to $t + 1$.

[4]A map of cartel presence is shown in Appendix Figure A4.

[5]The data from Alcocer (2023) shows various cases where cartels operate in the same territories without conflict, and are instead neutral or even allied.

3.4 Controls

To control for intergovernmental coordination due to party politics, I use local and state level election data from Magar (2018) and create three dummy variables: whether the mayor shares political affiliation with (1) only the governor, (2) only the president, and (3) both the governor and the president.

Implementing MUP may affect the capacity of police, so I control for the number of individuals at the municipal level assigned to public security. The data comes from federal censuses of local governments conducted in 2011, 2013, 2015, 2017, 2019, and 2021 (INEGI) and imputed values for the missing years. Election cycles have been shown to be critical for cartel activity (Buonanno et al. 2016; De Feo and De Luca 2017; Daniele and Dipoppa 2017; Albarracín 2018; Alesina et al. 2019; Trejo and Ley 2020; Dipoppa 2021; Bullock 2021), so I control for election years. Finally, cartels in Guanajuato primarily fight over the illicit oil theft market (Alcocer 2022), so I control for municipalities with oil pipelines.

For the models estimating the effect of the police reform on crime and violence, I also use the data on cartels from Alcocer (2023) as control variables since cartel dynamics tend to drive criminality. I use four control variables: (1) the number of cartel cells operating in a municipality, (2) the number of cartels with weak presence in the municipality, (3) the number of cartels with strong presence in the municipality, and (4) a dummy variable denoting whether two or more cartels were actively fighting over the municipality.

4 Research design

Estimating the effect of the police reform on public security outcomes is not straightforward given that criminality likely plays a role in whether and when some municipalities chose to adopt the reform, so the difference-in-differences' (DID) parallel trends assumption is unlikely to hold.[6]

To address this concern, this study uses the GSC method (Xu 2017), which builds on the synthetic control method (Abadie et al. 2010, 2015) and the interactive two-way fixed effects model (IFE) (Bai 2009). GSC allows the estimation of the average treatment effect on the treated (ATT) of a staggered treatment on an outcome. In essence, the GSC method creates counterfactuals for treated units by using pre-treatment observations to weight control units so they look similar to the treated units and pre-treatment outcome trends approximate each other. Appendix 3 and 4 discuss in more detail how the treated and control groups were selected and shows the timing that each treated unit received treatment. GSC has clear advantages over other approaches in this case. First, it allows for non-random interventions with staggered adoption, relaxes the parallel trends assumption required by DID, generalizes the synthetic controls method to allow multiple treated units, works well when there is a small number of treated units, and allows for treatment effect heterogeneity across units.

I estimate two separate models since the data on cartel presence is at the municipality-year level, while the data on crime is at the municipality-month level. All models are estimated using the following specification:

[6] Data shows that municipalities that adopted the reform had, on average, better established cartel presence, more cartels, and more cartel wars. However, they also had lower levels of violent and non-violent theft, and similar levels of homicides.

$$Y_{it} = \delta_{it} D_{it} + X_{it}^{'}\beta + \lambda_i^{'} f_t + \epsilon_{it} \tag{1}$$

where Y_{it} denotes the outcome of interest in municipality i at time t, D_{it} is the treatment indicator that takes on the value of 1 for municipalities that adopted the police reform once they implemented the reform and 0 otherwise, δ_{it} estimates the heterogeneous treatment effect on municipality i at time t, $X_{it}^{'}$ is a vector of observed covariates, $\lambda_i^{'}$ is a vector of unknown factor loadings, f_t denotes a vector of unobserved common factors, and ϵ_{it} are the error terms for municipality i at time t. The interactive two-way fixed effects also control for any additional common shocks and unobserved time-invariant and time-varying covariates. The number of factors are selected using a cross-validation procedure that minimizes the mean square prediction error (MSPE). Standard errors are estimated using bootstrapping with 1,000 runs. All models are estimated using Expectation Maximization algorithm.

For the analysis estimating the effect on cartels, t denotes years, Y_{it} denotes different measures of cartel presence, and $X_{it}^{'}$ includes controls for sociodemographic characteristics, illicit markets, local police capacity, and political factors.

For the models estimating the effect on crime and violence, Y_{it} denotes different measures theft and homicides, t denotes months for Y_{it} and D_{it}, and $X_{it}^{'}$ includes municipality-specific controls for cartel presence, sociodemographic characteristics, illicit markets, local police capacity, and political factors.

5 Results

Tables 2 and 3 show the average ATT over all time periods for increased intergovernmental coordination on different measures of cartel presence and crime and violence, respectively. Figures 1 and 2 plot both the average outcomes of the treatment and synthetic control units before and after the implementation of MUP to show parallel trends (first column), and the ATT per period with 95% confidence intervals to visualize the effect over time (second column).[7]

Table 2 shows that the effect of MUP on the strength of cartel presence is negative but not statistically significant. However, MUP does decrease the number of cartels operating in municipalities by almost three quarters of a cartel, which is a 0.65 standard deviation (SD) decrease. Moreover, MUP also decreased the prevalence of cartels wars by 37%.

Looking at the effects over time in Figure 1, I find that MUP decreases the strength of cartel presence, though these results are only statistically significant the third and fourth years after its implementation, the number of cartels by the second year and cartel wars within a year. Yet, while the effect on cartel wars appears to hold after five years, the effects on cartel strength and number of cartels is lost after five and six years, respectively.

Turning to the effects on crime and violence, Table 3 shows that MUP decreased violent theft rate by -1.88 per 100,000, which corresponds to a reduction of 0.66 SDs. Second, estimates suggest that MUP increases both overall homicide rates and cartel-related homicide rates by 0.94 and 0.5 per 100,000 (an increase of 0.22 SDs), respectively, and these results are statistically significant at the 0.1 level.

Looking at the temporal effects in Figure 2, I find that MUP has an almost immediate negative—by the third month—and lasting effect on violent theft. However, MUP only reduces non-violent theft after three years and revert back to no effect after four years.

[7] Appendix Tables A3, A4, A5, A6, A7, A8, and A9 show the ATT results used to create plots.

Table 2: Average treatment effect on the treated (ATT) of increased intergovernmental coordination on cartels averaged across treatment period.

	Dependent variable:		
	Cartel strength	Cartel number	Cartel war
	(1)	(2)	(3)
Police Reform	−0.346	-0.730^{***}	-0.370^{***}
	(0.239)	(0.207)	(0.105)
Municipality FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Unobserved factors	1	1	1
Period	2000-2021	2000-2021	2000-2021
Observations	726	726	726
Treated Muns	10	10	10
Control Muns	23	23	23
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: Average treatment effect on the treated (ATT) of increased intergovernmental coordination on crime rates averaged averaged across treatment period. Crimes measured per 100,000 inhabitants.

	Dependent variable:			
	Violent theft rate	Non-violent theft rate	Homicide rate	Young men homicide rate
	(1)	(2)	(3)	(4)
Police Reform	-1.883^{**}	−1.387	0.941^{*}	0.498^{*}
	(0.782)	(1.019)	(0.528)	(0.276)
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Unobserved factors	0	1	2	1
Period	1/2011-12/2021	1/2011-12/2021	1/2000-12/2020	1/2000-12/2020
Observations	4356	4356	8316	8316
Treated Muns	11	11	10	10
Control Muns	22	22	23	23
Note:				*p<0.1; **p<0.05; ***p<0.01

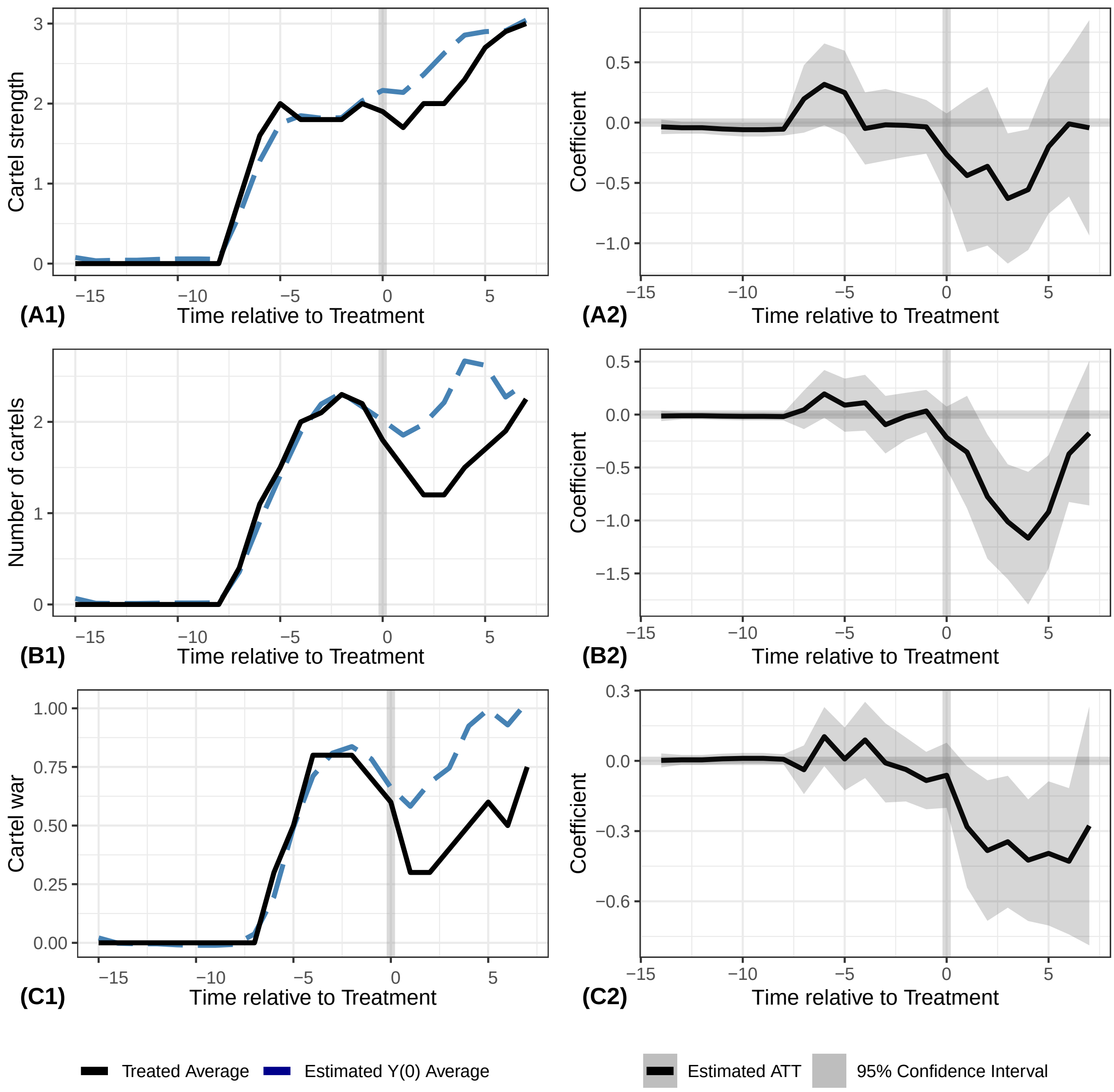

Figure 1: Average outcome trends for treated and synthetic control groups (left column) and average treatment effect on the treated (ATT) of police reform increasing intergovernmental coordination on cartels with 95% confidence intervals (right column). (A1-A2) Cartel strength, (B1-B2) number of cartels, (C1-C2) cartel war.

The effects on homicides and cartel-related homicides are also quick, with a positive statistically significant effect after two months. Yet, this effect mostly disappears after about 3.5 years.

6 Discussion

The motivation behind increasing intergovernmental police coordination in Mexico was to combat organized crime and reduce high-impact crimes. I find that this police reform accomplished most of its goals (at least within the first five years of its implementation): it weakened cartel presence, reduced the number of cartels, decreased the incidence of

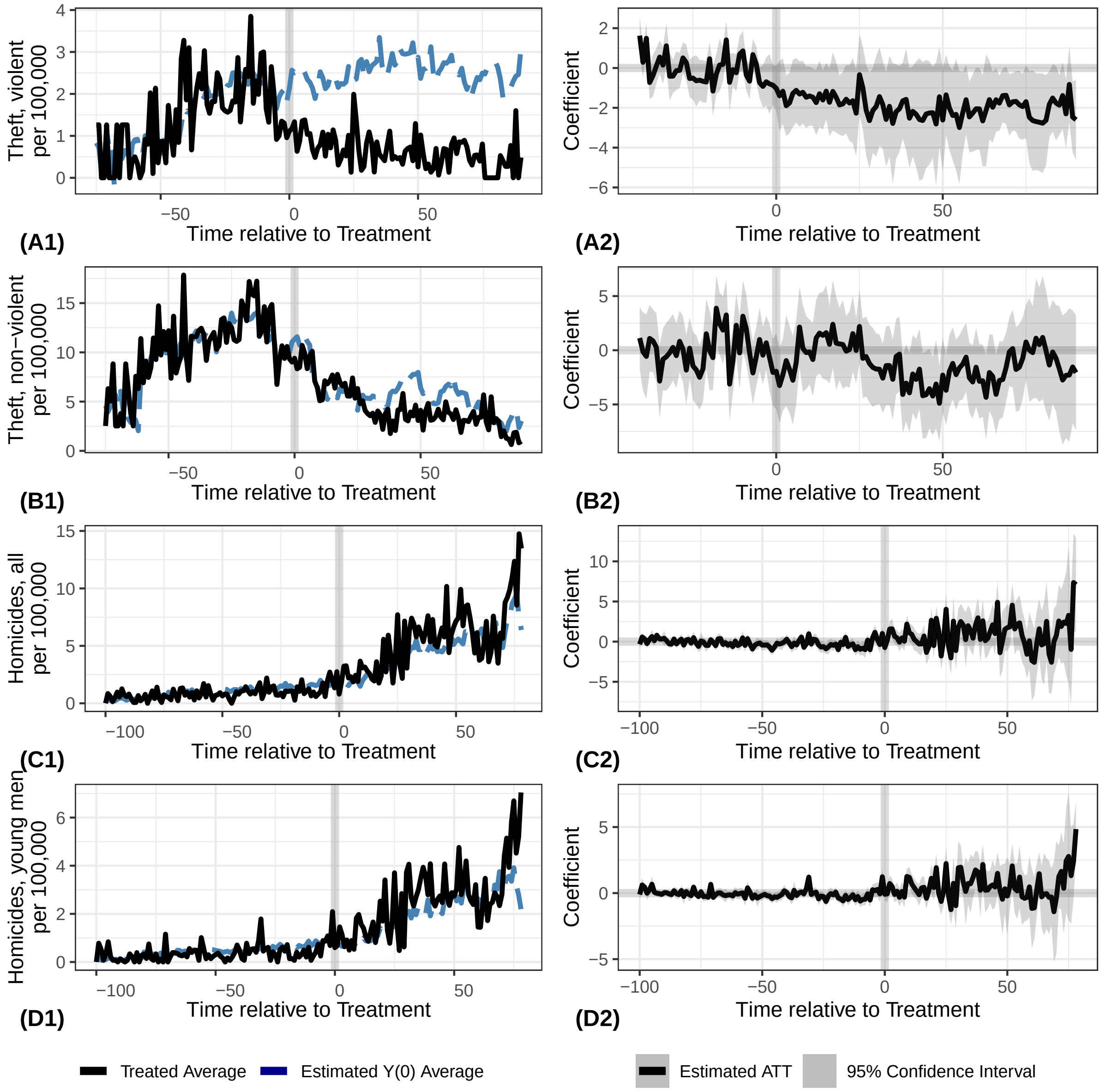

Figure 2: Average outcome trends for treated and synthetic control groups (left column) and average treatment effect on the treated (ATT) of police reform increasing intergovernmental coordination on crime and violence with 95% confidence intervals (right column). (A1-A2) Violent theft rate, (B1-B2) non-violent theft rate, (C1-C2) homicide rate, (D1-D2) cartel-related homicide rate.

cartels wars, and lowered violent crime. However, the reform also failed in one of its main aims, as it increased violence and cartel-related violence. These mixed results may explain why some advocates defend the reform while opponents deem it a failure.

The findings provide important nuances to ongoing debates. On the one hand, they run counter to most existing studies arguing that better intergovernmental coordination reduces violence, and are instead consistent with findings that government enforcement policies targeting criminal organizations generally increase violence. However, they also show that intergovernmental coordination on security issues can help the state combat violent crime and criminal governance. More broadly, the results suggest that intergovernmental coordination may be an important part of improving governance and citizen security in violent contexts, though it is clearly not a panacea.

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Appendices

A Police reform in Mexico

Between 2010 and 2014, three different police reforms were proposed, debated, and rejected in the national congress, two of which had the central purpose of increasing coordination between local, state, and federal police. First, President Calderon proposed a police reform in 2010, called "Single Command" (Mando Unico), to the Mexican legislature in which the federal police would take operational command of state police, and state police of would take operational command over local police that passed certain quality controls and take the over local police that did not meet these controls (Instituto Belisario Domínguez 2015). The Executive Secretary of the National Public Security System explained at the time that under this reform "all the police forces in the country would be obligated to have better coordination in order to give citizens, anywhere in the national territory, better security conditions" (NTX 2010). This reform was specifically designed to increase coordination between federal, state, and local police, as they would share an identity, information, operations, control, and strategies, among others. The reform would affect all 32 state police and over 2,000 local police. The reform was killed in its congressional committee.

In 2014, President Peña Nieto proposed a bill called Unique Police Command (Mando Unico Policial) that would disband the over 1,800 local police that existed at the time and give all local level policing responsibilities to state police forces. Widespread opposition to this reform led to an alternative proposal called Mixed Police Command (Mando Policial Mixto), which would increase coordination between state and local police by allowing local police that met certain criteria to continue operating, though under the operational control of state police. Police that did not meet these criteria would be eliminated and replaced by the state police. Yet, like the two previous attempts, this proposed reform was not approved by its congressional committee and never made it to the floor for a vote.

B Police reform in Guanajuato

Figure A1 shows the map of Guanajuato and the municipalities that, at some point between January 1, 2000 and December 31, 2021, adopted Unique Police Command, only adopted Unique State Command and not Unique Police Command, and those that did not adopt any police reform. This is the sampling frame from which the treatment and control groups are drawn from (see next section).

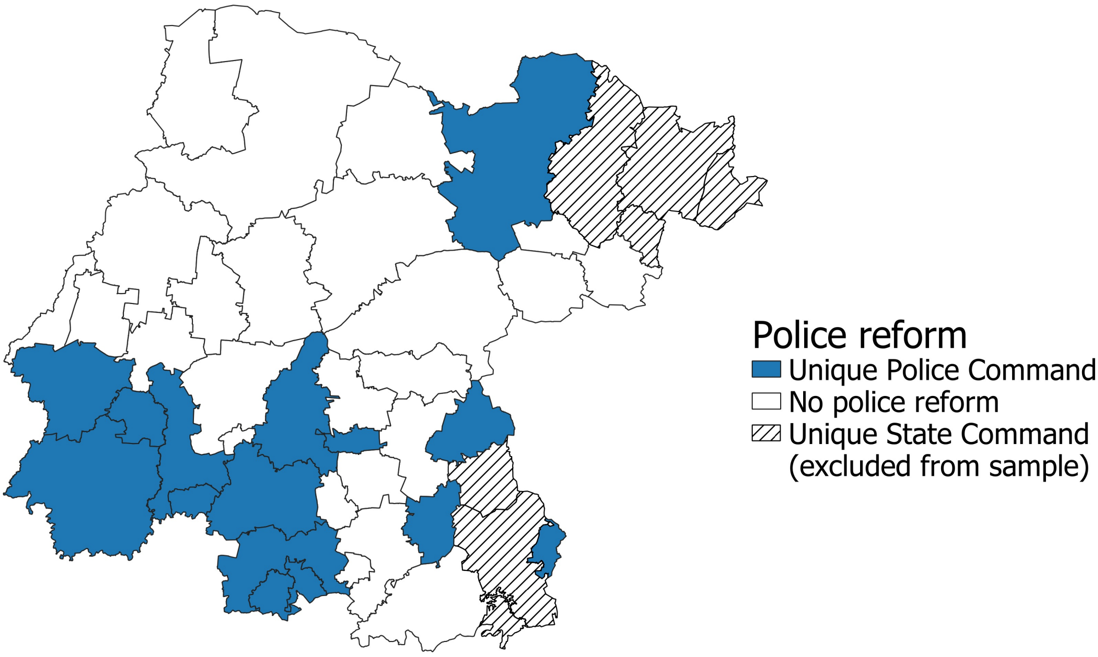

Figure A1: Municipalities in Guanajuato that adopted Unique Police Command at any point, only adopted Unique State Command, did not implement any police reform.

C Identifying treatment and control units

The first step of the GSC method is identifying the treated and control units that will be used to create the counterfactuals. In total, 15 of Guanajuato's 46 municipalities adopted MUP at some point. However, two municipalities only adopted it for one year and then revoked it, one adopted it for three years and then revoked it, and one adopted it for four years and then revoked it. The last to adopt it, and the only one to do so after 2018, did so in October 2021, so it is excluded from the year-municipality sample. Therefore, the final municipality-year data has 10 municipalities that adopted the treatment, and the municipality-month data has 11. To construct the control group, I exclude any municipality that implemented MUE (six municipalities) and the municipality of Leon, which is by far the largest municipality in the state of Guanajuato. I exclude Leon because it does not share common support with the rest of the sample for most covariates, and the GSC method could use this data to erroneously extrapolate a counterfactual. This process leaves 23 municipalities in the control group that is used to create the counterfactuals. Appendix Table A1 lists these municipalities and whether they are part of the treatment or control group, while Appendix Figures A2 and A3 visualize the timing each treated unit received treatment.

D Treatment status

Table A1: List of municipalities in sample.

Municipality ID	Municipality name	Ever treated
11001	Abasolo	1
11008	Manuel Doblado	1
11012	Cuerámaro	1
11021	Moroleón	1
11023	Pénjamo	1
11035	Santa Cruz de Juventino Rosas	1
11039	Tarimoro	1
11041	Uriangato	1
11042	Valle de Santiago	1
11044	Villagrán	1
11046	Yuriria	1
11002	Acámbaro	0
11003	San Miguel de Allende	0
11007	Celaya	0
11009	Comonfort	0
11011	Cortazar	0
11013	Doctor Mora	0
11014	Dolores Hidalgo Cuna de la Independencia Nacional	0
11015	Guanajuato	0
11017	Irapuato	0
11018	Jaral del Progreso	0
11022	Ocampo	0
11024	Pueblo Nuevo	0
11025	Purísima del Rincón	0
11026	Romita	0
11028	Salvatierra	0
11029	San Diego de la Unión	0
11030	San Felipe	0
11031	San Francisco del Rincón	0
11032	San José Iturbide	0
11036	Santiago Maravatío	0
11037	Silao	0
11040	Tierra Blanca	0

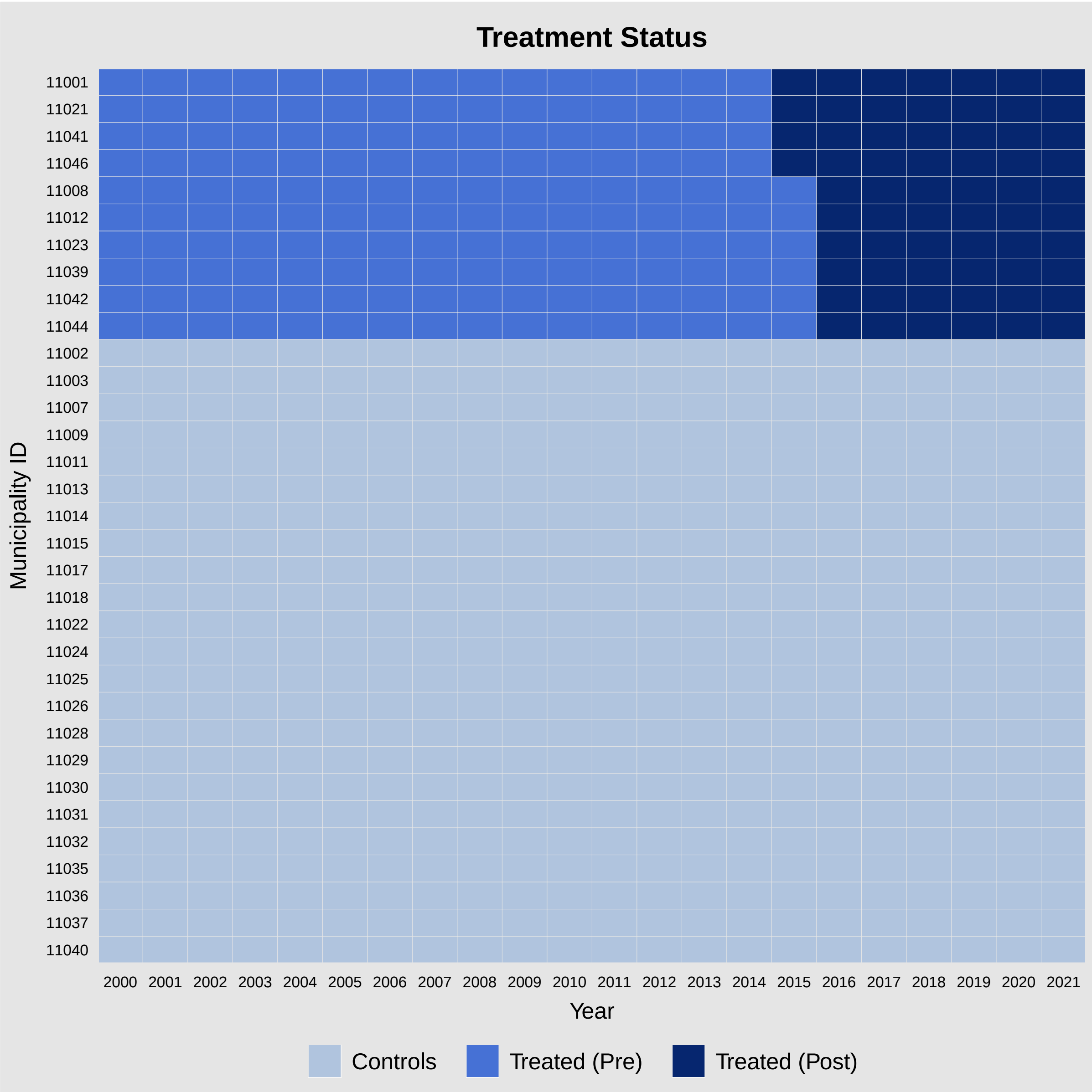

Figure A2: Treatment assignment by municipality for municipality-year analysis.

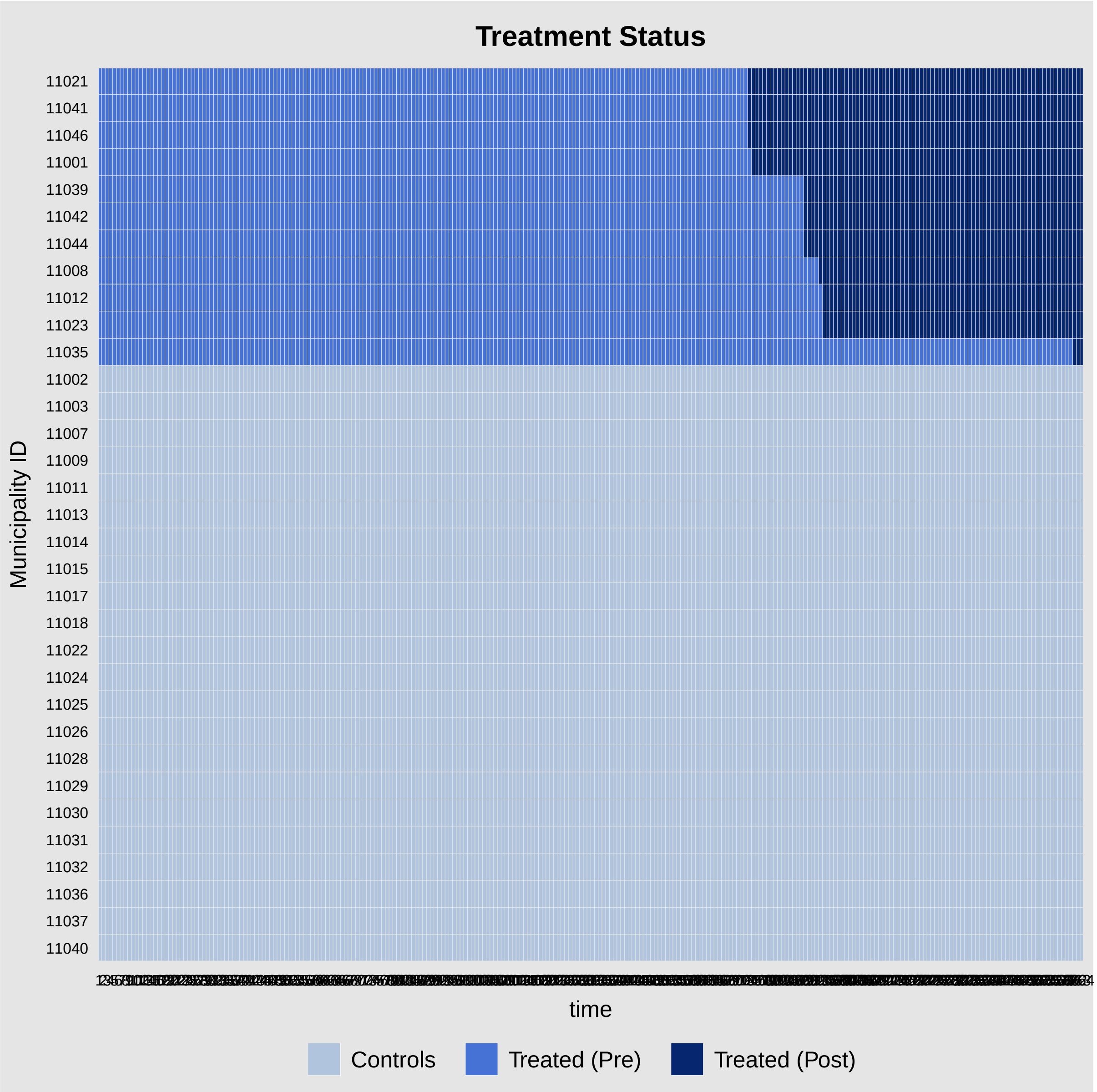

Figure A3: Treatment assignment by municipality for municipality-month analysis.

E Cartel activity in Guanajuato

The data on cartel presence in Guanajuato is from Alcocer (2023), and includes three datasets providing different information about the population of cartels operating in Guanajuato between January 2000 and December 2021: cartel geographic presence and strength of presence, descriptive cartel histories, and cartel dyad data on the relations between cartels (neutral, allied, rivals). For a more detailed discussion on definitions, measurement, data collection, and sources see Methodology document provided by Alcocer (2023). Table A2 lists all 16 cartels included in the datasets.

Full Name(s)	**Abbreviation**
Cartel de Sinaloa/Cartel del Pacifico	CDS
Organizacion Beltran Leyva/Cartel del Pacifico Sur	BLO
Mata Zetas/Los Antrax	MZ
Los Pelones	Pelones
Cartel La Union de Leon/La Union de Leon/Gente de Leon	CUL
Cartel Los Durango/Los Durango	CLD
Cartel Jalisco Nueva Generacion	CJNG
Cartel Nueva Plaza/Nueva Plaza	CNP
Cartel del 00	C00
Cartel Santa Rosa de Lima/Cartel de Guanajuato/Cartel del Marro	CSRL
La Familia Michoacana/La Familia	LFM
Los Caballeros Templarios	CT
Carteles Unidos	CU
Cartel del Golfo	CDG
Cartel de los Zetas/Los Zetas	Zetas
Grupo Sombra/Fuerzas Especiales Grupo Sombra	FEGS

Table A2: Criminal organizations included in MCO Guanajuato and the abbreviations used by the author.

Figure A4 maps notable cartel presence in Guanajuato in 2010 and 2020. The map on the left shows LFM and Zetas presence in 2010, and the map on the right shows CJNG and CSRL presence in 2020. The red line shows oil pipelines used to steal oil by cartels, which is a key control variable in the empirical models.

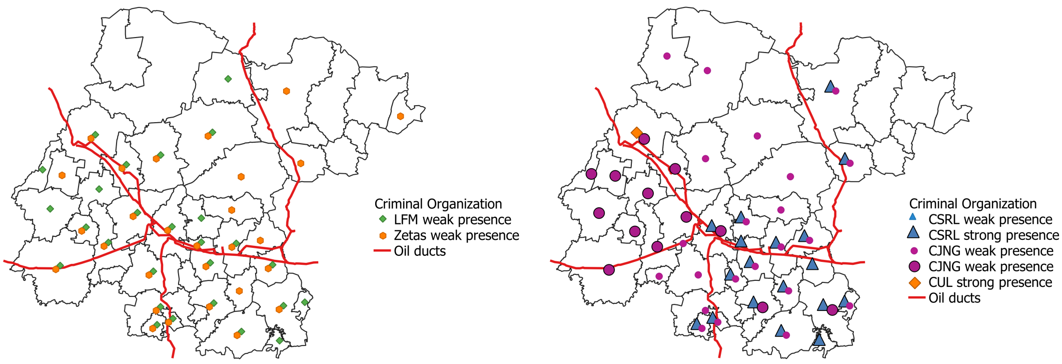

Figure A4: Cartel presence in Guanajuato in 2010 and 2020: (left) LFM and Zetas presence in 2010, and (right) CJNG and CSRL presence in 2020. Red lines show location of pol pipelines.

F Effect on cartels per period results

Table A3: ATT effect of increased intergovernmental coordination on cartel strength of presence per treatment period.

	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
0	-0.265	0.174	-0.605	0.076	0.128	0
1	-0.439	0.323	-1.073	0.195	0.175	10
2	-0.362	0.336	-1.020	0.295	0.280	10
3	-0.629	0.275	-1.169	-0.089	0.022	10
4	-0.556	0.255	-1.056	-0.056	0.029	10
5	-0.199	0.283	-0.755	0.356	0.481	10
6	-0.011	0.307	-0.613	0.591	0.972	10
7	-0.043	0.456	-0.936	0.850	0.924	4

Table A4: ATT effect of increased intergovernmental coordination on number of cartels per treatment period.

	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
0	-0.217	0.149	-0.510	0.076	0.146	0
1	-0.354	0.271	-0.885	0.177	0.191	10
2	-0.775	0.299	-1.362	-0.189	0.010	10
3	-1.012	0.277	-1.555	-0.470	0.0003	10
4	-1.167	0.320	-1.793	-0.540	0.0003	10
5	-0.919	0.273	-1.455	-0.384	0.001	10
6	-0.372	0.232	-0.826	0.082	0.109	10
7	-0.176	0.348	-0.858	0.506	0.613	4

Table A5: ATT effect of increased intergovernmental coordination on cartel wars per treatment period.

	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
0	-0.062	0.071	-0.201	0.077	0.385	0
1	-0.282	0.132	-0.541	-0.023	0.033	10
2	-0.383	0.153	-0.683	-0.083	0.012	10
3	-0.346	0.144	-0.627	-0.064	0.016	10
4	-0.424	0.133	-0.684	-0.164	0.001	10
5	-0.395	0.157	-0.703	-0.087	0.012	10
6	-0.429	0.159	-0.742	-0.117	0.007	10
7	-0.278	0.260	-0.788	0.233	0.287	4

G Effect on crime and violence per period results

Table A6: ATT effect of increased intergovernmental coordination on violent theft rates per treatment period.

Months relative to treatment	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
0	-1.018	0.575	-2.146	0.110	0.077	0
1	-1.397	0.901	-3.162	0.369	0.121	11
2	-1.166	0.845	-2.822	0.490	0.168	11
3	-1.893	0.776	-3.415	-0.372	0.015	11
4	-1.752	0.779	-3.278	-0.226	0.024	10
5	-1.271	0.862	-2.961	0.418	0.140	10
6	-1.123	0.827	-2.744	0.497	0.174	10
7	-1.310	0.837	-2.950	0.330	0.118	10
8	-1.220	0.807	-2.801	0.362	0.131	10
9	-1.469	0.786	-3.009	0.071	0.062	10
10	-1.404	0.758	-2.890	0.082	0.064	10
11	-1.467	0.739	-2.917	-0.018	0.047	10
12	-1.737	0.835	-3.374	-0.101	0.037	10
13	-1.293	0.848	-2.955	0.370	0.128	10
14	-1.608	0.763	-3.103	-0.112	0.035	10
15	-1.162	0.725	-2.583	0.259	0.109	10
16	-1.723	0.865	-3.418	-0.028	0.046	10
17	-1.175	1.005	-3.145	0.795	0.242	10
18	-1.469	0.904	-3.241	0.303	0.104	10
19	-1.852	0.765	-3.351	-0.353	0.015	10
20	-1.804	0.821	-3.412	-0.195	0.028	10
21	-1.567	0.880	-3.292	0.158	0.075	10
22	-1.762	0.969	-3.661	0.138	0.069	10
23	-1.641	1.096	-3.788	0.507	0.134	10
24	-2.272	1.103	-4.434	-0.109	0.039	10
25	-0.335	1.025	-2.344	1.674	0.744	10
26	-0.987	1.068	-3.080	1.106	0.355	10
27	-2.111	1.166	-4.396	0.175	0.070	10
28	-2.643	1.227	-5.049	-0.238	0.031	10
29	-2.135	1.089	-4.270	-0.001	0.050	10
30	-1.937	1.282	-4.450	0.577	0.131	10
31	-1.437	1.264	-3.914	1.039	0.255	10
32	-1.839	1.129	-4.052	0.375	0.104	10
33	-2.584	1.210	-4.956	-0.212	0.033	10
34	-1.924	1.291	-4.453	0.605	0.136	10
35	-2.786	1.551	-5.826	0.255	0.073	10
36	-2.193	1.208	-4.561	0.176	0.070	10
37	-2.049	1.098	-4.202	0.103	0.062	10
38	-1.648	0.976	-3.561	0.264	0.091	10
39	-1.575	1.301	-4.124	0.975	0.226	10
40	-2.523	1.271	-5.014	-0.031	0.047	10
41	-2.178	1.157	-4.446	0.089	0.060	10
42	-2.323	1.354	-4.976	0.330	0.086	10
43	-2.588	1.570	-5.666	0.489	0.099	10
44	-2.637	1.500	-5.576	0.302	0.079	10
45	-2.310	1.387	-5.029	0.409	0.096	10
46	-2.260	1.322	-4.852	0.332	0.087	10
47	-2.244	1.163	-4.524	0.036	0.054	10
48	-2.813	1.585	-5.920	0.295	0.076	10
49	-1.444	1.275	-3.943	1.056	0.258	10
50	-2.613	1.327	-5.214	-0.012	0.049	10
51	-1.348	1.033	-3.374	0.677	0.192	10
52	-2.011	1.067	-4.102	0.081	0.060	10
53	-2.387	1.155	-4.651	-0.122	0.039	10
54	-2.329	1.427	-5.126	0.468	0.103	10
55	-2.991	1.447	-5.827	-0.155	0.039	10
56	-2.246	1.050	-4.303	-0.189	0.032	10
57	-1.593	0.895	-3.348	0.161	0.075	10
58	-2.456	0.906	-4.231	-0.682	0.007	10
59	-2.261	0.992	-4.207	-0.316	0.023	10
60	-2.048	1.056	-4.117	0.021	0.052	10
61	-2.053	1.043	-4.097	-0.008	0.049	10
62	-2.657	1.171	-4.952	-0.363	0.023	10
63	-2.126	1.429	-4.927	0.675	0.137	10
64	-1.588	1.015	-3.578	0.402	0.118	10
65	-1.972	0.911	-3.758	-0.186	0.030	10
66	-1.594	0.816	-3.194	0.006	0.051	10
67	-1.765	0.708	-3.154	-0.377	0.013	10
68	-1.388	0.685	-2.730	-0.045	0.043	10
69	-1.371	0.738	-2.816	0.075	0.063	10
70	-1.854	0.791	-3.404	-0.304	0.019	10

Table A7: ATT effect of increased intergovernmental coordination on non-violent theft rates per treatment period.

Months relative to treatment	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
0	-1.939	1.785	-5.438	1.560	0.277	0
1	-3.260	1.772	-6.732	0.212	0.066	11
2	-2.253	1.701	-5.587	1.080	0.185	11
3	-0.952	2.142	-5.151	3.246	0.657	11
4	-1.765	2.055	-5.793	2.263	0.390	10
5	-2.773	2.091	-6.871	1.325	0.185	10
6	-1.113	1.971	-4.975	2.749	0.572	10
7	2.140	1.883	-1.550	5.831	0.256	10
8	0.172	2.040	-3.826	4.170	0.933	10
9	-0.218	1.718	-3.585	3.150	0.899	10
10	-0.149	1.527	-3.142	2.845	0.922	10
11	-0.858	1.711	-4.212	2.495	0.616	10
12	1.134	1.808	-2.411	4.678	0.531	10
13	1.579	1.899	-2.143	5.301	0.406	10
14	1.375	2.040	-2.623	5.373	0.500	10
15	1.622	2.220	-2.730	5.974	0.465	10
16	0.543	1.831	-3.046	4.132	0.767	10
17	2.397	2.077	-1.674	6.468	0.248	10
18	0.647	2.196	-3.656	4.951	0.768	10
19	0.584	1.708	-2.764	3.931	0.733	10
20	0.534	2.087	-3.557	4.625	0.798	10
21	-0.081	1.658	-3.330	3.169	0.961	10
22	0.063	1.791	-3.447	3.573	0.972	10
23	1.535	1.791	-1.975	5.045	0.391	10
24	-0.021	1.541	-3.041	2.999	0.989	10
25	2.200	1.709	-1.150	5.551	0.198	10
26	-0.748	1.877	-4.426	2.930	0.690	10
27	-0.580	1.882	-4.267	3.108	0.758	10
28	-1.232	1.836	-4.831	2.367	0.502	10
29	-1.581	1.862	-5.230	2.067	0.396	10
30	-1.735	1.684	-5.035	1.565	0.303	10
31	-1.749	1.637	-4.958	1.459	0.285	10
32	-2.574	1.632	-5.772	0.625	0.115	10
33	-1.418	1.855	-5.053	2.217	0.444	10
34	-1.410	1.864	-5.063	2.244	0.449	10
35	-2.685	1.879	-6.369	0.999	0.153	10
36	-0.573	1.782	-4.066	2.920	0.748	10
37	-0.354	1.759	-3.801	3.093	0.841	10
38	-4.083	1.808	-7.626	-0.539	0.024	10
39	-3.033	1.818	-6.595	0.530	0.095	10
40	-3.932	1.865	-7.588	-0.276	0.035	10
41	-2.191	1.830	-5.778	1.397	0.231	10
42	-2.690	1.912	-6.438	1.058	0.159	10
43	-1.740	1.887	-5.439	1.959	0.357	10
44	-4.201	2.011	-8.141	-0.260	0.037	10
45	-4.102	2.044	-8.109	-0.095	0.045	10
46	-3.544	1.871	-7.210	0.123	0.058	10
47	-4.226	1.846	-7.844	-0.609	0.022	10
48	-3.116	2.080	-7.194	0.961	0.134	10
49	-4.897	1.780	-8.386	-1.408	0.006	10
50	-2.293	1.771	-5.765	1.179	0.196	10
51	-3.697	1.636	-6.904	-0.490	0.024	10
52	-1.942	1.711	-5.296	1.412	0.256	10
53	-1.213	1.691	-4.528	2.102	0.473	10
54	-2.248	1.652	-5.487	0.991	0.174	10
55	-1.626	1.534	-4.632	1.381	0.289	10
56	-1.280	1.664	-4.541	1.981	0.442	10
57	-0.637	1.621	-3.813	2.540	0.695	10
58	-2.549	1.654	-5.790	0.693	0.123	10
59	-2.928	1.724	-6.307	0.451	0.089	10
60	-1.562	1.848	-5.184	2.060	0.398	10
61	-2.868	1.760	-6.316	0.581	0.103	10
62	-2.817	1.689	-6.127	0.492	0.095	10
63	-4.344	1.982	-8.229	-0.460	0.028	10
64	-2.054	1.802	-5.586	1.477	0.254	10
65	-2.418	1.963	-6.264	1.429	0.218	10
66	-4.071	1.870	-7.736	-0.407	0.029	10
67	-2.789	1.840	-6.395	0.817	0.130	10
68	-2.704	1.793	-6.218	0.811	0.132	10
69	-1.614	1.626	-4.801	1.573	0.321	10
70	-0.147	1.614	-3.310	3.016	0.928	10

Table A8: ATT effect of increased intergovernmental coordination on homicide rates per treatment period.

Months relative to treatment	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
0	-0.741	0.438	-1.601	0.118	0.091	0
1	0.169	0.466	-0.745	1.084	0.716	10
2	1.571	0.508	0.576	2.567	0.002	10
3	1.597	0.628	0.365	2.828	0.011	10
4	0.665	0.472	-0.261	1.591	0.159	10
5	0.476	0.489	-0.482	1.434	0.330	10
6	-0.065	0.582	-1.206	1.075	0.911	10
7	0.463	0.577	-0.668	1.595	0.422	10
8	0.047	0.609	-1.147	1.241	0.939	10
9	2.189	0.541	1.129	3.250	0.0001	10
10	1.104	0.560	0.006	2.202	0.049	10
11	0.908	0.630	-0.327	2.144	0.150	10
12	0.275	0.715	-1.126	1.677	0.700	10
13	-0.012	0.612	-1.211	1.187	0.984	10
14	-0.295	0.664	-1.597	1.007	0.657	10
15	-0.286	0.717	-1.691	1.118	0.689	10
16	0.702	0.697	-0.665	2.069	0.314	10
17	-1.352	0.753	-2.828	0.123	0.072	10
18	-0.601	0.754	-2.079	0.878	0.426	10
19	2.665	0.786	1.124	4.207	0.001	10
20	-0.492	0.797	-2.054	1.070	0.537	10
21	2.909	0.768	1.403	4.415	0.0002	10
22	1.303	0.751	-0.170	2.775	0.083	10
23	-1.793	0.848	-3.454	-0.131	0.034	10
24	0.230	0.899	-1.532	1.992	0.798	10
25	4.036	1.001	2.075	5.997	0.0001	10
26	-0.531	0.973	-2.438	1.375	0.585	10
27	-2.024	1.024	-4.031	-0.017	0.048	10
28	2.553	1.552	-0.489	5.595	0.100	10
29	-1.113	1.187	-3.438	1.213	0.348	10
30	1.777	1.196	-0.568	4.122	0.137	10
31	2.508	1.115	0.323	4.692	0.024	10
32	2.067	1.067	-0.024	4.158	0.053	10
33	0.249	1.736	-3.153	3.651	0.886	10
34	1.989	1.292	-0.543	4.521	0.124	10
35	1.404	1.294	-1.131	3.939	0.278	10
36	0.425	1.082	-1.696	2.547	0.694	10
37	2.059	0.960	0.178	3.940	0.032	10
38	2.967	1.254	0.511	5.424	0.018	10
39	0.275	1.420	-2.509	3.058	0.847	10
40	2.591	1.264	0.114	5.068	0.040	10
41	0.117	1.152	-2.141	2.375	0.919	10
42	0.403	1.115	-1.782	2.588	0.718	10
43	1.246	1.147	-1.001	3.494	0.277	10
44	2.098	1.347	-0.542	4.738	0.119	10
45	1.000	1.370	-1.685	3.686	0.465	10
46	4.904	1.361	2.236	7.572	0.0003	10
47	-1.379	1.576	-4.468	1.710	0.382	10
48	0.077	1.916	-3.679	3.832	0.968	10
49	1.533	1.355	-1.123	4.188	0.258	10
50	1.744	1.486	-1.169	4.656	0.241	10
51	1.832	1.244	-0.605	4.270	0.141	10
52	4.543	1.357	1.883	7.204	0.001	10
53	1.577	1.643	-1.642	4.797	0.337	10
54	2.163	1.617	-1.006	5.333	0.181	10
55	2.341	1.768	-1.124	5.806	0.185	10
56	0.762	1.685	-2.541	4.065	0.651	10
57	-0.177	1.536	-3.187	2.833	0.908	10
58	-1.574	1.542	-4.597	1.449	0.308	10
59	0.101	1.805	-3.436	3.639	0.955	8
60	-2.359	2.524	-7.305	2.587	0.350	7
61	-2.586	2.130	-6.760	1.589	0.225	7
62	-0.195	2.046	-4.206	3.816	0.924	7
63	1.599	1.879	-2.084	5.282	0.395	7
64	-0.414	2.190	-4.706	3.878	0.850	4
65	-0.244	2.606	-5.352	4.864	0.925	4
66	2.529	2.512	-2.395	7.453	0.314	4
67	-1.537	2.519	-6.474	3.400	0.542	4
68	-2.570	1.981	-6.453	1.312	0.194	4
69	0.005	2.106	-4.123	4.133	0.998	4
70	0.792	1.918	-2.968	4.552	0.680	4

Table A9: ATT effect of increased intergovernmental coordination on cartel-related homicide rates per treatment period.

Months relative to treatment	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
0	-0.087	0.244	-0.566	0.392	0.722	0
1	-0.061	0.321	-0.691	0.569	0.850	10
2	0.726	0.326	0.086	1.366	0.026	10
3	0.494	0.297	-0.088	1.077	0.096	10
4	-0.103	0.313	-0.716	0.511	0.743	10
5	0.142	0.345	-0.533	0.818	0.680	10
6	-0.324	0.347	-1.004	0.356	0.350	10
7	0.124	0.364	-0.590	0.839	0.733	10
8	-0.309	0.403	-1.099	0.480	0.442	10
9	1.258	0.310	0.651	1.866	0.00005	10
10	1.196	0.399	0.415	1.978	0.003	10
11	0.695	0.368	-0.026	1.416	0.059	10
12	0.410	0.361	-0.296	1.117	0.255	10
13	0.161	0.334	-0.493	0.815	0.630	10
14	-0.126	0.422	-0.954	0.702	0.765	10
15	0.390	0.425	-0.443	1.224	0.359	10
16	0.438	0.428	-0.402	1.277	0.307	10
17	-0.398	0.406	-1.192	0.397	0.327	10
18	0.236	0.355	-0.461	0.932	0.507	10
19	1.120	0.555	0.033	2.208	0.043	10
20	0.420	0.490	-0.540	1.381	0.391	10
21	1.925	0.554	0.840	3.010	0.001	10
22	-0.004	0.482	-0.948	0.940	0.994	10
23	-0.635	0.510	-1.634	0.364	0.213	10
24	0.159	0.586	-0.989	1.307	0.786	10
25	2.238	0.590	1.082	3.395	0.0001	10
26	-0.164	0.612	-1.363	1.035	0.789	10
27	-1.254	0.570	-2.370	-0.137	0.028	10
28	0.736	1.035	-1.292	2.764	0.477	10
29	-0.954	0.865	-2.649	0.742	0.270	10
30	1.918	1.015	-0.071	3.907	0.059	10
31	1.957	0.843	0.304	3.610	0.020	10
32	0.849	0.569	-0.265	1.964	0.135	10
33	0.121	1.306	-2.439	2.682	0.926	10
34	0.732	0.808	-0.853	2.316	0.365	10
35	0.705	1.132	-1.514	2.925	0.533	10
36	1.185	0.784	-0.353	2.722	0.131	10
37	1.753	0.730	0.322	3.184	0.016	10
38	1.599	0.781	0.068	3.130	0.041	10
39	0.213	1.041	-1.827	2.253	0.838	10
40	2.168	0.764	0.670	3.666	0.005	10
41	0.219	0.871	-1.488	1.927	0.801	10
42	0.234	0.714	-1.165	1.633	0.743	10
43	0.504	0.628	-0.726	1.734	0.422	10
44	0.621	0.954	-1.249	2.490	0.515	10
45	0.460	0.780	-1.068	1.988	0.555	10
46	1.498	0.806	-0.081	3.078	0.063	10
47	0.204	0.948	-1.654	2.063	0.829	10
48	-0.470	1.357	-3.130	2.191	0.729	10
49	0.329	0.973	-1.578	2.236	0.735	10
50	-0.221	1.491	-3.144	2.701	0.882	10
51	0.494	0.892	-1.256	2.243	0.580	10
52	2.059	0.872	0.350	3.768	0.018	10
53	0.351	0.963	-1.537	2.240	0.715	10
54	0.165	1.080	-1.951	2.281	0.878	10
55	1.216	1.209	-1.154	3.586	0.315	10
56	-0.286	1.083	-2.408	1.836	0.792	10
57	-0.394	0.900	-2.158	1.369	0.661	10
58	-0.323	0.889	-2.065	1.418	0.716	10
59	0.474	1.179	-1.836	2.784	0.688	8
60	-1.160	1.531	-4.160	1.840	0.449	7
61	-1.124	1.211	-3.498	1.250	0.354	7
62	0.261	1.023	-1.744	2.265	0.799	7
63	1.471	0.810	-0.117	3.060	0.069	7
64	-0.286	1.207	-2.651	2.080	0.813	4
65	-0.075	1.587	-3.185	3.035	0.962	4
66	-0.039	1.369	-2.723	2.644	0.977	4
67	-0.323	1.414	-3.093	2.448	0.820	4
68	-0.297	1.103	-2.459	1.865	0.788	4
69	-1.414	1.940	-5.217	2.389	0.466	4
70	-0.353	2.180	-4.625	3.919	0.871	4