Democratization and drug violence in Mexico

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2013

Abstract

Democracy is largely associated with reducing internal violence. However, under certain conditions, democratization can unleash unprecedented levels of organized criminal violence. Based on a formal model, this research analyzes the onset, escalation and concentration of drug violence in Mexico. In contexts where state authorities coexist with criminal groups, democratization undermines peaceful configurations between authorities and criminals, and motivates law enforcement. The intensification of aggressive security policies is a key catalyst disrupting the relative military balance among criminals and triggering struggles between rival criminal organizations. Criminal conflict is also highly territorial as violence tends to cluster in valuable territories. Empirical support comes from a machine-generated database of daily event data at municipal level in Mexico comprising about 9.8 million observations. The research design relies on instrumental variables to disentangle the dynamics between different—yet overlapping—processes of law enforcement and violence among criminal groups.

*Postdoctoral Fellow, Mario Einaudi Center of International Studies, Cornell University (2013-2014). This research was possible thanks to the support of the National Science Foundation; the Science Research Council - Open Society Foundations; the United States Institute of Peace; Kellogg Institute at the University of Notre Dame; the Harry Frank Guggenheim Foundation; and the Program on Order, Conflict and Violence at Yale University. Contact: fjo23@cornell.edu

1 Introduction

High levels of organized criminal violence are a central concern in the developing world. The preponderance of violence perpetrated by criminal groups in third-wave democracies is particularly puzzling because democracy is expected to reduce intra-state violence (Davenport 2009). To understand the determinants of large-scale organized criminal violence in developing democracies, this research addresses three inter-related questions referring to the onset, escalation and concentration of this type of violence: Why do authorities launch full-fledged campaigns against organized crime? Why does organized criminal violence escalate so rapidly? Finally, why is violence concentrated more in some areas than in others?

Following research on state-sponsored protection rackets (Snyder & Duran-Martinez 2009), warlord competition (Skaperdas 2002) and territorial disputes (Carter 2010), this article presents a contest success model to provide an integrative explanation for the onset, escalation and geographic concentration of drug violence. The central argument claims that democratization motivates authorities to implement punitive strategies against crime, thus triggering waves of turf competition among criminals. In contexts where government authorities coexist with criminal groups, increasing levels of political competition associated with democratization undermine these peaceful configurations and motivate politicians to fight crime. The intensification of enforcement disrupts the relative military balance between criminal groups and triggers territorial struggles among rival criminal organizations. These violent interactions tend to cluster in areas favorable to crime-related activities.

With a specific focus on violence perpetrated by drug-trafficking organizations (DTOs), this article centers on Mexico. Studying the Mexican war on drugs provides an unique opportunity to test the proposed argument because this country recently underwent a process of democratization and is currently ravaged by a wave of drug violence that has generated approximately 60,000 people killed in only six years, a death toll surpassing that of other forms of political conflict such as civil wars. Lessons from the Mexican case can also help to understand the dynamics of organized criminal violence in other developing democracies affected by even higher levels of violence (Bergman & Whitehead 2009, Arias & Goldstein 2010).

Based on research using automated textual annotation (Schrodt 2009, Leetaru & Schrodt 2013), the empirical evidence comes from Organized Criminal Violence Event Data–Mexico (OCVED), a large database of daily events of drug violence and law enforcement in Mexico between 2000 and 2010 at the municipal level. The database, comprising about 9.8 million observations, was generated using *Eventus ID*, a novel software for automated event coding from newspaper reports in Spanish (Osorio & Reyes 2012). OCVED provides detailed information on who did what to whom, when and where in the Mexican war on drugs.

To overcome the endogeneity of distinct—yet overlapping—processes of law enforcement and violent criminal competition, the research design relies on instrumental variables. The results show that democratization motivates politicians to fight crime. An increase in the effective number of parties and divided governments are associated with the intensification of law enforcement. Results also show that enforcing the law is a key catalyst of inter-cartel violence. This effect is consistent across a broad menu of violent and non-violent enforcement tactics. The empirical assessment also reveals the centrality of strategic territories as violence concentrates in areas favorable to the reception, and international distribution of illegal drugs.

The article begins by reviewing research linking democratization, violence and organized crime. It then presents a formal model of violent competition among criminal groups. The third part describes the data and the subsequent section reports the statistical analysis. Finally, the fifth section offers some concluding remarks.

2 Democratization, violence and organized crime

Research on organized crime offers limited explanations to understanding large-scale organized crime violence as it considers overt criminal violence as an empirical anomaly (Reuter 1989, Gambetta 1993, Volkov 2002). In this view, criminal groups often rely on intimidation, but rarely make overt use of violence as it attracts enforcement and imposes material and human costs (Reuter 1989). In addition, conflict scholars have largely neglected the study of criminal organizations as politically relevant actors. Besides some studies linking organized crime and political order (Tilly 1985, Olson 2000, Skarbek 2011) and the role of drugs and arms contraband for fueling violence (Fearon 2005, Dube, Dube & Garcia-Ponce 2012), conflict scholars have understudied large-scale criminal violence despite its lethality and organizational character. This paper bridges these two bodies of literature by studying sustained campaigns of violence conducted by criminal organizations.

Although democracy is largely associated with reducing domestic violence (Davenport 2009), conflict scholars have identified a link between democratization and political violence. Some argue that semi-democracies are more prone to internal violence than stable democracies or autocracies (Hegre et al. 2001). Others claim that conflict also depends on the rate of political change characteristic of democratic transitions (Mansfield & Snyder 2005, Cederman, Hug & Krebs 2010). These explanations generally agree that the failure of political elites to mobilize citizens massively franchised through democratization is likely to generate violent outcomes. However, this argument fails to consider a key difference between political and criminal violence. In political conflict, rebels use violence for *challenging the status quo* motivated by political or economic goals (Gurr 1970, Collier 2004). In contrast, criminals do not seek to overthrow state authorities and impose their own government agenda. Criminal violence is primarily used in the course of resisting law enforcement that affects criminal's economic interests. Thus organized criminals use violence for *preserving the status quo* that allows them freedom of movement and to extract economic benefits from illegal markets. This distinction makes it difficult to extend the political mobilization argument to explain criminal violence.

The link between political change and drug violence in Mexico has not passed unnoticed. Some argue that democratization undermines rural patronage networks (Villareal 2002) and erodes state-sponsored protection rackets (Snyder & Duran-Martinez 2009). In this view, criminal violence erupts because the state lost the ability to contain criminal groups. Unfortunately, this approach assigns a passive role to the state that does not correspond to the unprecedented deployment of law enforcement to combat criminal groups. In contrast, this study assigns a proactive role to the state and argues that violence among criminal organizations is caused by the disruptive effect of law enforcement. This article contributes to studies disentangling the endogenous relationship between enforcement and criminal violence (Dell 2011, Calderón et al. 2012, Levitt 1997). In doing so, it expands the temporal and spatial variation, as well as the menu of violent and non-violent enforcement tactics considered by previous research.

3 Theoretical model

Based on a contest success model, the theoretical explanation elucidates how democratization motivates politicians to fight crime and and how law enforcement alters the relative military balance between criminal groups and generates a turf war among DTOs. According to this account, state action is not neutral: state crackdowns weaken criminal's capability to protect its territory, thus motivating the territorial expansion of a rival DTO. As long as criminals have the ability to recover from the damage inflicted by law enforcement or attacks from rival groups, they are likely to keep fighting to control profitable territories. Consequently, when the state simultaneously fights several criminal organizations within its territory, it generates a Hobbesian war of all against all.

3.1 Players and actions

The model consists of a sequential game of complete information. Consider three players: the State (S), a Target DTO (T) and a Challenger DTO (C). The game is played in a sequence of five steps. First, Nature decides the degree of democracy along a continuum from low to high levels of democracy (D), where $D \in [0, 1]$. Second, the State chooses whether to enforce the law against the Target (E) or not ($\sim E$). Third, if the State enforces the law, the Target DTO decides to retaliate against the State (R) or not ($\sim R$). In the fourth step, a Challenger DTO decides to invade (I) the Target's territory or not ($\sim I$). Finally, if the Challenger invades, the Target decides whether to fight back (F) or not ($\sim F$) against the Challenger. Figure 1 illustrates the extensive form of the game.

[Insert Figure 1 about here]

The model is based on two key assumptions: (i) criminal organizations are primarily motivated by economic benefits[1] and; (ii) there is *order* in the status quo: government authorities and organized criminals coexist in a peaceful arrangement.[2] This theory is expected to be valid at least in those cases where these scope conditions hold.

3.2 Fighting crime in new democracies

The link between democratization and drug violence is located within the Hobbesian tradition of conflict research, in which violence emerges as the collapse of political order (Hobbes 1651, Tilly 1985, Kalyvas, Shapiro & Masoud 2008). The model assumes that at low levels of democratic development, state authorities coexist with criminals on a basis of corruption. Parameter $B > 0$ represents the bribes received by government officials in exchange for not

[1]This assumption also implies that criminal organizations are not mainly driven by political goals. Although criminals may use violence to resist or inhibit law enforcement, they are not ideologically motivated to overthrow the government. In consequence, criminals are not expected to unilaterally initiate an attack against the state.

[2]This assumption corresponds to what Snyder & Duran-Martinez (2009) call "state-sponsored protection rackets". This implies that the state lacks the monopoly of violence and allows for the coexistence between state authorities and parallel power structures as addressed by O'Donnell (1993).

enforcing the law. In contrast, higher levels of democratic development motivate authorities to provide public goods, such as public security. The political benefits of enforcing the law in a democratic setting are determined by $G > 0$. The model assumes that $G > B$ at high levels of democratic development, whereas $G < B$ under a non-democratic regime.

Peaceful configurations do not need to be explicit "pacts" between the state and DTOs, but can be achieved as a behavioral equilibrium. The small number of relevant political actors characteristic of authoritarian regimes favors peaceful arrangements between the state and DTOs in various ways. A reduced number of political actors makes it easier for criminals to bargain with government officials and cheaper to bribe them. The limited number of political actors facilitates collective action among corrupt politicians. In addition, the hierarchical chain of command characteristic of non-democratic regimes increases the feasibility of the agreement. Finally, the lack of effective elite circulation through electoral means favors the long-term stability of these arrangements in non-democratic settings.

The process of democratization constitutes an exogenous force undermining corrupt configurations and generating political motivations for authorities to enforce the law. Democratization increases the number of relevant political actors at different levels of government. Increasing competition motivates politicians to provide public goods, including public security. For organized criminals, a larger number of political actors increases the difficulty of bargaining with authorities and the costs of bribing them. For corrupt authorities, the entrance of new political actors makes collective action more difficult. Partisan plurality at different levels of government breaks the chain of command and reduces the feasibility of corrupt configurations. In addition, elections favoring effective elite circulation reduce the duration of peaceful agreements and increase uncertainty about the potential for future arrangements (Przeworski 1991). Under democracy, political actors also have direct incentives to enforce the law as they seek to win citizen support by deliberately breaking corrupt agreements and framing themselves as honest politicians.

3.3 Shifting military capabilities

A central conjecture of this model indicates that criminals fight each other for territorial control. Let $\tau > 0$ be the value of a strategiv territory and assume that all DTOs value it in the same way. The military capabilities of the Target used for controlling a territory are denoted by $M \in [0, 1]$. The Challenger's military power is defined relative to the Target's strength as $(1 - M)$. Relative military capacity is a contest success function whose value is the probability of winning a battle against a rival over a disputed territory (Jia, Skaperdas & Vaidya 2012). The Target enjoys the share of the territory it manages to control, $M\tau$, and the Challenger controls the remaining area, $(1 - M)\tau$.

Let $\gamma \in [0, 1]$ be the severity of military damage caused to the Target by an attack from either the State or the Challenger, such that $\gamma M < M$. If γ has values close to 1, then M is barely affected, while values of γ close to 0 indicate substantial damage to the Target. The severity of damage can vary depending on the sequential actions of each player such that γ^V, where $V = (E - R\sigma + I - F\sigma)$. Parameters E, R, I and F denote the set of violent actions available to each player. If any player opts to use violence, its respective action (E, R, I or F) takes the value of 1, otherwise it is 0. If the Target fights back, it may neutralize some of the damage and reestablish part of the relative military balance by a factor of $\sigma \in [0, 1]$, which represents the Target's recovery capability. The Target can reestablish the relative military balance in two ways: it can increase its own capabilities (e.g., recruiting more hitmen, using more cruel tactics or getting more powerful weapons) or it can reduce the military strength of its opponent (e.g., killing a rival). Values of σ close to 1 indicate a strong Target capable of reestablishing the relative military balance in either of these two ways. If σ is close to 0, it reflects a weak Target incapable of recovering its military position.

The relative military balance shifts back and forth as a function of the severity of military damage (γ) and the effectiveness of recovery (σ). If no actor uses violence, then $\gamma^0 = 1$ and the military balance is not altered. If either the State or the Challenger attack the Target and latter does not fight back, the attack diminishes the Target's military capabilities by

γM. However, if the Target fights back against its aggressor, the reaction helps to offset part of the damage and the net power balance is $\gamma^{(1-\sigma)}M$. In addition, if both the State and the Challenger attack the Target and the latter does not respond, the Target's military capability is damaged by $\gamma^2 M$. If the Target is attacked by the State and the Challenger but the Target only fights back against one of them, this leaves a net balance of $\gamma^{2-\sigma}M$. Finally, if the Target is attacked by both aggressors and fights them both, the Target neutralizes part of the damage and the net military balance becomes $\gamma^{2-2\sigma}M$.

3.4 Payoffs

This section discusses the payoffs of the game tree presented in Figure 1. Numbers in brackets at the end of each branch represent the sequence of payoffs. First consider the Status Quo (Payoff 1) where there is no violence. If the State does not enforce the law, it receives benefits only from bribes (B). In the absence of law enforcement, the Target enjoys the benefits of a militarily controlled territory ($M\tau$) and the Challenger obtains only a fraction of the territory it can secure given its military strength ($(1-M)\tau$).

In Payoff 2, the State receives bribes for not enforcing the law. The Challenger invades and undermines the military capabilities of the Target by ($M\gamma\tau$) and improves its own relative strength. The model assumes that violent actions perpetrated by player i against any other player j incur a cost $K_{ij} > 0$ for using violence.[3] Therefore the invasion incurs a cost of K_{CT} for the Challenger and leads to a payoff of ($(1-M\gamma)\tau - K_{CT}$).

In Payoff 3 the lack of law enforcement gives the State the benefits of corruption. The Challenger launches an invasion and the Target resists the attack. After the violent inter-

[3]The model assumes that γ and K_{ij} are different types of costs. Parameter γ refers to damage caused to a rival *as a consequence of the use* of violence (e.g., wounding or killing enemies). In contrast, parameter K_{ij} refers to the costs incurred by the perpetrator *to fund the use* of violence (e.g., recruiting more hitmen).

action, the Target enjoys part of the territory that it managed to recover from the invasion $((M\gamma^{1-\sigma})\tau - K_{TC})$ and the Challenger gained a fraction of the territory after facing some resistance from the Target $((1 - M\gamma^{1-\sigma})\tau - K_{CT})$.

In scenarios 4–9, the authorities enforce the law. In Payoff 4, the State fights the Target but there is no retaliation against enforcement nor violence among criminals. State crackdowns give authorities political benefits for providing public security at some cost of enforcement $(G - K_{ST})$. Enforcement weakens the Target's military capability to defend its territory $(M\gamma\tau)$ and improves the relative power of the Challenger by $(1 - M\gamma)\tau$.

In Payoff 5, the State obtains the political benefit of fighting crime $(G - K_{ST})$. The damage caused by law enforcement to the Target increases the Challenger's relative strength. If the Challenger decides to launch an invasion against the Target, it will further improve its position by $((1 - M\gamma^2)\tau - K_{CT})$. If the Target does not defend itself from any aggressor, the sequential attacks reduce its military capacity by $(\gamma^2 M\tau)$.

In Payoff 6, both the State and the Challenger attack the Target, which fights the invaders but not the government. The payoff for the State is $(G - K_{ST})$. The sequential attacks by the government and the Challenger severely undermine the Target's strength, but the Target's reaction against the Challenger helps it to recover part of the military loss $((M\gamma^{2-\sigma})\tau - K_{TC})$. After facing the Target's resistance, the Challenger enjoys a position indirectly improved by the State's actions and further improved through the invasion $((1 - M\gamma^{2-\sigma})\tau - K_{CT})$.

Payoff 7 represents the situation in which the State enforces the law and the Target retaliates against the authorities. Criminal retaliation against enforcement diminishes the State's political benefits from fighting crime by a factor of $\lambda > 1$, thus leaving a payoff for the State defined by $(G - \lambda - K_{ST})$. After being damaged by a crackdown and retaliating against the government, the Target's payoff is $((M\gamma^{1-\sigma})\tau - K_{TS})$. In addition, since the Challenger is not invading, it only obtains the benefits of a military position indirectly improved by law enforcement, $((1 - M\gamma^{1-\sigma})\tau)$.

In Payoff 8, both the State and the Challenger attack the Target, and the Target resists enforcement but not the invasion. The confrontation between authorities and the Target diminishes the State's benefits $(G - \lambda - K_{ST})$ and undermines the Target's military strength. In addition, if the Challenger launches an invasion and is not repelled by the Target, the attack would further weaken the Target by $(M\gamma^{2-\sigma}\tau - K_{TS})$ and substantially improve the Challenger's control over the territory $((1 - M\gamma^{2-\sigma})\tau - K_{CT})$.

Finally, Payoff 9 represents the situation of war by all against all. The State reaps the political benefits of fighting crime, even though it faces retaliation and incurs some costs $(\Omega G - \lambda - K_{ST})$. Enforcement reduces the Target's strength and indirectly improves the Challenger's relative position. By retaliating, the Target recovers some of the military position damaged by law enforcement. If the Challenger decides to invade, it will further weaken the Target and improve its own relative position. However, if the Target fights back, it recovers part of its relative power position. These violent interactions shift the military balance back and forth between the criminal groups, thus giving a payoff of $(M\gamma^{2-2\sigma}\tau - K_{TS} - K_{TC})$ to the Target and $((1 - M\gamma^{2-2\sigma})\tau - K_{CT})$ to the Challenger.

3.5 Equilibrium

The sub-game perfect equilibrium is identified through backward induction. I start at the bottom of the game tree in order to find the conditions under which the Target fights the Challenger. The comparison between Payoffs 2 and 3 indicates that if the State does not enforce the law, the Target will fight the Challenger if $(\gamma^{1-\sigma} - \gamma) > \frac{K_{TC}}{M\tau}$. We can define $\theta = (\gamma^{1-\sigma} - \gamma)$ as the Target's net military capability recovered by fighting back after being attacked. Parameter $\frac{K_{TC}}{M\tau}$ represents the attractiveness of engaging in a confrontation given the costs of fighting, the probability of winning and the value of the territory. Rewriting the equilibrium condition as $\theta > \frac{K_{TC}}{M\tau}$ indicates that the Target will fight the Challenger if the net military position recovered by force is worth the effort.

Now compare Payoffs 5 and 6 where authorities enforce the law and the Target does not retaliate against the government. In this situation, the Target will use violence against the Challenger if $\theta > \frac{K_{TC}}{\gamma M \tau}$. In this case, parameter γ on the right-hand side represents the additional damage on the Target caused by law enforcement. Therefore the Target will fight the Challenger if the net military capacity regained by force is larger than the attractiveness of defending the territory after suffering a crackdown.

Payoffs 8 and 9 reflect scenarios where authorities fight crime and the Target retaliates against the State. The Target will fight the invader if $\theta > \frac{K_{TC}}{\gamma^{1-\sigma} M \tau}$. Parameter $\gamma^{1-\sigma}$ on the right-hand side refers to the Target's military strength recovered by retaliating against law enforcement. In this case, the Target will repel the invasion if the proportion of military strength recovered by fighting the Challenger is larger than the relative attractiveness of battling over the disputed territory, even after the Target suffered law enforcement and retaliated against it.

In general, the analysis indicates the same underlying logic for the Target: if the proportion of relative military capacity recovered by force is larger than the attractiveness of fighting for a valuable territory, then the Target will fight back.

The second level of the model helps to identify the conditions under which the Challenger will invade knowing that the Target will fight. Comparing Payoffs 1 and 3 indicates that in the absence of law enforcement, the Challenger will invade the Target if $1 - \gamma^{1-\sigma} > \frac{K_{CT}}{M \tau}$. Parameter $(1-\gamma^{1-\sigma})$ represents the Challenger's net gain of military capability after launching an invasion and facing the Target's resistance. In addition, parameter $\frac{K_{CT}}{M \tau}$ represents the costs of invading given the value of the territory and the Target's military strength. We can define $\pi = (1 - \gamma^{1-\sigma})$ and rewrite the equilibrium condition as $\pi > \frac{K_{CT}}{M \tau}$. This indicates that the Challenger will invade if the net military gain is larger than the attractiveness of invading, knowing that the Target will fight back.

Consider Payoffs 4 and 6, in which the State enforces the law and the Target does not retaliate against the government. The equilibrium indicates that the Challenger will launch an invasion if $\pi > \frac{K_{CT}}{\gamma M \tau}$. Parameter γ on the right-hand side refers to the additional damage caused by law enforcement to the Target. This indicates that the Challenger will invade if the net military gain of doing so is larger than the attractiveness of fighting, even when the Target is likely to resist the invasion after being weakened by the State.

Comparing Payoffs 7 and 9 shows that the Challenger will invade if the utility of doing so is larger than the utility of not invading, even knowing that the Target will resist the invasion. The Challenger will fight under the following condition: $\pi > \frac{K_{CT}}{\gamma^{1-\sigma} M_{\tau}}$. Parameter $\gamma^{1-\sigma}$ on the right-hand side represents the interaction between the State and the Target. According to the model, the Challenger will carry out an invasion if the net military gain of doing so is larger than the attractiveness of invading, even knowing that the Target will resist the invasion after retaliating against the State.

The model gives another important insight about the non-neutral effect of State actions: law enforcement weakens the Target criminal organization and indirectly improves the relative military position of the Challenger. Therefore regardless of the Target's reaction against its aggressors, the Challenger has more incentives to invade when the State enforces the law against the Target than when it does not.

Now consider the Target's decision to retaliate against the State. The equilibrium analysis indicates that the Target will react against law enforcement if $\theta > \frac{K_{TS}}{\gamma^{1-\sigma} MT}$. As defined above, θ represents the Target's net military capacity recovered through fighting back after being attacked, in this case by the State. In addition, parameter $\gamma^{1-\sigma}$ on the right-hand side indicates the Target's military capability recovered after resisting the Challenger's invasion. In consequence, the Target will retaliate against law enforcement if the military strength recovered from doing so is larger than the attractiveness of fighting the State, even after the Target and the Challenger have battled over a disputed territory.

Finally, comparing Payoffs 3 and 9 reveals the conditions favorable to law enforcement. Knowing that the Target and the Challenger will engage in territorial conflict and the Target will retaliate against law enforcement, the State will launch a campaign against crime under the condition $G > B + \lambda + K_{ST}$. Even given the costs of enforcing the law and receiving attacks in resistance of law enforcement, the State will fight crime if the political benefits of providing security as a public good are larger than the benefits of corruption from not enforcing the law. As mentioned above, the model assumes that $G > B$ at high levels of democratic development, and $G < B$ at low levels of democracy.

Table 1 summarizes the equilibrium conditions for the different processes of violence inherent to the war on drugs. Based on these conditions, it is possible to derive some hypotheses for empirical evaluation. H_1: Increased democratization is associated with higher levels of law enforcement. H_2: Increased law enforcement is associated with higher levels of violent competition among DTOs. H_3: More valuable territories are associated with higher levels of violence among DTOs.

[Insert Table 1 about here]

4 Data

To assess the theoretical implications, the empirical analysis relies on Organized Criminal Violence Event Data–Mexico (OCVED), a large database containing fine-grained event data on drug violence. Building this database required the development of *Eventus ID*, a novel automated coding protocol for identifying events from news reports written in Spanish (Osorio & Reyes 2012). Following research using computerized textual annotation (Schrodt 2009), Eventus ID identifies three key components of event data: the perpetrator of an action, known as the *source*; the specific *action* being conducted; and the *target* receiving the action. OCVED contains geo-referenced events of violent and non-violent law enforcement, criminal violence against the state and violence among rival DTOs. The database covers all Mexican municipalities (N=2,456) on a daily basis between January 1, 2000 and December 31, 2010 (T=4,017 days), for a total ($N \times T$) of 9,865,752 municipality-days. In this manner, OCVED provides detailed information on who did what to whom, when and where in the Mexican war on drugs with a total of 251,167 events coded.

To minimize concerns of uneven coverage in newspaper-generated databases (Davenport

& Ball 2002), this study gathers press releases from 105 sources including four federal and 32 local government agencies, and daily reports from 11 national newspapers and 58 local newspapers between 2000 and 2010.[4] A team of human coders selected 41,838 reports explicitly mentioning violent actions undertaken either by DTOs or authorities fighting crime.[5]

OCVED disentangles the bulk of drug violence by identifying distinct types of violence. The variable *violent enforcement* measures the daily number of events in which the state attacked, wounded or killed presumed members of a criminal organization in a municipality. Criminal *retaliation* is measured as the daily number of violent actions perpetrated by DTOs against government authorities (e.g., shooting, ambushing, kidnapping, wounding, torturing, killing and mutilating). In addition, *inter-cartel violence* is measured as the number of violent events between rival DTOs that occurred in a municipality-day. Using data aggregated at the national level, Panel A in Figure 2 shows the time series of violent law enforcement, criminal retaliation against the state and inter-cartel violence. The graph reveals a consistent positive

[4]Considering various sources of information often results in multiple reports of a single event. In order to minimize concerns of double-counting, duplicates were identified and excluded from the database using standard statistical procedures.

[5]Violent episodes included a wide variety of events such as arrests, seizures, shootings, kidnappings, homicides, confrontations, ambushes, attacks, discovery of bodies, mutilation, beheading and torture, among other events. News reports were considered if they included information about the traditional *modus operandi* of organized criminals such as the use of high-caliber weapons, violence perpetrated by groups of armed men, use of convoys of vehicles, multiple victims, bodies with multiple bullet wounds, bodies shot execution-style in the head, signs of torture or mutilation, or written messages left near the victims. The criteria excluded reports of ordinary crimes (e.g., robbery, burglary, crimes of passion), actions perpetrated by guerrilla groups, speeches, statements, claims, accusations, demands, opinions or editorials.

trend in the three processes of violence and shows that conflict between DTOs is the most prominent type of violence.

[Insert Figure 2 about here]

The database also contains data on non-violent enforcement. The variable *arrests* measures the daily number of detentions of presumed DTO members; *seizure of assets* counts the number of events in which authorities confiscated real estate or vehicles belonging to criminal organizations; *seizure of drugs* measures the number of events of drug interdiction, and *seizure of weapons* measures the number of events in which the state confiscated weapons, ammunition or explosives. Panel B in Figure 2 shows the time series of non-violent enforcement including arrests, seizures of criminal assets, drug seizures and confiscation of weapons. The trends show that arrests and drug seizures constitute the majority of non-violent enforcement actions. Comparing Panels A and B in Figure 2 also reveals that state violence constitutes only a small fraction of a broader array of enforcement tactics.

This study relies on a narrow operationalization of democratization focused on two variables. The *effective number of parties* (ENP) measures the number of relevant political parties at the presidential level using the formula presented by Laakso & Taagepera (1979). Analyzing political competition at the executive level is relevant in the Mexican case because the president has the prerogative of commanding the Army, Navy and Federal Police for fighting organized crime. The variable *divided government* measures the degree of partisan division across three levels of government (president, governors and mayors), it takes the value of 0 if the three levels of government belong to the same party and 1 otherwise. In the context of Mexican politics, divided government works as a measure of improving democratic conditions due to the 70 years of party hegemony by the Institutional Revolutionary Party (PRI) (Magaloni 2006). This variable serves as a proxy for the effect of democratization on eroding peaceful configurations between criminals and politicians across government tiers.

Different variables serve to identify the characteristics of drug-strategic territories. *Drug production* measures marijuana and poppy production on a four-level scale (0–3) at municipal level as reported by Secretaría de la Defensa Nacional (2011). After the 9/11 terrorist attacks, tightened security measures implemented by the U.S. government made international drug trafficking more difficult, thus increasing the strategic value of Mexican territory for drug smuggling. Variable *9/11* takes the value of 1 after September 11, 2001 and 0 otherwise. Variables *Gulf* and *Pacific* identify municipalities located along Mexico's coasts, which are areas favorable for the reception of drug shipments from abroad. These variables take the value of 1 for the strip of three adjacent municipalities located along the Gulf of Mexico or the Pacific coastline and 0 otherwise. Variable *North* identifies territories favorable for international drug distribution and takes the value of 1 for the strip of three contiguous municipalities located along the Mexico–U.S. border. To allow for the temporal variation of these geographic variables in the statistical analysis, measures of Gulf, Pacific and North are interacted with variable 9/11.

It is difficult to observe criminal groups' capacity for causing damage or for recovering from an attack. Two variables serve as proxies for these concepts. *Rifles* measures the production of assault rifles in units of 100,000 (Bureau of Alchohol, Tobacco, Firearms and Explosives 2012), thus reflecting the increased fire power available to DTOs after the end of the Federal Assault Weapons Ban (Dube, Dube & Garcia-Ponce 2012)). In addition, *Unemployment* measures the percentage of unemployed population and serves as a proxy for the recovery capability of DTOs. Unemployment increases the human reserve that criminals can use to replace foot-soldiers at low cost (Fajnzylber, Lederman & Loayza 2002, Weinstein 2007). Theoretically, criminal organizations can alter the relative military balance by undermining their rival's military capabilities or by improving their own. Empirically, gun availability—measured by *rifles*—increases their potential for damaging a rival, and the availability of recruitment—represented by *unemployment*—improves their own military capabilities.

The model also includes several control variables. *Corruption* is measured as the percentage of the state population who reported paying a bribe to avoid being arrested (Transparencia Mexicana 2012). *Cocaine price* is the price a gram of pure cocaine (U.S. Department of

Justice 2011). Following other efforts to estimate drug consumption in Mexico (Rios 2012, Madrazo & Guerrero 2012), the variable *local drug markets* measures the number of cases of hospitalization caused by consumption of illegal narcotics as reported in Mexican morbidity statistics (Secretaría de Salud 2012). To account for changes in the traditional family structure, the model includes the number of *divorces* and *young mothers* measured as the municipal proportion of women between 12 and 19 years old who are mothers of at least one child. The analysis includes the log of *population* by municipality, and the degree of *poverty* at municipal level (Consejo Nacional de Evaluación de la Política de Desarrollo Social 2012).

5 Statistical analysis

Political violence conflates highly dynamic and endogenous processes of conflict. As stated by Kalyvas, Shapiro & Masoud (2008), violence is used by those challenging the existing order and by those fighting to preserve it. There is thus a risk of endogeneity in hypothesis H_2 which states that law enforcement generates violence among DTOs. It could also be the case that conflict among criminals motivates authorities to impose order by force. To address concerns of endogeneity, this research follows other studies using instrumental variables (IV) to disentangle reciprocal processes of violence (Miguel, Satyanath & Sergenti 2004, Levitt 1997). The IV approach is used to first assess the effect of democratization on law enforcement, and then evaluate the impact of predicted levels of law enforcement on violence among DTOs. The model estimation is based on a two-stage least-squares for panel data with fixed effects at the municipal level. To improve the model fit, measures of violent and non-violent enforcement, as well as criminal retaliation and inter-cartel violence are logged.

The two-stage analysis considers violence among criminals and law enforcement as endogenous variables. The instrumental variables are the effective number of parties and the degree of divided government. The other variables are considered as exogenous covariates.

The first stage model is expressed as

$$\mathbf{E}_{it} = \alpha + \theta_1 \mathbf{P}_{it} + \theta_2 \mathbf{D}_{it} + \delta \mathbf{X}_{it} + \mu_{it}, \tag{1}$$

where $\mathbf{E}_{it}$ represents law enforcement in municipality i on day t, vector $\mathbf{P}_{it}$ is the effective number of parties, $\mathbf{D}_{it}$ is the measure of divided government, and $\mathbf{X}_{it}$ a vector with all other exogenous covariates. Equation (1) is the mathematical expression of hypothesis H_1.

The reduced form expresses the relationship expected in hypothesis H_2, in which the predicted levels of law enforcement caused by democratization have an impact on inter-cartel violence. The second stage is defined as

$$\mathbf{Y}_{it} = \alpha' + \beta_1 \mathbf{E'}_{it} + \delta' \mathbf{X}_{it} + \mu'_{it}. \tag{2}$$

$\mathbf{Y}_{it}$ represents inter-cartel violence and $\mathbf{E'}_{it}$ represents the predicted level of enforcement caused by democratization and political strain. The other right-hand variables are the same as in Equation (1).

Following Angrist & Pischke (2009), we can think of instrumental variables as initiating a causal chain where the instruments $\mathbf{P}_{it}$ and $\mathbf{D}_{it}$ affect the variable of interest $\mathbf{E}_{it}$, which in turn affects the outcome $\mathbf{Y}_{it}$. In this way, the model captures the effect of law enforcement on violent competition among criminals caused by the exogenous variation of democratization. This identification strategy addresses the problem of endogeneity while being consistent with the data generation process expected from the theory, thus favoring consistency between the ontology and the methodology (Hall 2003).

The instrumental variable approach helps remove the endogenous relations between the different processes of violence and allows the effect of law enforcement on inter-cartel violence be identified. In the context of the Mexican case, the three decades of democratic struggle generate variation in the number of political parties and government division that is plausibly exogenous to levels of violence among criminals. In consequence, the change in incentives caused by the process of democratization is conceivably independent from the wave of drug violence during the period under study. In addition, these types of political variables have been successfully used by other researchers to identify the effect of law enforcement on criminal violence (Levitt 1997, Dell 2011) .

The IV analysis is specified as a two-stage least-squares (2SLS) model for panel data with fixed effects clustered at the municipal level.[6] Tables 2 and 3 present the results of the first and second stage respectively. In general, the first stage provides strong support for hypothesis H_1, which state that democratization motivates politicians to fight crime. Model 1 in Table 2 reports the effect of the effective number of political parties and divided government on violent law enforcement and Models 2–5 on non-violent tactics such as arrests, and seizures of assets, drugs and weapons. Estimates of control variables are omitted from Table 2 but are available in the on-line appendix.

[Insert Table 2 about here]

As expected from the theory, results suggest that democratization erodes peaceful agreements between authorities and criminals, and increases political incentives to enforce the law. Based on the estimates of Model 1, Panel A Figure 3 shows that increasing the effective number of political parties motivates the use of violent enforcement. In addition, Panel B indicates that divided governments rely more on violent enforcement than unified governments. Models 2–5 also show that increasing the number of effective parties and disrupting partisan alignment across government tiers have a consistent positive effect on arrests, seizures of criminal assets, drugs and weapons. In general, these results support H_1, which states that democratization alters the political incentives to fight crime and motivate authorities to use a broad menu of violent and non-violent tactics to crackdown criminal organizations.

[Insert Figure 3 about here]

[6]The Appendix contains the robustness check with several other model specifications that largely confirm the results presented in this manuscript.

These findings help to elucidate the conditions of precarious political competition that facilitated a peaceful equilibrium between corrupt authorities and DTOs during the period of PRI political hegemony. The hierarchical chain of command characteristic of the hegemonic party system facilitated non-aggressive coexistence between the state and criminals. In addition, the lack of effective elite circulation gave certainty and stability to these agreements. In contrast, the gradual process of democratization deeply affected the Mexican political arena and disrupted these peaceful configurations. As opposition parties entered the political scene, implicit agreements between corrupt officials and DTOs became more difficult to sustain. Political competition also created incentives for new government authorities to fight crime as a strategy to distinguish themselves from the old regime and gain popular support.

In general, the first stage instruments report high levels of statistical significance and large F-statistics across models, suggesting that the measures of effective number of political parties and government division constitute strong instruments for the exogenous variation of law enforcement. Angrist & Pischke (2009) and Stock, Wright & Yogo (2002) indicate that strong instruments usually yield an F-statistic larger than 10 at acceptable levels of significance. The F-statistics reported in Table 2 are several times larger than the basic threshold. The Angrist-Pischke χ^2 test of underidentification is rejected in all models, thus suggesting that the endogenous regressors are identified. The Kleibergen-Paap Wald F statistic for weak identification is larger than the Stock-Yogo critical value of tolerable bias level at 10% across all models, thus rejecting the null hypothesis of weak identification. Finally, the Anderson-Rubin Wald F test rejects the null hypothesis that the coefficients of the endogenous regressors are jointly equal to zero.

Table 3 reports the estimates for the second stage. The results provide strong support for hypothesis H_2 which claims that fighting crime has a disruptive effect on criminal organizations and triggers waves of inter-cartel violence. The coefficients of violent and non-violent enforcement report a consistent positive effect on inter-cartel violence at high levels of statistical significance across models in Table 3. The Hansen J test for overidentification suggest that the instruments are uncorrelated with the residuals of the second stage across all models, thus providing further evidence for the validity of the instruments.

[Insert Table 3 about here]

Based on Model 1, Figure 4 illustrates the relationship between the predicted degree of violent enforcement generated by the exogenous variation of the effective number of parties and government division on the intensity of violence among DTOs. The graph shows that intensifying the predicted levels of violent enforcement from minimum to maximum is associated with a remarkable increase from 0.7 to 1,130 events of inter-cartel violence. Models 2–5 in Table 3 show that the disruptive effect of violent enforcement is substantially larger than the impact of non-violent tactics such as arrests and seizures of assets, drugs and weapons. This finding is consistent with the theoretical expectation to the extent that violent enforcement is likely to cause more severe military damage to DTOs than non-violent actions, thus leading to more intense waves of conflict among criminals. This is an interesting finding because, according to the total number of enforcement actions recorded in the database, the state used violence against DTOs only in 3.26 percent of the events, whereas the remaining 96.74 percent corresponds to non-violent enforcement. It is surprising how such a small proportion of lethal state action is capable of triggering substantial spirals of violence among criminals.

[Insert Figure 4 about here]

The statistical analysis in Table 3 provides support for hypothesis H_3 which states that more valuable territories tend to contain higher levels of conflict. However, the multiple measures of strategic value reveal that different territories concentrate different dynamics of violence. Results do not provide statistical evidence for the association between illegal crop production areas and violence among criminal groups. This finding contradicts the expectations of Angrist & Kugler (2008) and Fearon (2004), and suggests that violence is not caused by struggles for the control of marijuana and opium cultivation. In contrast, models 2–5 indicate that tighter security measures implemented by the U.S. government after the 9/11 terrorist attacks increased the overall strategic value of Mexico as a drug transportation route, thus increasing levels of violence among criminals. Testimonies collected during fieldwork in Mexico suggest that stricter U.S. security at the border after the 9/11 attacks slowed down the flow of drug smuggling into the U.S. and caused drugs to accumulate in Mexican territory, which turned border towns into large storage facilities and increased the risk of battles among DTOs to capture such territories.

Results in models 2–5 also show that territories along the northern border are battlegrounds for the control of entry points to the U.S. drug market. The position of a municipality on the U.S.–Mexico border after 9/11 is associated with higher levels of violent competition among DTOs than areas distant to the border. In addition, with the exception of model 3, all other model specifications in Table 3 consistently report that inter-cartel violence is more intense along the Pacific coast. The geo-strategic location of these territories is highly valuable because these areas are favorable for the reception of aerial and maritime drug shipments from South America. In contrast, according to models 1, 2 and 5, territories located along the Gulf of Mexico tend to experience lower levels of violence after 9/11. This negative result might be associated with the increasing monitoring of suspicious vessels and airplanes conducted by the U.S. along the Caribbean (Michel 2012). The territorial centrality of drug violence in different territories supports the implications of the theoretical model and is consistent with other findings addressing the relevance of subnational geographic variation to understanding the dynamics of domestic conflict (Buhaug & Ketil Rod 2006, Buhaug, Gates & Lujala 2009).

The statistical assessment provides mixed support for the relevance of military damage measured by the production of assault weapons in the U.S. This variable shows a negative sign in models 2 and 3, and a positive effect in models 4 and 5 in Table 3. In consequence, there is partial support for the argument that readily available weapons and the considerable financial resources derived from illicit markets allow DTOs to rapidly increase their firepower to combat other criminals or resist government authorities. The flipping signs and small coefficients of this variable casts doubt about the link between the production of assault rifles in the U.S. and increasing homicides in Mexico (Dube, Dube & Garcia-Ponce 2012).

As expected, unemployment shows a positive impact on violence among DTOs. This variable is used as a proxy for criminal capability for recovery from an attack by recruiting new members from the unemployed population. Models 2–5 in Table 3 report that unemployment is associated with intensified inter-cartel violence. This result is consistent with Humphreys & Weinstein (2007) linking unemployment with violence. As mentioned in the theoretical section, criminals can shift the relative military balance by either damaging the rival's military strength or by enhancing their own military capabilities through increased firepower or new recruits. The comparison between the availability of weapons and the abundance of potential recruits among the unemployed population suggests that DTOs rely more on cheap human resources than on military technology for shifting the relative military balance.

The statistical analysis finds weak support or contradictory findings for alternative explanations for the escalation of violence. The coefficients of corruption; the value of international drug markets measured by the price of cocaine in the U.S.; local drug markets measured by morbidity statistics of drug hospitalization; divorces; and the proportion of young mothers largely fail to reach statistical significance or flip their sings across models. In any case, the magnitude of most of these coefficients is barely distinguishable from zero. Finally, the effect of poverty at municipal level is associated with higher levels of inter-cartel violence in most model specifications. This confirms long standing explanations of domestic conflict linking poverty and violence (Collier 2004).

The simultaneous evaluation of competing explanations reveals that dynamic variables such as predicted levels of violent and non-violent enforcement have more explanatory power to account for the escalation of inter-cartel violence than structural variables used in other explanations. This finding contributes to the literature on the micro-dynamics of conflict by emphasizing the need for incorporating rapidly changing and interactive variables operating within the context of structural factors.

In general, the empirical assessment provides strong support for the predictions derived from the theoretical model. Democratization, measured by the effective number of parties and government division, constitutes a plausible source of exogenous variation in levels of violent and non-violent enforcement. The IV approach shows that the efforts of Mexican authorities to fight crime unleashed an unprecedented wave of territorial violence among rival criminal groups. Stricter U.S. border controls after 9/11 increased the propensity of drug violence on the Mexican side. In addition, inter-cartel violence became particularly intense in municipalities favorable for the reception of shipments along the Pacific coast, and in territories along the Mexico–U.S. border. Finally, the results indicate the relevance of criminal's recovery capabilities for engaging in sustained campaigns of violence by recruiting new members from high unemployment.

6 Conclusions

Democratization is largely associated with reducing internal violence. However, under certain situations, improving democratic conditions can also unleash unprecedented levels of violence among criminal groups. In a context where government authorities coexist with powerful criminal organizations, increased electoral competition and divided governments undermine preexisting agreements between politicians and criminals, and motivate authorities to fight organized crime in an effort to gain citizen support. As illustrated by the Mexican war on drugs, the convergence of these factors may prove lethal.

This study finds that political competition plays a central role in motivating punitive strategies against crime and that the intensification of law enforcement triggers waves of violence among criminal groups fighting to control strategic territories. The results reveal that the entrance of new parties to the political scene is associated with increased levels of enforcement. This is indicative of how political competition motivates authorities to provide public goods including public security. The results also indicate that divided governments are associated with increased efforts to fight crime. The entrance of new political actors across different levels of government disrupted the long-standing PRI hegemony that enabled a peaceful coexistence between the state and criminals.

The use of instrumental variables constitutes a plausible identification strategy capable of overcoming the endogenous relationship among overlapping processes of conflict. The results indicate that increased law enforcement caused by the exogenous variation of the effective number of political parties and government division exacerbates violent competition among criminal groups. This effect holds for violent enforcement and non-violent tactics such as arrests and seizures of assets, drugs and weapons. The empirical analysis also supports the argument about the centrality of territorial conflict among criminal groups. The results indicate that inter-cartel violence tends to concentrate in territories favorable for the reception of illegal crops along the Pacific coast and international entry points along the U.S.–Mexico border. Finally, as expected from the theory, criminal groups' ability to recover from an attack is important factor for explaining criminal conflict.

This research contributes to our understanding of the micro-determinants of conflict by disentangling different processes of violence and integrating them into a unifying theoretical explanation. A key implication of the model is that state actions have a disruptive effect on the relative military balance among competing groups, which triggers violence between rivals. In the Mexican case, law enforcement weakens the military capabilities of a criminal organization and indirectly improves the relative position of a rival group. If the territory is valuable enough, law enforcement may unleash territorial struggles among rival organizations as indirectly empowered criminals invade the territories of a weakened opponent. This type of mechanism can be useful for understanding a broader set of cases characterized by conflict among multiple armed groups fighting the state and battling among each other. In this way, "competition" constitutes an additional dimension to the traditional "repression-dissent" conceptualization of conflict (Davenport 2007), thus leading to a more sophisticated understanding of political violence as "repression-dissent-competition."

Empirically, this research relies on a novel machine-generated database of about 9.8 million observations comprising daily information at the municipal level on who did what to whom, when and where in the Mexican war on drugs. This paper also contributes to a recent trend of conflict research relying on "big data" (Leetaru & Schrodt 2013). The use of this fine-grained data indicates that understanding the complexities of conflict processes requires a combination of dynamic and interactive factors as well as structural variables. By focusing on organized crime violence, this research addresses the importance of studying criminal organizations as largely neglected actors capable of engaging in large-scale systematic campaigns of violence. In contrast to protesters, insurgents or terrorists, organized criminals do not primarily use violence to *change the status quo* for economic or political reasons. Rather, criminal organizations mainly exercise violence in an effort to *preserve the status quo* that allows them to extract economic rents from illegal markets. Finally, studying the Mexican war on drugs reveals the deleterious consequences of promoting quasi-military strategies to fight crime in new democracies and helps elucidate the challenges of democratic consolidation and security in the developing world.

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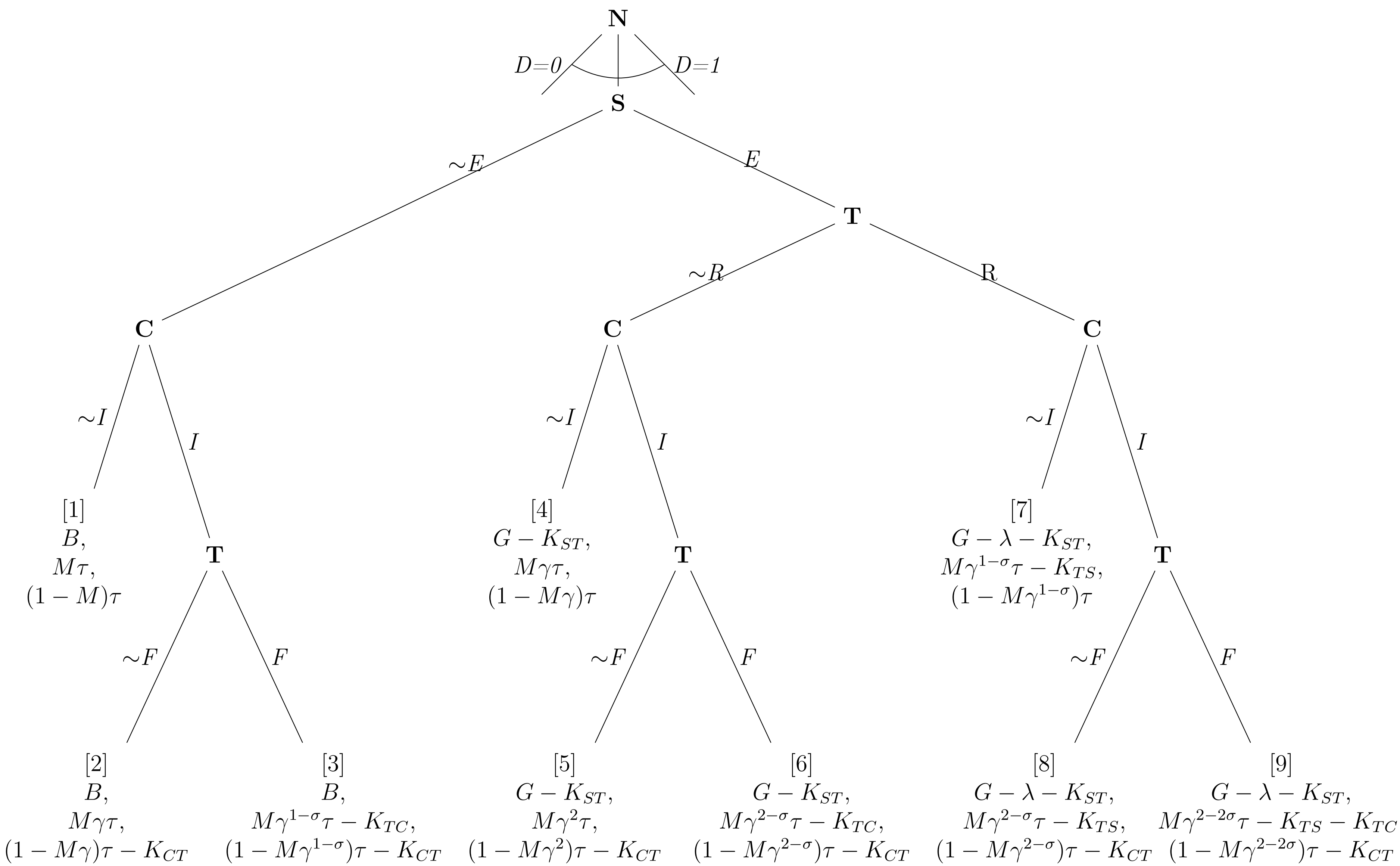
Figure 1: The Game of Drug Violence.



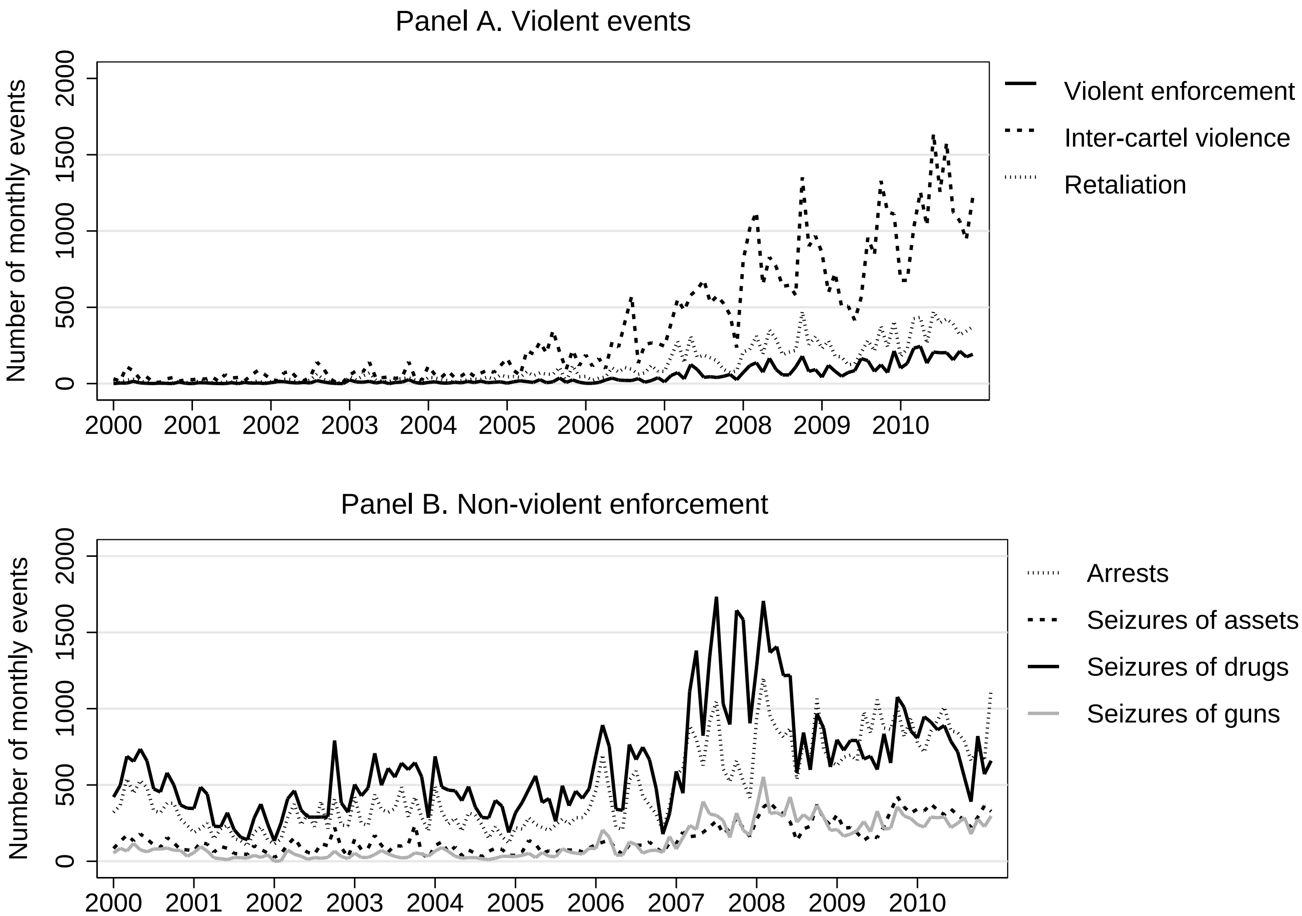


Figure 2: Dynamics of drug violence in Mexico (Jan. 2000 – Dec. 2010)

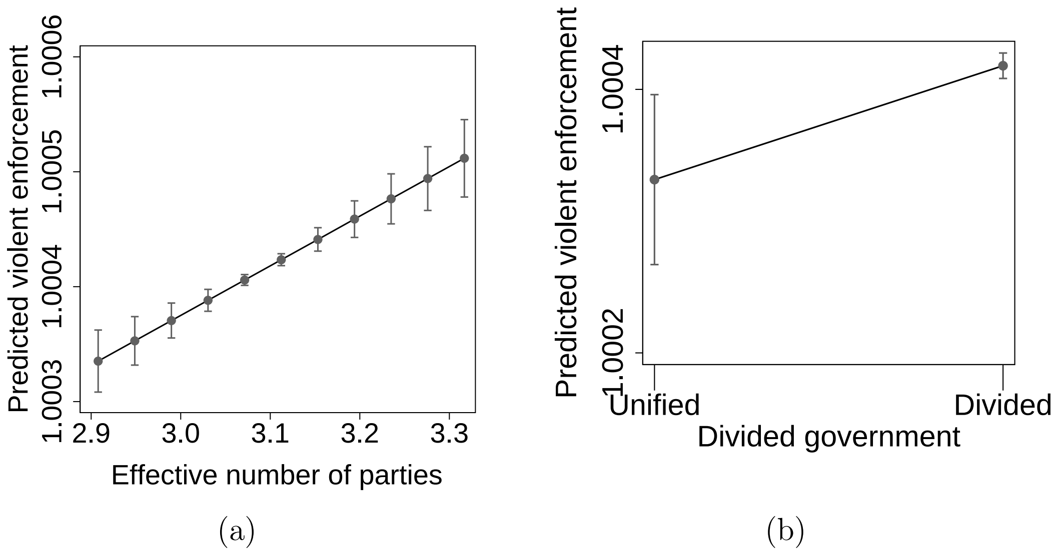


Figure 3: Effect of political competition and divided government on violent enforcement

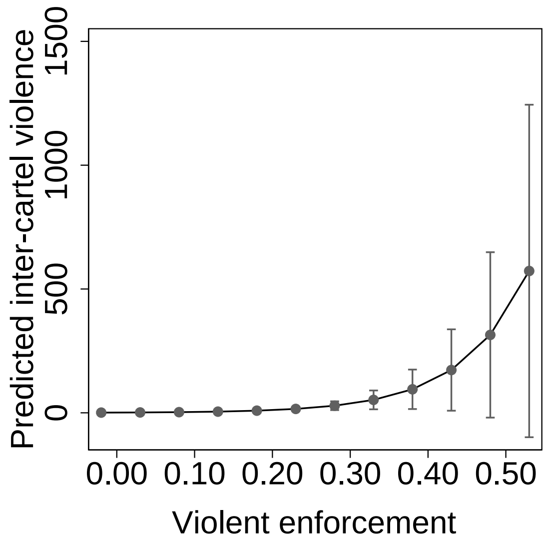


Figure 4: Effect of violent enforcement on inter-cartel violence

Table 1: Equilibrium conditions for violence in the war on drugs

Target fights the Challenger	Challenger invades the Target	Target retaliates against the State	State enforces the law
$\theta > \frac{K_{TC}}{M\tau}$	$\pi > \frac{K_{CT}}{M\tau}$		
$\theta > \frac{K_{TC}}{\gamma M\tau}$	$\pi > \frac{K_{CT}}{\gamma M\tau}$		
$\theta > \frac{K_{TC}}{\gamma^{1-\sigma} M\tau}$	$\pi > \frac{K_{CT}}{\gamma^{1-\sigma} M\tau}$	$\theta > \frac{K_{TS}}{\gamma^{1-\sigma} M\tau}$	$G > B + \lambda + K_{ST}$

Table 2: First Stage: Determinants of violent and non-violent enforcement

ENP	0.0004***	0.0043***	0.0017***	0.0071***	0.0026***
	(0.0001)	(0.0005)	(0.0002)	(0.0007)	(0.0003)
Divided government	0.0001**	0.0007**	0.0002**	0.0007*	0.0002*
	(0.0000)	(0.0003)	(0.0001)	(0.0004)	(0.0001)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
F statistic	26.55***	41.54***	50.36***	68.17***	50.43***
Angrist-Pischke χ^2	53.13***	83.10***	100.76***	136.39***	100.89***
Kleibergen-Paap F	26.55	41.54	50.36	68.17	50.43
Stock-Yogo 10% value	19.93	19.93	19.93	19.93	19.93
Anderson-Rubin F	59.92***	59.92***	59.92***	59.13***	59.92***
Levels of significance: * p< 0.1, ** p< 0.05, *** p< 0.01					

Table 3: Second Stage: Determinants of inter-cartel violence

	(1)	(2)	(3)	(4)	(5)
Violent enforcement	11.801***				
	(1.470)				
Arrests		1.246***			
		(0.118)			
Seizures of assets			3.085***		
			(0.238)		
Seizures of drugs				0.712***	
				(0.067)	
Seizures of guns					1.950***
					(0.171)
Rifles (100 K)				0.001*	
				(0.001)	
Retaliation (log)	-2.201***	0.165***	0.200***	0.357***	0.241***
	(0.363)	(0.024)	(0.019)	(0.019)	(0.018)
Drug production	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
9/11	0.000	0.001***	0.000*	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gulf after 9/11	-0.002***	-0.001**	0.000	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
North after 9/11	-0.002	0.006***	0.005***	0.006***	0.002*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Pacific after 9/11	0.002***	0.003***	0.001	0.002**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rifles (100 K)	-0.000	-0.000*	-0.000***	0.001*	0.000**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Unemployment	-0.000	0.000*	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corruption	0.000***	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cocaine price	-0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local drug markets	0.000	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Divorces	0.000	-0.000**	-0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young mothers	0.008**	-0.002	0.001	-0.006**	-0.004**
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Poverty	-0.001	0.001*	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population (log)	-0.003	-0.002	0.002*	0.002	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
Sargan statistic	2.234	0.682	0.288	9.040	7.353
Sargan p-value	0.135	0.409	0.591	0.003	0.007
Levels of significance: * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$					

Appendix: Robustness check.

This appendix contains a variety of robustness tests for the statistical analysis and it will be available on-line when the manuscript is accepted for publication. The different model specifications considered in the robustness check include the following:

- **Instrumental variables (IV) model with fixed effects and clusters at the municipal level**. The first and second stages of this model are reported in Tables 5 and 6. The predicted effect of the instruments on the different measures of violent and non-violent enforcement from the first stage are reported in Figures 5 and 6. The effects of the predicted levels of law enforcement on violence among criminal organizations are presented in Figure 7. This model specification corresponds to the one presented in Tables 2 and 3 in the manuscript. To improve the model fit, IV models consider the natural logarithm of the different variables measuring events of law enforcement, retaliation and inter-cartel violence.

- **IV model with fixed effects without municipal clusters**. The first and second stages of this model are reported in Tables 7 and 8. The predicted effect of the instruments on the different measures of violent and non-violent enforcement from the first stage are reported in Figures 8 and 9. The effects of the predicted levels of law enforcement on violence among criminal organizations are presented in 10.

- **IV model with random effects and clusters at the municipal level**. The first and second stages of this model are reported in Tables 9 and 10. The predicted effect of the instruments on the different measures of violent and non-violent enforcement from the first stage are reported in Figures 11 and 12. The effects of the predicted levels of law enforcement on violence among criminal organizations are presented in 13.

- **Negative binomial (NB) model with random effects and clusters at the municipal level**. The first and second stages of this model are reported in Tables 11 and

12. Coefficients from negative binomial models are expressed in log of expected counts. The predicted effect of the instruments on the different measures of violent and non-violent enforcement from the first stage are reported in Figures 14 and 15. The effects of the predicted levels of law enforcement on violence among criminal organizations are presented in 16. To facilitate the interpretation of negative binomial results, the Figures present their predictions in terms of incidence rate ratios (IRR). Instead of using the natural logarithm of event data as in IV models, negative binomial models rely on direct measures of events of law enforcement, retaliation and inter-cartel violence as count data. The presence of hyperdispersion in event variables indicates the need to use negative binomial distributions.

- **Negative binomial model with fixed effects and clusters at the municipal level**. The first and second stages of this model are reported in Tables 13 and 14. The predicted effect of the instruments on the different measures of violent and non-violent enforcement from the first stage are reported in Figures 17 and 18. The effects of the predicted levels of law enforcement on violence among criminal organizations are presented in 19.

Table 4 summarizes the key results from the different model specifications considered in this robustness tests. All models provide strong support for H_1 stating that democratization motivates authorities to enforce the law against organized criminals. The effective number of political parties and divided government report positive coefficients at high levels of statistical significance for the full array of violent and non-violent law enforcement tactics across all models. The F-statistic in all different models are several times larger than the basic threshold of 10 and report high levels of statistical significance, thus suggesting that the effective number of political parties and divided government constitute strong instruments for the exogenous variation of law enforcement (Angrist & Pischke 2009, Stock, Wright & Yogo 2002).

Table 4: Summary of robustness tests.

Model		First stage						Second stage		
		Instruments		Tests				Effect on inter-cartel violence	S/HJ test	
		ENP	Div. gov.	F statistic	AP χ^2	KP/CD F	AR F		χ^2	p-value
IV model, FE	1. Violent enfor.	0.0004***	0.0001**	26.55***	53.13***	26.55	59.92***	11.801***	0.34	0.5596
& clustered.	2. Arrests	0.0043***	0.0007**	41.54***	83.10***	41.54	59.92***	1.246***	0.036	0.8495
Tables 5 & 6	3. Seizure assets	0.0017***	0.0002**	50.36***	100.76***	50.36	59.92***	3.085***	0.007	0.9339
	4. Seizure drugs	0.0071***	0.0007*	68.17***	136.39***	68.17	59.13***	0.712***	0.854	0.3554
	5. Seizure guns	0.0026***	0.0002*	50.43***	100.89***	50.43	59.92***	1.950***	1.935	0.1642
IV model, FE	6. Violent enfor.	0.0004***	0.0001***	57.69***	115.39***	57.69	987.22***	11.984***	1.195	0.2743
& no clusters.	7. Arrests	0.0043***	0.0007***	497.46***	994.91***	497.46	987.22***	1.231***	0.273	0.601
Tables 7 & 8	8. Seizure assets	0.0017***	0.0002***	241.48***	482.97***	241.48	987.22***	3.085***	0.015	0.9032
	9. Seizure drugs	0.0071***	0.0007***	918.23***	1836.46***	918.23	987.22***	0.769***	8.427	0.0037
	10. Seizure guns	0.0026***	0.0002***	582.52***	1165.05***	582.52	987.22***	2.106***	7.781	0.0053
IV model, RE	11. Violent enfor.	0.0005***	0.0001***	99.67***	199.35***	99.67	1658.03***	11.863***	4.144	0.0418
& clustered.	12. Arrests	0.0046***	0.0006***	534.25***	1068.50***	534.25	1047.88***	1.224***	0.166	0.6841
Tables 9 & 10	13. Seizure assets	0.0019***	0.0002***	247.58***	495.17***	247.58	045.59***	3.136***	0.000	0.9885
	14. Seizure drugs	0.0072***	0.0006***	986.88***	1973.76***	986.88	1098.89***	0.763***	7.425	0.0064
	15. Seizure guns	0.0028***	0.0002***	633.33***	1266.67***	633.33	1052.98***	2.088***	7.215	0.0072
NB model, RE	16. Violent enfor.	5.2298***	0.3748***	250.92***				9.218***		
& clustered	17. Arrests	1.9054***	0.1137***	641.21***				13.847***		
Tables 11 & 12	18. Seizure assets	2.2517***	0.1561***	300.78***				15.928***		
	19. Seizure drugs	1.6558***	0.1188***	579.42***				25.279***		
	20. Seizure guns	3.7058***	0.2009***	395.44***				22.819***		
NB model, FE	21. Violent enfor.	5.1613***	0.3406***	224.72***				19.165***		
& clustered.	22. Arrests	1.8974***	0.1104***	626.00***				15.080***		
Tables 13 & 14	23. Seizure assets	2.2226***	0.1529***	278.46***				22.501***		
	24. Seizure drugs	1.6489***	0.1168***	557.43***				26.836***		
	25. Seizure guns	3.6783***	0.1845***	371.97***				28.424***		

Levels of significance: * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$.
Model specification: Instrumental variables (IV) model; Negative binomial (NB) model; Fixed effects (FE); Random effects (RE).
Tests: Angrist-Pischke (AP) χ^2 test; Kleibergen-Paap (KP) F test; Cragg-Donald (CD) F test; Anderson-Rubin (AR) F test; Sargan (S) χ^2 test; Hansen J (HJ) χ^2 test. Some tests are not available for NB models.

Stata offers a variety of additional tests for evaluating the assumptions for valid instruments in IV regression analysis. These tests are calculated using Stata commands `-xtivreg2-` for fixed effects models and `-xtivreg3-` for random effects.[7] Unfortunately these tests are not available for two-stages negative binomial models. The coefficient of the Angrist-Pischke (AP) χ^2 test of underidentification reports a large magnitude at high levels of significance in all IV models, thus suggesting that the endogenous regressors are identified. The Kleibergen-Paap (KP) and the Cragg-Donald (CD) Wald F tests for weak identification report coefficients larger than the Stock-Yogo critical value of bias tolerance at 10%, which is calculated at 19.93. This suggests that the instruments are robust. Finally, the Anderson-Rubin (AR) Wald F test for weak-instrument-robust inference indicates a large coefficient at high levels of confidence across all models, thus rejecting the null hypothesis stating that the endogenous regressors are jointly equal to zero.

Table 4 also provides a summary for the second stage of all models. The variables of violent and non-violent law enforcement consistently show a positive and statistically significant effect on inter-cartel violence across all models. This provides strong support for hypothesis H_2 indicating that law enforcement has a disrupting effect on the relative military balance among organized criminals and triggers waves of violence between rival cartels. With a few exceptions, Sargan and Hansen J tests for overidentification suggest that the effective number of parties and divided government are not correlated with the error terms of the second stage. Even in models 9, 10, 11, 14 and 15 where the overidentification test rejects the null hypothesis, the magnitude of the χ^2 statistic is not too big. Thus minimizing concerns with the instruments.

The rest of the Appendix presents the complete results of the different model specifications considered in the robustness check.

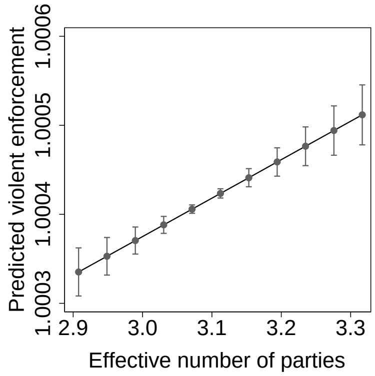
[7]Thanks to Mark Schaffer for sharing his `-xtivreg3-` command capable of calculating a broad array of tests for IV models with random effects.

Table 5: First Stage: Determinants of violent and non-violent enforcement. IV model with fixed effects and clusters at municipal level.

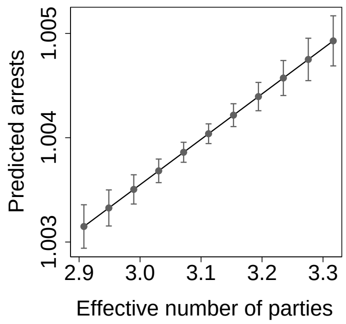
	(1) Violent Enforcement	(2) Arrests	(3) Seizures of Assets	(4) Seizures of Drugs	(5) Seizures of Guns
ENP	0.0004***	0.0043***	0.0017***	0.0071***	0.0026***
	(0.0001)	(0.0005)	(0.0002)	(0.0007)	(0.0003)
Divided government	0.0001**	0.0007**	0.0002**	0.0007*	0.0002*
	(0.0000)	(0.0003)	(0.0001)	(0.0004)	(0.0001)
Retaliation (log)	0.2230***	0.1861***	0.0635***	0.0531***	0.0780***
	(0.0102)	(0.0128)	(0.0042)	(0.0081)	(0.0050)
Drug production	-0.0000	-0.0001	-0.0000	-0.0002	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
9/11	0.0000	-0.0009***	-0.0001	-0.0008***	-0.0003***
	(0.0000)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Gulf after 9/11	0.0002**	0.0012*	-0.0001	0.0007	0.0003
	(0.0001)	(0.0006)	(0.0002)	(0.0009)	(0.0002)
North after 9/11	0.0007***	0.0014	0.0007	0.0020	0.0026***
	(0.0002)	(0.0012)	(0.0005)	(0.0014)	(0.0007)
Pacific after 9/11	0.0000	-0.0004	0.0005***	0.0001	0.0003
	(0.0001)	(0.0006)	(0.0002)	(0.0006)	(0.0002)
Rifles (100 K)	0.0000	0.0001***	0.0001***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment	0.0001***	0.0007***	0.0002***	-0.0001	0.0002*
	(0.0000)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Corruption	-0.0000*	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cocaine price	0.0000***	-0.0000***	0.0000	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Local drug markets	-0.0000	0.0001	0.0000	0.0001	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Divorces	-0.0000**	-0.0000*	-0.0000***	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Young mothers	-0.0013***	-0.0037*	-0.0027***	-0.0009	-0.0018**
	(0.0004)	(0.0019)	(0.0007)	(0.0017)	(0.0009)
Poverty	0.0004***	0.0029***	0.0009***	0.0031***	0.0012***
	(0.0001)	(0.0008)	(0.0002)	(0.0007)	(0.0003)
Population (log)	0.0007**	0.0062*	0.0014*	0.0056**	0.0029*
	(0.0004)	(0.0036)	(0.0008)	(0.0028)	(0.0016)
Constant	-0.0084**	-0.0696**	-0.0187**	-0.0670***	-0.0342**
	(0.0034)	(0.0333)	(0.0078)	(0.0259)	(0.0153)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
F statistic	26.55***	41.54***	50.36***	68.17***	50.43***
Angrist-Pischke χ^2	53.13***	83.10***	100.76***	136.39***	100.89***
Kleibergen-Paap F	26.55	41.54	50.36	68.17	50.43
Stock-Yogo 10% value	19.93	19.93	19.93	19.93	19.93
Anderson-Rubin F	59.92***	59.92***	59.92***	59.13***	59.92***
Levels of significance: * p< 0.1, ** p< 0.05, *** p< 0.01					

Table 6: Second Stage: Determinants of inter-cartel violence. IV model with fixed effects and clusters at municipal level.

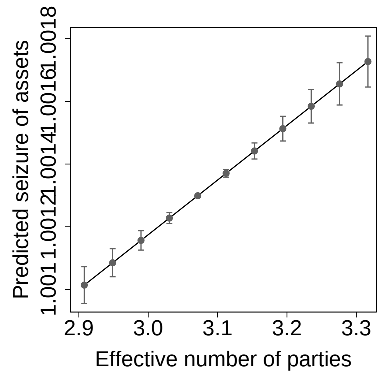
	(1)	(2)	(3)	(4)	(5)
Violent enforcement	11.801***				
	(1.470)				
Arrests		1.246***			
		(0.118)			
Seizures of assets			3.085***		
			(0.238)		
Seizures of drugs				0.712***	
				(0.067)	
Seizures of guns					1.950***
					(0.171)
Rifles (100 K)				0.001*	
				(0.001)	
Retaliation (log)	-2.201***	0.165***	0.200***	0.357***	0.241***
	(0.363)	(0.024)	(0.019)	(0.019)	(0.018)
Drug production	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
9/11	0.000	0.001***	0.000*	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gulf after 9/11	-0.002***	-0.001**	0.000	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
North after 9/11	-0.002	0.006***	0.005***	0.006***	0.002*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Pacific after 9/11	0.002***	0.003***	0.001	0.002**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rifles (100 K)	-0.000	-0.000*	-0.000***	0.001*	0.000**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Unemployment	-0.000	0.000*	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corruption	0.000***	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cocaine price	-0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local drug markets	0.000	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Divorces	0.000	-0.000**	-0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young mothers	0.008**	-0.002	0.001	-0.006**	-0.004**
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Poverty	-0.001	0.001*	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population (log)	-0.003	-0.002	0.002*	0.002	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
Hansen J statistic	0.340	0.036	0.007	0.854	1.935
Hansen J p-value	0.5596	0.8495	0.9339	0.3554	0.1642
Levels of significance: * p< 0.1, ** p< 0.05, *** p< 0.01					



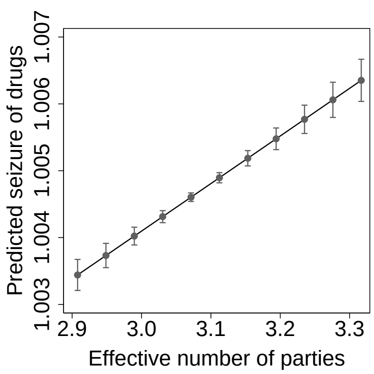
(a) Violent enforcement



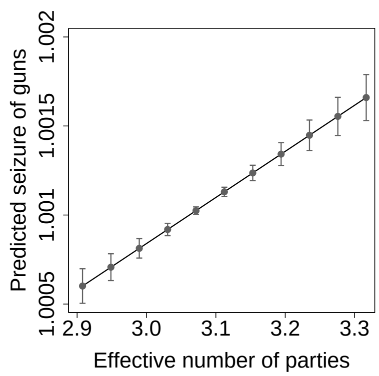
(b) Arrests



(c) Assets

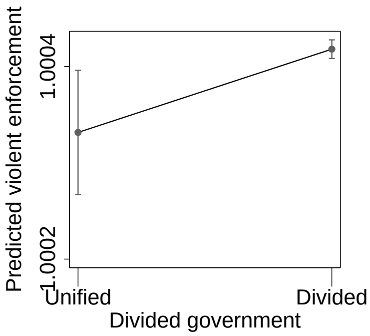


(d) Drugs

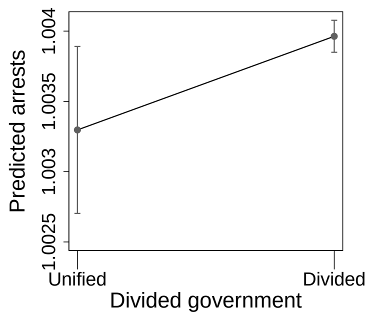


(e) Guns

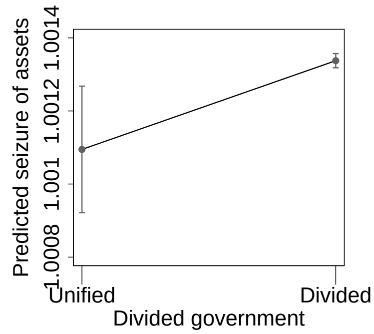
Figure 5: Effect of the effective number of political parties on law enforcement. Predictions from IV model with fixed effects and municipal clusters (Table 5)



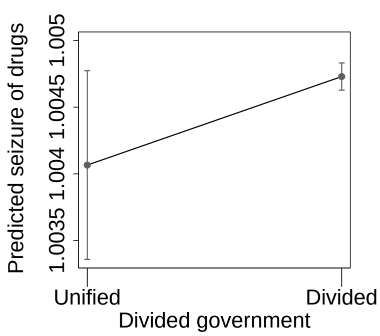
(a) Violent enforcement



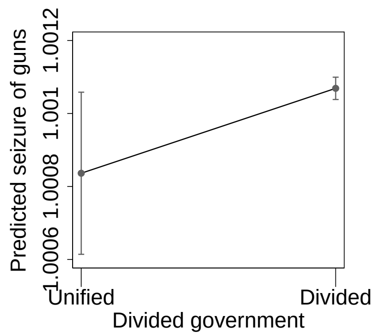
(b) Arrests



(c) Assets

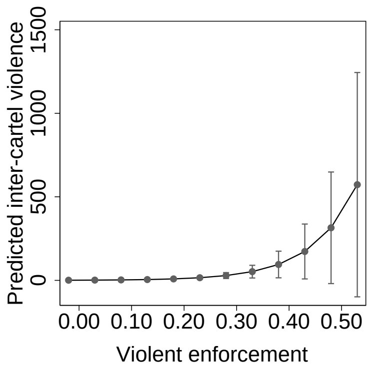


(d) Drugs

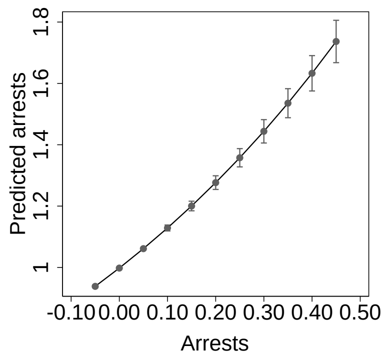


(e) Guns

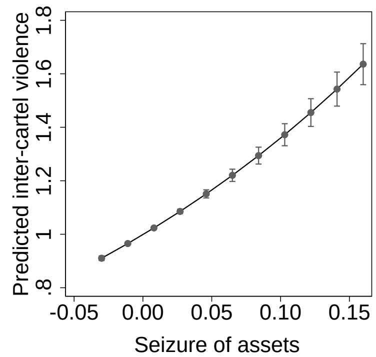
Figure 6: Effect of divided government on law enforcement. Predictions from IV model with fixed effects and municipal clusters (Table 5)



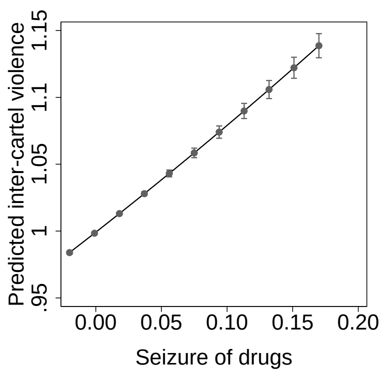
(a) Violent enforcement



(b) Arrests



(c) Assets



(d) Drugs

(e) Guns

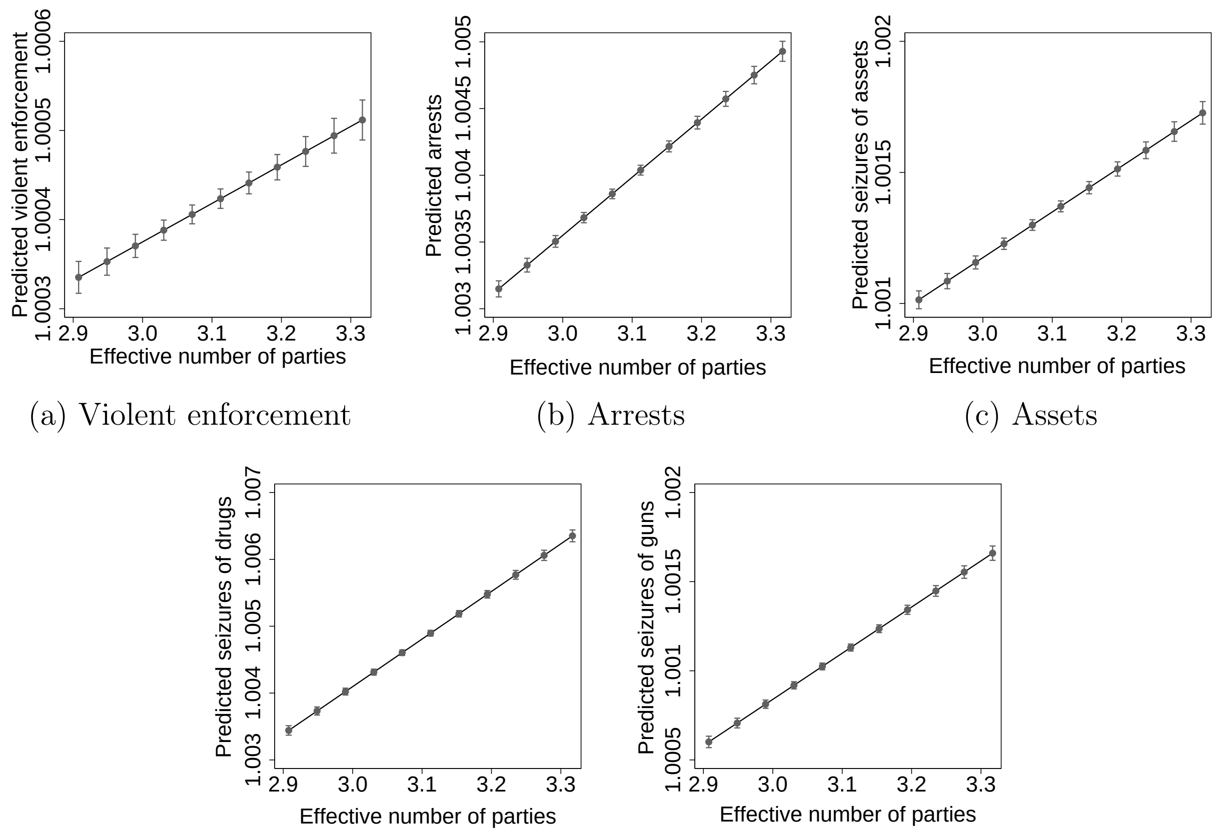
Figure 7: Effect of law enforcement on inter-cartel violence. Predictions from IV model with fixed effects and municipal clusters (Table 6)

Table 7: First Stage: Determinants of violent and non-violent enforcement. IV model with fixed effects and no clusters.

	(6) Violent Enforcement	(7) Arrests	(8) Seizures of Assets	(9) Seizures of Drugs	(10) Seizures of Guns
ENP	0.0004***	0.0043***	0.0017***	0.0071***	0.0026***
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Divided government	0.0001***	0.0007***	0.0002***	0.0007***	0.0002***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Retaliation	0.2230***	0.1861***	0.0635***	0.0531***	0.0780***
	(0.0002)	(0.0006)	(0.0004)	(0.0007)	(0.0003)
Drug violence	-0.0000	-0.0001***	-0.0000	-0.0002***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
9/11	0.0000	-0.0009***	-0.0001	-0.0008***	-0.0003***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Gulf after 9/11	0.0002***	0.0012***	-0.0001	0.0007***	0.0003***
	(0.0000)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
North after 9/11	0.0007***	0.0014***	0.0007***	0.0020***	0.0026***
	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0001)
Pacific after 9/11	0.0000	-0.0004**	0.0005***	0.0001	0.0003***
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Rifles (100 K)	0.0000**	0.0001***	0.0001***	0.0000**	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment	0.0001***	0.0007***	0.0002***	-0.0001***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Corruption	-0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cocaine price	0.0000***	-0.0000***	0.0000	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Local drug markets	-0.0000***	0.0001***	0.0000**	0.0001***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Divorces	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Young mothers	-0.0013***	-0.0037***	-0.0027***	-0.0009	-0.0018***
	(0.0001)	(0.0005)	(0.0003)	(0.0006)	(0.0003)
Poverty	0.0004***	0.0029***	0.0009***	0.0031***	0.0012***
	(0.0000)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Population (log)	0.0007***	0.0062***	0.0014***	0.0056***	0.0029***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Constant	-0.0084***	-0.0696***	-0.0187***	-0.0670***	-0.0342***
	(0.0006)	(0.0019)	(0.0011)	(0.0023)	(0.0010)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
F statistic	57.69***	497.46***	241.48***	918.23***	582.52***
Angrist-Pischke χ^2	115.39***	994.91***	482.97***	1836.46***	1165.05***
Cragg-Donald F	57.69	497.46	241.48	918.23	582.52
Stock-Yogo 10% value	19.93	19.93	19.93	19.93	19.93
Anderson-Rubin F	987.22***	987.22***	987.22***	987.22***	987.22***
Levels of significance: * p< 0.1, ** p< 0.05, *** p< 0.01					

Table 8: Second Stage: Determinants of inter-cartel violence. IV model with fixed effects and no clusters.

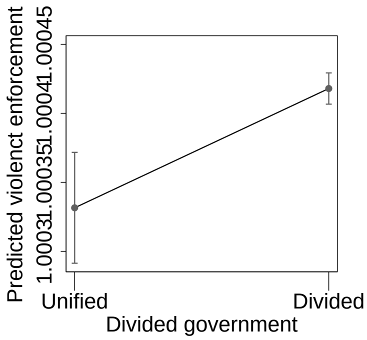
	(6)	(7)	(8)	(9)	(10)
Violent enforcement	11.984***				
	(1.129)				
Arrests		1.231***			
		(0.045)			
Seizures of assets			3.085***		
			(0.151)		
Seizures of drugs				0.769***	
				(0.024)	
Seizures of guns					2.106***
					(0.075)
Retaliation	-2.277***	0.167***	0.200***	0.355***	0.232***
	(0.252)	(0.009)	(0.010)	(0.002)	(0.006)
Drug violence	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
9/11	0.000	0.001***	0.000***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gulf after 9/11	-0.002***	-0.001***	0.000	-0.001***	-0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
North after 9/11	-0.002	0.006***	0.005***	0.006***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Pacific after 9/11	0.002***	0.003***	0.001***	0.003***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Rifles (100 K)	-0.000	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.000	0.000***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corruption	0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cocaine price	-0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local drug markets	0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Divorces	0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young mothers	0.008***	-0.003***	0.001	-0.006***	-0.003***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty	-0.000	0.001***	0.002***	0.002***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Population (log)	-0.003**	-0.002***	0.002***	0.002***	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
Sargan statistic	1.195	0.273	0.015	8.427	7.781
Sargan p-value	0.2743	0.6010	0.9032	0.0037	0.0053
Levels of significance: * p< 0.1, ** p< 0.05, *** p< 0.01					



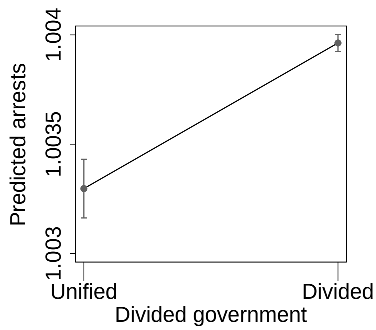
(a) Violent enforcement (b) Arrests (c) Assets

(d) Drugs (e) Guns

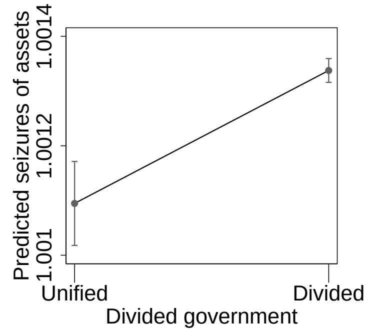
Figure 8: Effect of the effective number of political parties on law enforcement. Predictions from IV model with fixed effects and no clusters (Table 7)



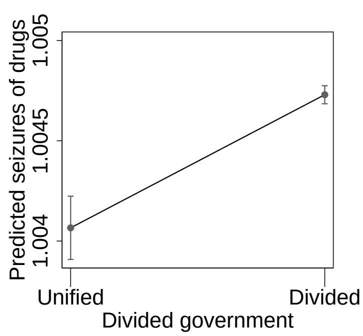
(a) Violent enforcement



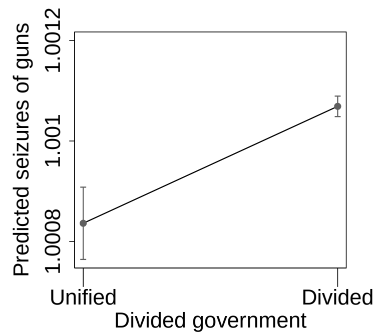
(b) Arrests



(c) Assets

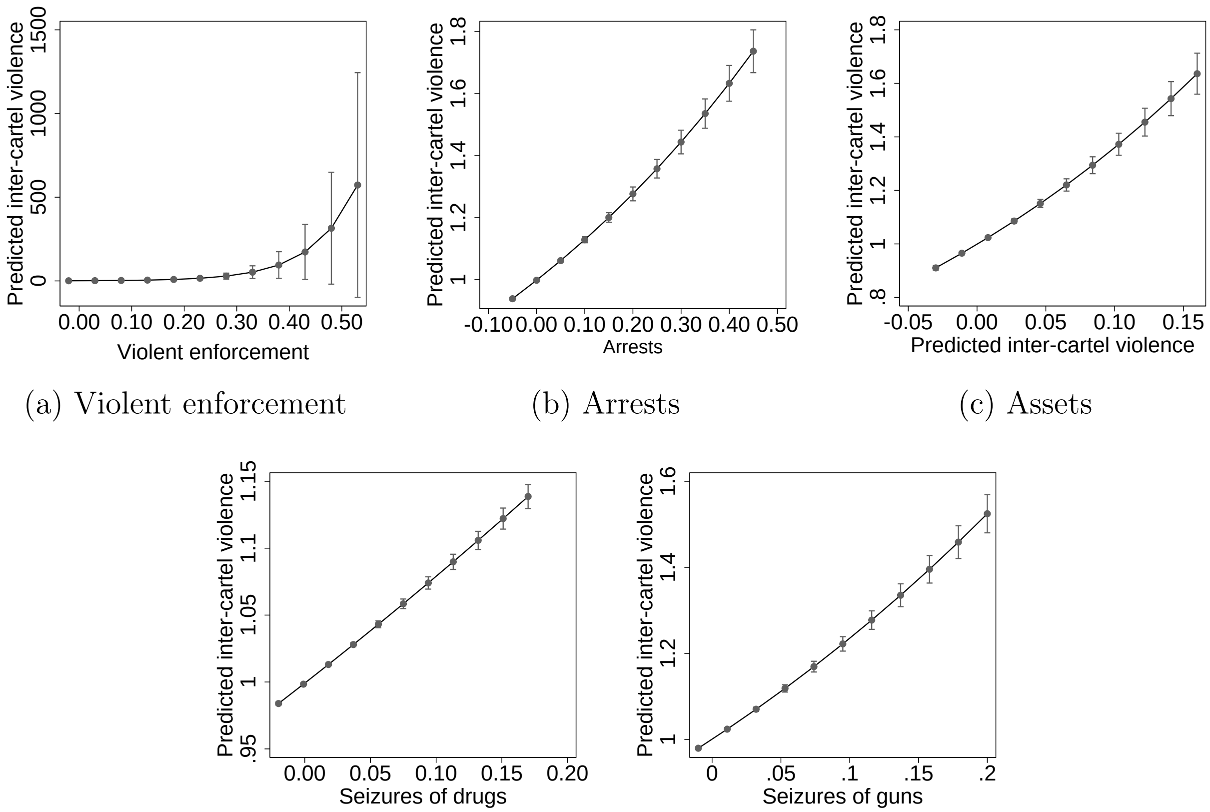


(d) Drugs



(e) Guns

Figure 9: Effect of divided government on law enforcement. Predictions from IV model with fixed effects and no clusters (Table 7)



(a) Violent enforcement (b) Arrests (c) Assets

(d) Drugs (e) Guns

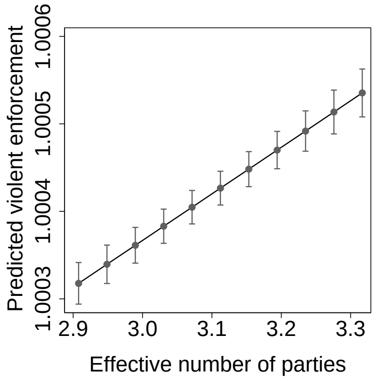
Figure 10: Effect of law enforcement on inter-cartel violence. Predictions from IV model with fixed effects and no clusters (Table 8)

Table 9: First Stage: Determinants of violent and non-violent enforcement. IV model with random effects and clusters at municipal level.

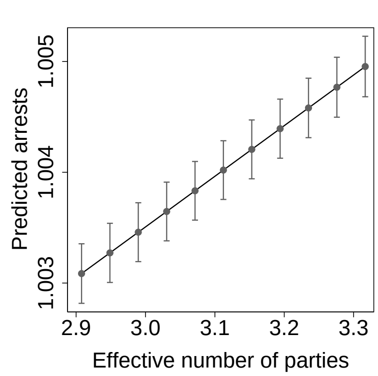
	(11) Violent Enforcement	(12) Arrests	(13) Seizures of Assets	(14) Seizures of Drugs	(15) Seizures of Guns
ENP	0.0005***	0.0046***	0.0019***	0.0072***	0.0028***
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Divided government	0.0001***	0.0006***	0.0002***	0.0006***	0.0002***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Retaliation	0.2242***	0.1875***	0.0650***	0.0544***	0.0796***
	(0.0002)	(0.0006)	(0.0004)	(0.0007)	(0.0003)
Drug production	0.0000***	-0.0001	0.0001***	-0.0001	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
9/11	0.0000	-0.0010***	-0.0002***	-0.0010***	-0.0003***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Gulf after 9/11	0.0001**	0.0010***	-0.0001	0.0006***	0.0002***
	(0.0000)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
North after 9/11	0.0007***	0.0028***	0.0019***	0.0039***	0.0032***
	(0.0000)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Pacific after 9/11	0.0000	-0.0002	0.0008***	0.0005***	0.0004***
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Rifles (100 K)	0.0000***	0.0001***	0.0001***	0.0000**	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Unemployment	0.0001***	0.0007***	0.0002***	-0.0000*	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Corruption	-0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cocaine price	0.0000***	-0.0000***	0.0000**	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Local drug markets	0.0000***	0.0001***	0.0000***	0.0001***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Divorces	-0.0000***	-0.0000***	-0.0000***	-0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Young mothers	-0.0007***	-0.0037***	-0.0020***	-0.0006	-0.0014***
	(0.0001)	(0.0005)	(0.0003)	(0.0006)	(0.0002)
Poverty	0.0000	0.0004***	-0.0002***	0.0001	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Population (log)	0.0001***	0.0033***	0.0009***	0.0036***	0.0007***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Constant	-0.0034***	-0.0429***	-0.0145***	-0.0488***	-0.0146***
	(0.0001)	(0.0009)	(0.0004)	(0.0011)	(0.0003)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
F statistic	99.67***	534.25***	247.58***	986.88***	633.33***
Angrist-Pischke χ^2	199.35***	1068.50***	495.17***	1973.76***	1266.67***
Cragg-Donald F	99.67	534.25	247.58	986.88	633.33
Stock-Yogo 10% value	19.93	19.93	19.93	19.93	19.93
Anderson-Rubin F	1658.03***	1047.88***	1045.59***	1098.89***	1052.98***
Levels of significance: * p< 0.1, ** p< 0.05, *** p< 0.01					

Table 10: Second Stage: Determinants of inter-cartel violence. IV model with random effects and clusters at municipal level.

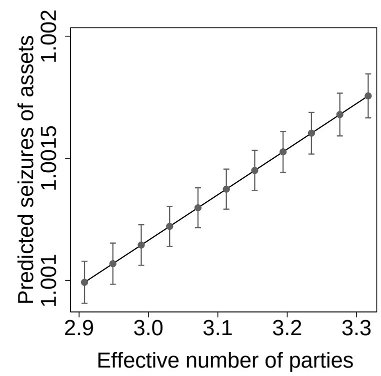
	(11)	(12)	(13)	(14)	(15)
Violent enforcement	11.863***				
	(0.851)				
Arrests		1.224***			
		(0.044)			
Seizures of assets			3.136***		
			(0.151)		
Seizures of drugs				0.763***	
				(0.025)	
Seizures of guns					2.088***
					(0.071)
Retaliation	-2.245***	0.168***	0.197***	0.356***	0.233***
	(0.191)	(0.008)	(0.010)	(0.002)	(0.006)
Drug production	0.001***	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
9/11	-0.000	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gulf after 9/11	-0.001***	-0.001***	0.000	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
North after 9/11	0.001	0.005***	0.005***	0.004***	0.002***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Pacific after 9/11	0.002***	0.003***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rifles (100 K)	-0.000	-0.000***	-0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.000**	0.000***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corruption	0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cocaine price	-0.000***	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local drug markets	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Divorces	0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young mothers	0.003**	-0.003***	0.001	-0.007***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Poverty	-0.000	0.001***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population (log)	-0.000	-0.001***	-0.000	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
Sargan statistic	4.144	0.166	0.000	7.425	7.215
Sargan p-value	0.0418	0.6841	0.9885	0.0064	0.0072
Levels of significance: * p< 0.1, ** p< 0.05, *** p< 0.01					



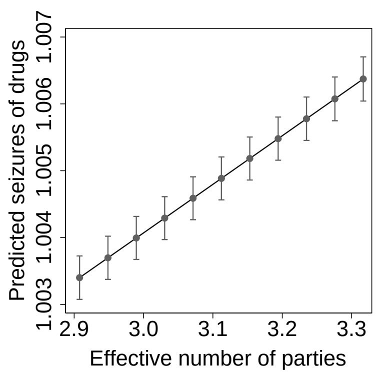
(a) Violent enforcement



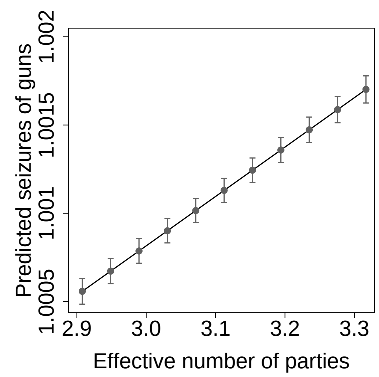
(b) Arrests



(c) Assets

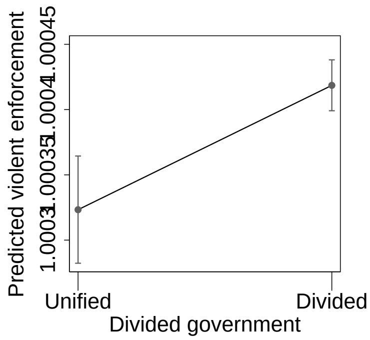


(d) Drugs

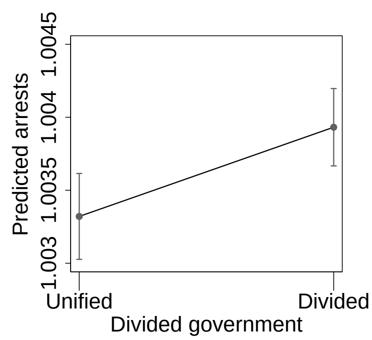


(e) Guns

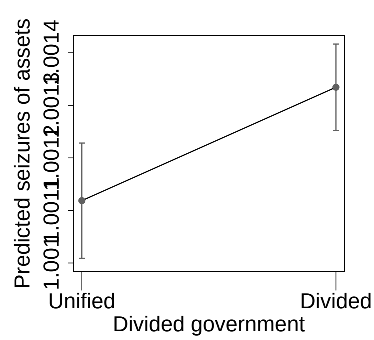
Figure 11: Effect of the effective number of political parties on law enforcement. Predictions from IV model with random effects and clusters at municipal level (Table 9).



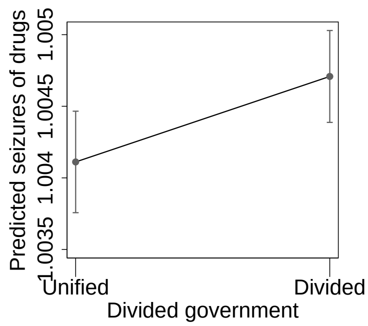
(a) Violent enforcement



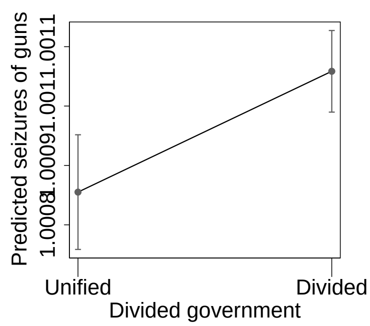
(b) Arrests



(c) Assets

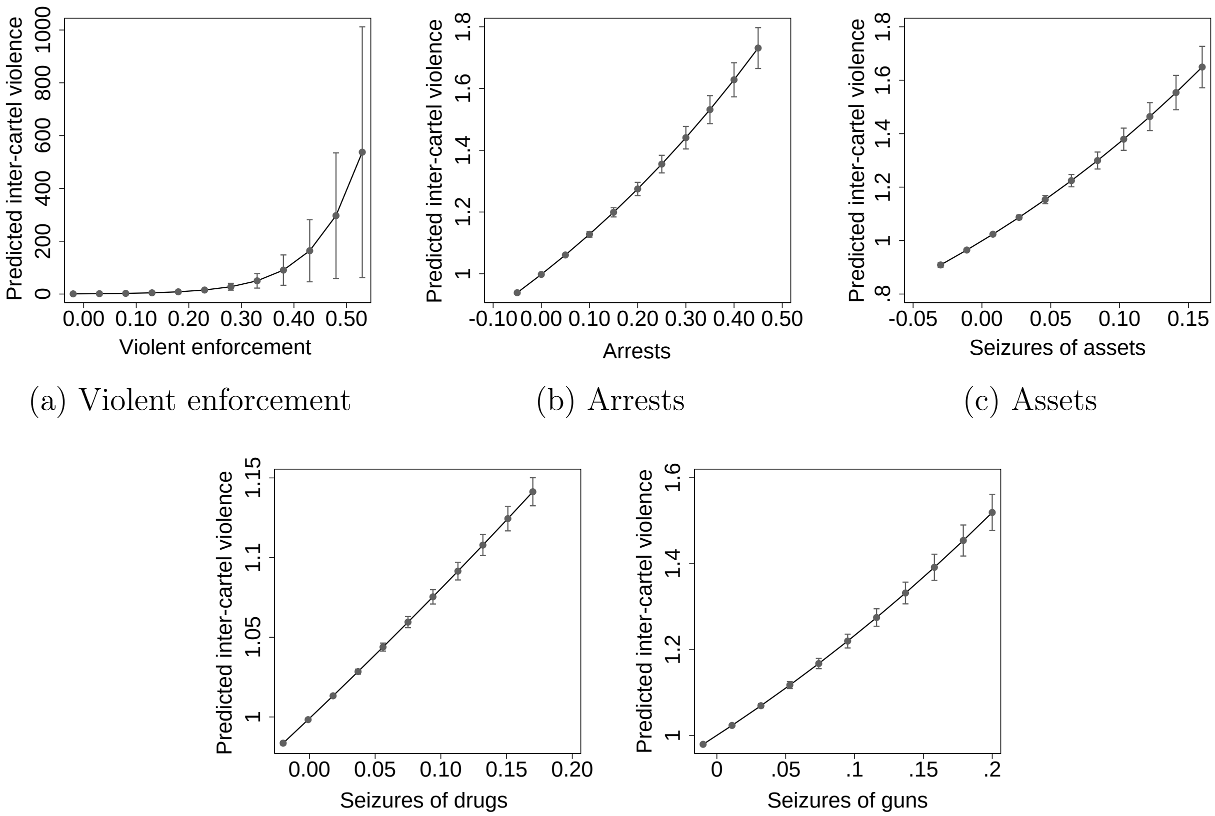


(d) Drugs



(e) Guns

Figure 12: Effect of divided government on law enforcement. Predictions from IV model with random effects and clusters at municipal level (Table 9).



(a) Violent enforcement

(b) Arrests

(c) Assets

(d) Drugs

(e) Guns

Figure 13: Effect of law enforcement on inter-cartel violence. Predictions from IV model with random effects and clusters at municipal level (Table 10).

Table 11: First Stage: Determinants of violent and non-violent enforcement. Negative binomial model with random effects and municipal clusters.

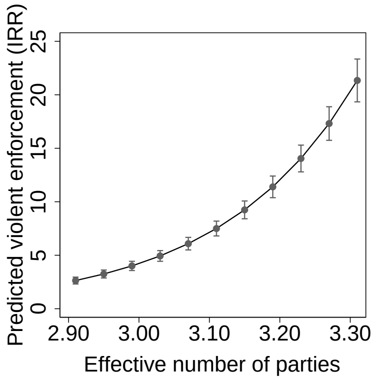
	(16) Enforcement	(17) Arrests	(18) Assets	(19) Drugs	(20) Guns
ENP	5.2298***	1.9054***	2.2517***	1.6558***	3.7058***
	(0.1460)	(0.0360)	(0.0622)	(0.0332)	(0.0768)
Divided government	0.3748***	0.1137***	0.1561***	0.1188***	0.2009***
	(0.0701)	(0.0191)	(0.0319)	(0.0179)	(0.0399)
Drug production	0.0414	0.0663***	0.0514***	0.1216***	0.1072***
	(0.0288)	(0.0094)	(0.0147)	(0.0080)	(0.0171)
9/11	1.2257***	-0.4042***	-0.3107***	-0.4351***	-0.3246***
	(0.1369)	(0.0239)	(0.0399)	(0.0223)	(0.0527)
Gulf after 9/11	-0.0074	0.2395***	0.2843***	0.2614***	0.3365***
	(0.0931)	(0.0289)	(0.0553)	(0.0249)	(0.0554)
North after 9/11	0.6182***	0.0603**	0.1093***	0.2011***	0.2962***
	(0.0860)	(0.0238)	(0.0418)	(0.0200)	(0.0450)
Pacific after 9/11	0.4474***	-0.1199***	0.1700***	-0.0260	-0.1045**
	(0.0967)	(0.0254)	(0.0419)	(0.0204)	(0.0477)
Rifles (100 K)	-0.0240***	0.0339***	0.0314***	0.0198***	0.0149***
	(0.0079)	(0.0026)	(0.0043)	(0.0026)	(0.0051)
Unemployment	0.1231***	0.0745***	0.0477***	0.0286***	0.0738***
	(0.0130)	(0.0044)	(0.0073)	(0.0041)	(0.0084)
Corruption	-0.0178***	-0.0061***	-0.0031***	-0.0027***	-0.0011
	(0.0018)	(0.0006)	(0.0010)	(0.0006)	(0.0011)
Cocaine price	0.0106***	-0.0036***	0.0015***	-0.0058***	-0.0013**
	(0.0010)	(0.0003)	(0.0004)	(0.0003)	(0.0006)
Local drug markets	-0.0004	0.0009***	0.0007**	0.0015***	0.0008**
	(0.0005)	(0.0001)	(0.0003)	(0.0001)	(0.0003)
Divorces	-0.0001**	-0.0000	-0.0001***	0.0001***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Young mothers	1.1582***	0.9291***	0.5552**	1.7277***	1.2278***
	(0.4081)	(0.1292)	(0.2207)	(0.1116)	(0.2454)
Poverty	-0.3490***	-0.3217***	-0.3338***	-0.3391***	-0.4926***
	(0.0414)	(0.0184)	(0.0278)	(0.0143)	(0.0307)
Population (log)	0.2385***	-0.0162**	0.1503***	0.0679***	0.1004***
	(0.0203)	(0.0076)	(0.0136)	(0.0064)	(0.0130)
Constant	-27.2378***	-8.3563***	-12.7946***	-8.7521***	-17.4927***
	(0.5666)	(0.1388)	(0.2437)	(0.1231)	(0.2919)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208
F-statistic	250.92***	641.21***	300.78***	579.42***	395.44***

Coefficients are in log of expected counts. Standard errors in parentheses.
The levels of significance are: * p< 0.1, ** p< 0.05, *** p< 0.01

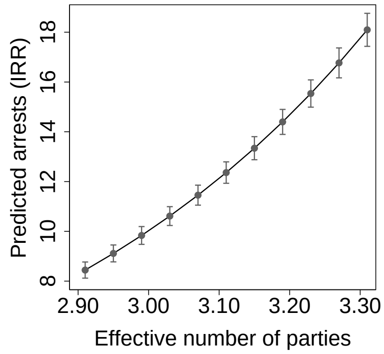
Table 12: Second Stage: Determinants of inter-cartel violence. Negative binomial model with random effects and municipal clusters.

	(16)	(17)	(18)	(19)	(20)
Violent enforcement	9.218***				
	(0.222)				
Arrests		13.847***			
		(0.210)			
Seizures of assets			15.928***		
			(0.283)		
Seizures of drugs				25.279***	
				(0.392)	
Seizures of guns					22.819***
					(0.396)
Drug production	0.076***	0.007	0.042***	-0.078***	0.017
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
9/11	1.296***	1.637***	1.412***	1.679***	1.343***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Gulf after 9/11	0.326***	-0.058	-0.015	-0.038	0.089**
	(0.041)	(0.043)	(0.043)	(0.043)	(0.042)
North after 9/11	0.077**	0.238***	0.138***	-0.107***	-0.056*
	(0.034)	(0.031)	(0.032)	(0.033)	(0.033)
Pacific after 9/11	0.182***	0.521***	0.057*	0.347***	0.472***
	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)
Rifles (100 K)	0.145***	-0.005	0.038***	0.053***	0.076***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Unemployment	0.061***	-0.080***	0.035***	0.081***	0.018***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Corruption	0.007***	0.007***	0.001	-0.001**	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cocaine price	-0.004***	0.005***	-0.002***	0.007***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local drug markets	0.001***	-0.002***	-0.001***	-0.004***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Divorces	0.000***	0.000	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young mothers	0.162	-1.470***	0.364**	-2.365***	-0.278*
	(0.151)	(0.155)	(0.149)	(0.155)	(0.151)
Poverty	-0.158***	0.286***	0.071***	0.175***	-0.008
	(0.019)	(0.020)	(0.019)	(0.019)	(0.019)
Population (log)	-0.005	0.146***	-0.140***	-0.021**	-0.039***
	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)
Constant	-7.164***	-8.474***	-4.789***	-8.011***	-6.313***
	(0.131)	(0.123)	(0.143)	(0.124)	(0.131)
Observations	9,868,208	9,868,208	9,868,208	9,868,208	9,868,208

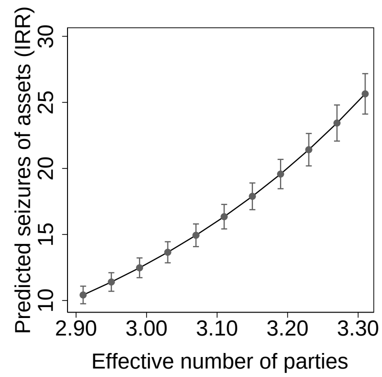
Coefficients are in log of expected counts. Bootstrapped standard errors in parentheses. The levels of significance are: * p< 0.1, ** p< 0.05, *** p< 0.01



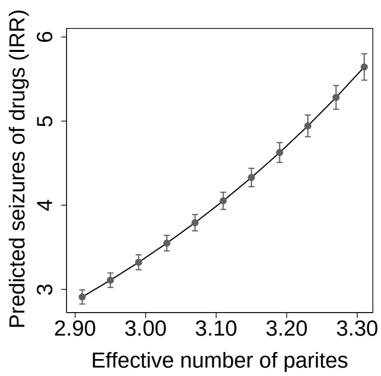
(a) Violent enforcement



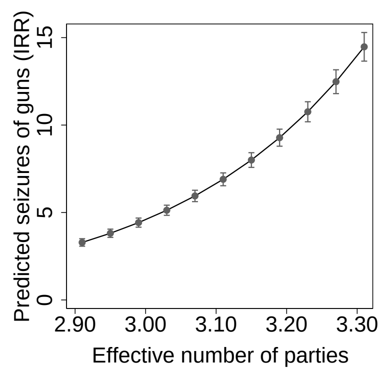
(b) Arrests



(c) Assets

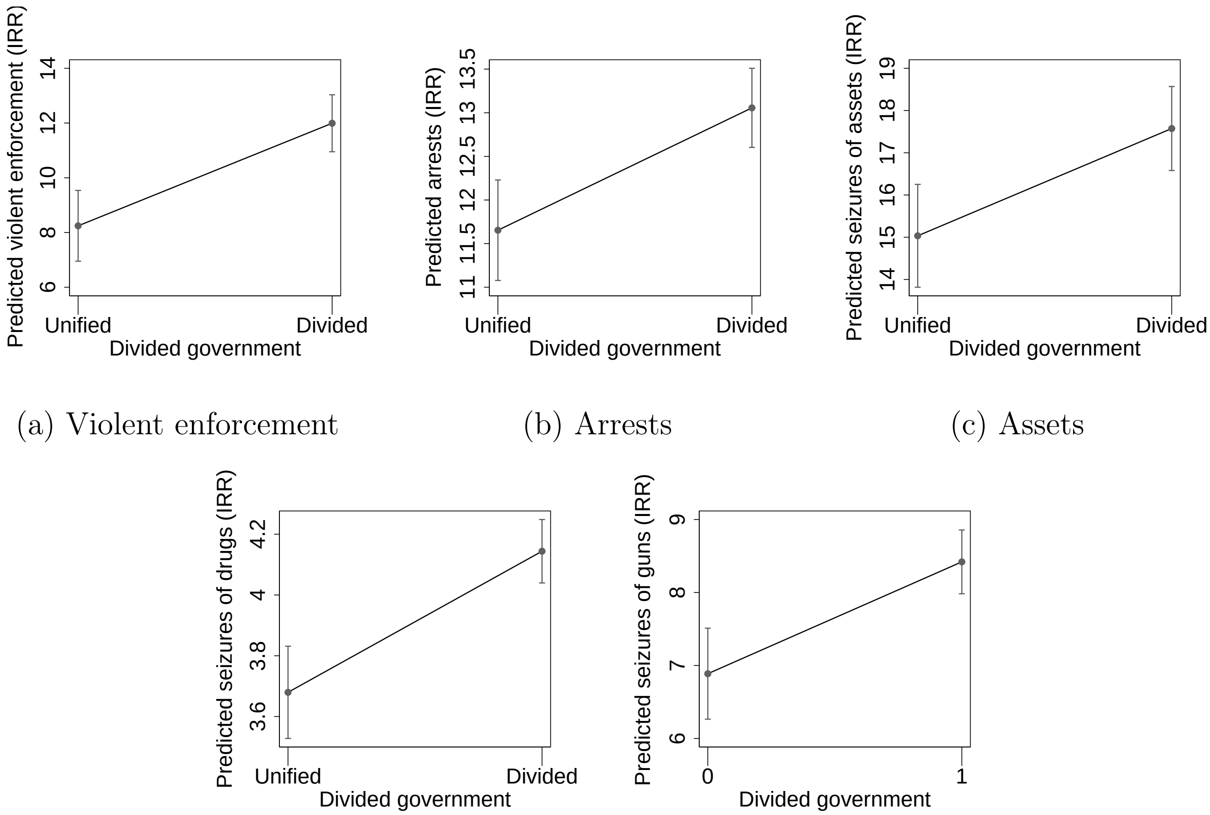


(d) Drugs



(e) Guns

Figure 14: Effect of the effective number of political parties on law enforcement. Predictions in incidence rate ratios (IRR) from negative binomial model with random effects and municipal clusters (Table 11)



(a) Violent enforcement

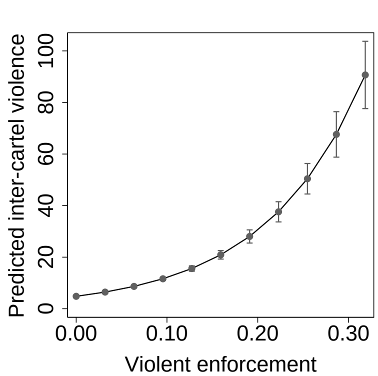
(b) Arrests

(c) Assets

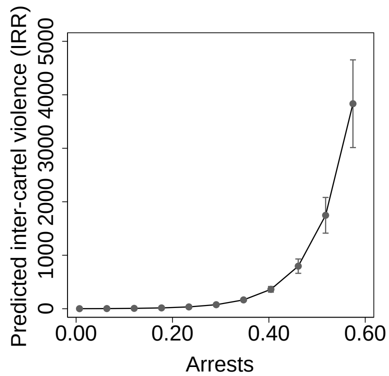
(d) Drugs

(e) Guns

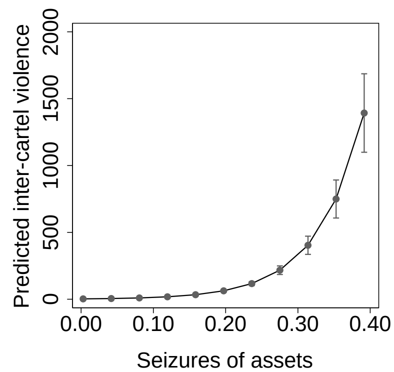
Figure 15: Effect of divided government on law enforcement. Predictions in incidence rate ratios (IRR) from negative binomial model with random effects and municipal clusters (Table 11)



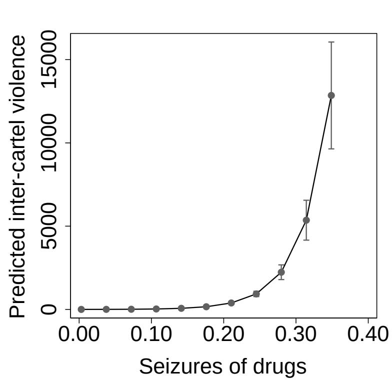
(a) Violent enforcement



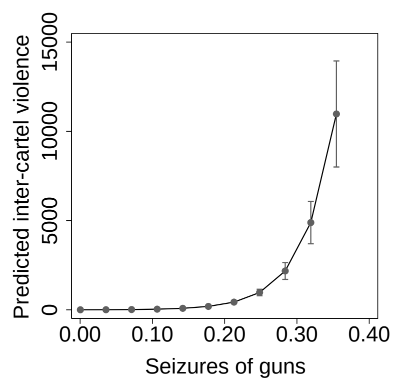
(b) Arrests



(c) Assets



(d) Drugs



(e) Guns

Figure 16: Effect of law enforcement on inter-cartel violence. Predictions in incidence rate ratios (IRR) from negative binomial model with random effects and municipal clusters (Table 12)

Table 13: First Stage: Determinants of violent and non-violent enforcement. Negative binomial model with fixed effects and municipal clusters.

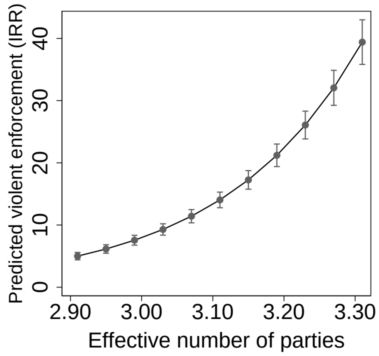
	(21) Enforcement	(22) Arrests	(23) Assets	(24) Drugs	(25) Guns
ENP	5.1613***	1.8974***	2.2226***	1.6489***	3.6783***
	(0.1465)	(0.0360)	(0.0623)	(0.0332)	(0.0769)
Divided government	0.3406***	0.1104***	0.1529***	0.1168***	0.1845***
	(0.0725)	(0.0192)	(0.0321)	(0.0179)	(0.0404)
Drug production	-0.0195	0.0617***	0.0263*	0.1162***	0.0827***
	(0.0304)	(0.0095)	(0.0150)	(0.0081)	(0.0175)
9/11	1.3367***	-0.3880***	-0.2518***	-0.4226***	-0.2786***
	(0.1375)	(0.0240)	(0.0402)	(0.0223)	(0.0529)
Gulf after 9/11	-0.1612	0.2135***	0.2191***	0.2464***	0.2869***
	(0.1064)	(0.0292)	(0.0573)	(0.0251)	(0.0574)
North after 9/11	0.5970***	0.0625***	0.0905**	0.2025***	0.3053***
	(0.0916)	(0.0240)	(0.0424)	(0.0201)	(0.0459)
Pacific after 9/11	0.3843***	-0.1428***	0.0889**	-0.0389*	-0.1670***
	(0.1137)	(0.0257)	(0.0432)	(0.0205)	(0.0494)
Rifles (100 K)	-0.0187**	0.0344***	0.0334***	0.0204***	0.0162***
	(0.0079)	(0.0026)	(0.0043)	(0.0026)	(0.0051)
Unemployment	0.0847***	0.0697***	0.0326***	0.0246***	0.0612***
	(0.0136)	(0.0044)	(0.0074)	(0.0042)	(0.0085)
Corruption	-0.0183***	-0.0059***	-0.0025**	-0.0025***	-0.0002
	(0.0019)	(0.0006)	(0.0010)	(0.0006)	(0.0011)
Cocaine price	0.0105***	-0.0035***	0.0016***	-0.0057***	-0.0011*
	(0.0010)	(0.0003)	(0.0004)	(0.0003)	(0.0006)
Local drug markets	-0.0002	0.0010***	0.0008***	0.0015***	0.0009***
	(0.0005)	(0.0001)	(0.0003)	(0.0001)	(0.0003)
Divorces	-0.0000	-0.0000	-0.0000**	0.0001***	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Young mothers	-0.3460	0.7875***	0.1201	1.6451***	0.7737***
	(0.4435)	(0.1304)	(0.2270)	(0.1123)	(0.2519)
Poverty	-0.1966***	-0.2638***	-0.2182***	-0.3094***	-0.4013***
	(0.0518)	(0.0191)	(0.0318)	(0.0146)	(0.0344)
Population (log)	0.1539***	-0.0281***	0.1247***	0.0608***	0.0734***
	(0.0235)	(0.0078)	(0.0146)	(0.0064)	(0.0137)
Constant	-25.5512***	-8.1199***	-12.2377***	-8.6181***	-16.9447***
	(0.5837)	(0.1396)	(0.2492)	(0.1235)	(0.2947)
Observations	2,856,798	5,219,382	4,267,116	5,335,904	3,736,740
F-statistic	224.72***	626.00***	278.46***	557.43***	371.97***

Coefficients are in log of expected counts. Standard errors in parentheses.
The levels of significance are: * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$

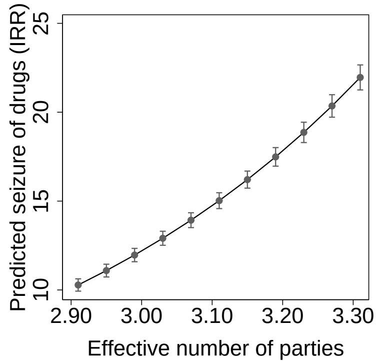
Table 14: Second Stage: Determinants of inter-cartel violence. Negative binomial model with fixed effects and municipal clusters.

	(21)	(22)	(23)	(24)	(25)
Violent enforcement	19.165***				
	(0.345)				
Arrests		15.080***			
		(0.220)			
Seizures of assets			22.501***		
			(0.348)		
Seizures of drugs				26.836***	
				(0.407)	
Seizures of guns					28.424***
					(0.457)
Drug production	0.106***	0.003	0.069***	-0.082***	0.030***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
9/11	1.236***	1.652***	1.355***	1.694***	1.314***
	(0.048)	(0.048)	(0.049)	(0.048)	(0.048)
Gulf after 9/11	0.365***	-0.093**	-0.091**	-0.071	0.039
	(0.041)	(0.044)	(0.044)	(0.043)	(0.043)
North after 9/11	-0.186***	0.241***	0.138***	-0.118***	-0.121***
	(0.035)	(0.031)	(0.032)	(0.033)	(0.033)
Pacific after 9/11	0.049	0.542***	0.103***	0.343***	0.527***
	(0.034)	(0.035)	(0.034)	(0.034)	(0.035)
Rifles (100 K)	0.123***	-0.023***	-0.017***	0.046***	0.055***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Unemployment	0.015***	-0.092***	0.029***	0.080***	0.006
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Corruption	0.011***	0.007***	-0.000	-0.002***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cocaine price	-0.005***	0.006***	-0.002***	0.008***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Local drug markets	0.001***	-0.002***	-0.003***	-0.005***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Divorces	0.000***	0.000	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young mothers	0.871***	-1.564***	0.768***	-2.603***	-0.222
	(0.153)	(0.157)	(0.152)	(0.157)	(0.153)
Poverty	-0.140***	0.317***	0.102***	0.212***	0.043**
	(0.019)	(0.020)	(0.020)	(0.020)	(0.019)
Population (log)	-0.061***	0.182***	-0.184***	-0.020**	-0.034***
	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)
Constant	-6.222***	-8.846***	-3.942***	-8.004***	-6.182***
	(0.133)	(0.125)	(0.144)	(0.125)	(0.130)
Observations	4,725,168	4,725,168	4,725,168	4,725,168	4,725,168

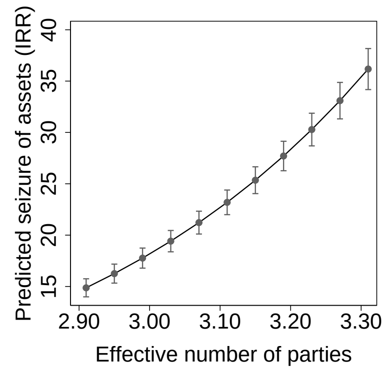
Coefficients are in log of expected counts. Bootstrapped standard errors in parentheses. The levels of significance are: * p< 0.1, ** p< 0.05, *** p< 0.01



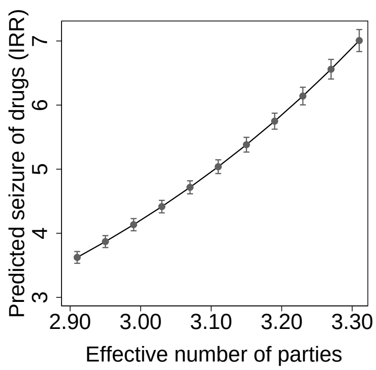
(a) Violent enforcement



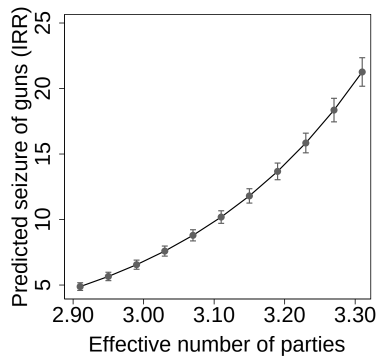
(b) Arrests



(c) Assets

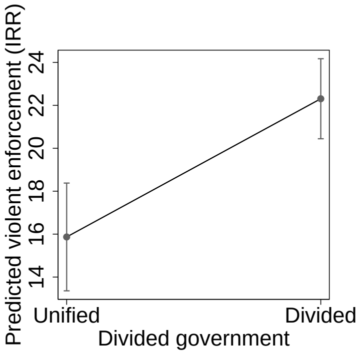


(d) Drugs

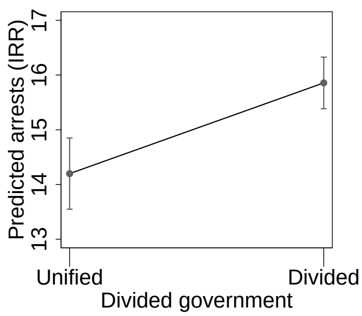


(e) Guns

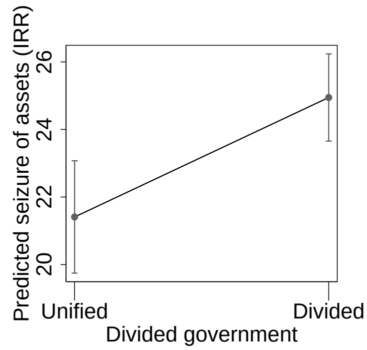
Figure 17: Effect of the effective number of political parties on law enforcement. Predictions in incidence rate ratios (IRR) from negative binomial model with fixed effects and municipal clusters (Table 13)



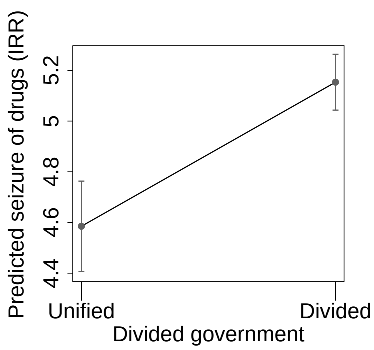
(a) Violent enforcement



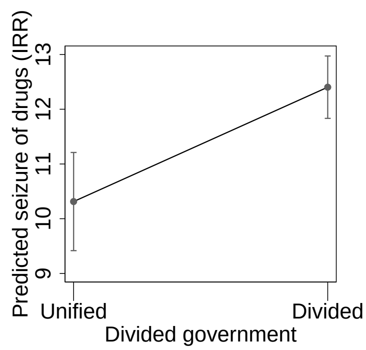
(b) Arrests



(c) Assets

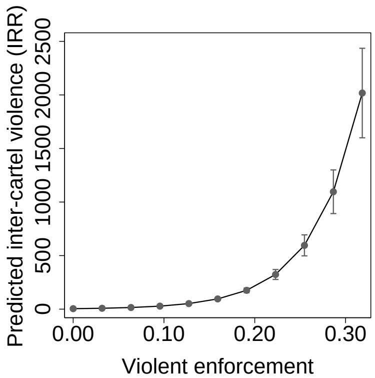


(d) Drugs

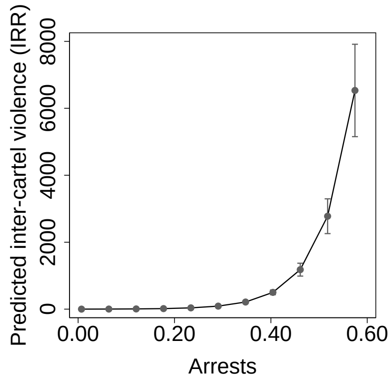


(e) Guns

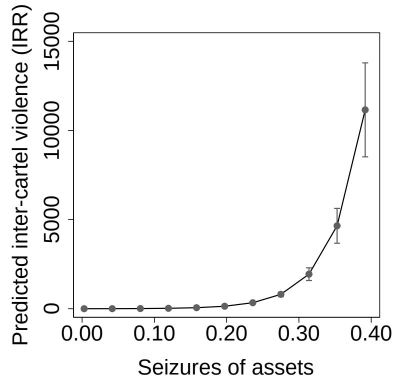
Figure 18: Effect of divided government on law enforcement. Predictions in incidence rate ratios (IRR) from negative binomial model with fixed effects and municipal clusters (Table 13)



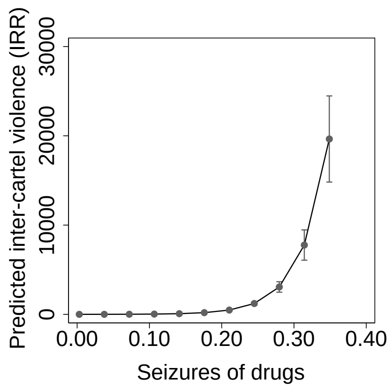
(a) Violent enforcement



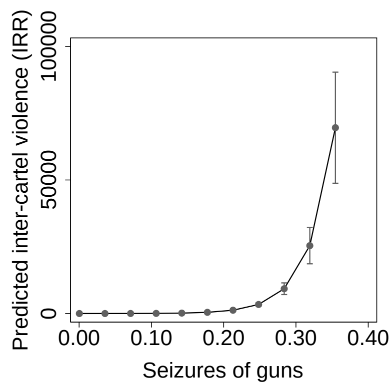
(b) Arrests



(c) Assets



(d) Drugs



(e) Guns

Figure 19: Effect of law enforcement on inter-cartel violence. Predictions in incidence rate ratios (IRR) from negative binomial model with fixed effects and municipal clusters (Table 14)