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ORGANIZED CRIME, VIOLENCE AND STATE RESPONSE

Presentata da: Alessio Carrozzo Magli

Coordinatore Dottorato | **Supervisore**

Andrea Mattozzi | Paolo Vanin

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Introduction

Modern states have shown long-term coexistence with large-scale organized crime, resulting in significant socio-economic impact. Drawing from three main literature strains, this PhD thesis investigates the determinants of organized-crime-related violence and how this is influenced by state anti-mafia policies.

The first relevant strand of the literature analyses the strategic use of violence by criminal organizations to influence politicians and public policy (Dal Bó et al., 2006; Alesina et al., 2019). The second one studies a complementary aspect, namely how law enforcement actions can either decrease (Lessing, 2017) or increase (Abadie et al., 2014) violence perpetrated by criminal groups against the state, as well as how they affect overall crime rates (Kugler et al., 2005).

The first chapter of this thesis[1] is motivated by this lack of univocal consensus regarding the impact of state responses on the level of mafia-related violence. This includes both internal violence, such as "mafia wars", and external violence, such as attacks on public officers and civilians. Briefly, this chapter explores how the strategic interactions between organized crime and the state shape the implementation of various types of anti-mafia policies, including economic responses and law enforcement measures, and how these policies, in turn, affect the level of violence.

Specifically, I document the surge in lethal attacks against public officers and civilians that followed the introduction of asset confiscation in several countries plagued by the presence of mighty criminal organizations (Italy, Mexico, Colombia). Additionally, I present evidence supporting the effectiveness of a well-designed harsh imprisonment regime in deterring such violent escalations. From a methodological standpoint, my analysis combines a Stackelberg model to study the strategic interplay between organized crime and the state with a wealth of econometric approaches for empirical analysis. These include instrumental variable analysis, staggered difference-in-differences (DID), synthetic control methods, and non-linear regression techniques. For instance, I designed a novel instrument for asset confiscations by exploiting an exogenous variation in US heroin demand interacted with cities' access to network infrastructure. The latter variable is adapted according to the specific context: In Southern Italy, this involved calculating each city's weighted average distance to commercial ports, considering the ports' sizes, as ports are a primary channel for drug trafficking. In Mexico, I used the road distance from each city to the U.S. border.

The last strand of the literature relates to the effects of state repression on violence within criminal organizations.

In relation to this, the subsequent sections of my thesis aim to unravel the puzzling disparity

[1] Which is also my Job Market Paper.

between the theoretical predictions and the empirical findings regarding the impact of state crackdowns on conflict intensity among criminal clans. Specifically, whereas the theory predicts a deterrent effect of a repressive policy targeting the strongest and most aggressive clans (Kleiman, 2011; Castillo and Kronick, 2020), several empirical studies found a surge in violence following state actions against the incumbent criminals (Dell, 2015; Osorio, 2015).
Formally, I develop a theoretical model that aligns with this counter-intuitive evidence, shedding lights on the underlying mechanisms, namely the collapse of the existing balance of power with the possible entrance of new strains of criminals (Chapter two) and the higher incentive for stronger clans to preserve the status quo and exploit their relative strength for rent extraction (Chapter three). In particular, the second chapter delves into the effects of state repression on mafia, employing an n-player conflict model with asymmetric distribution of clans' military and economic strength. In contrast, the third chapter combines theoretical conflicts models with network game theory to analyze how the size, power, and wealth of actors and coalitions influence their propensity to engage in warfare. The theoretical predictions are empirically tested employing data on militarized interstate disputes, with a supplementary empirical analysis using data on the Mexican drug cartels' wars currently underway.

References

A. Abadie, M. C. Acevedo, M. Kugler, and J. Vargas. Inside the war on drugs: Effectiveness and unintended consequences of, 2014.

A. Alesina, S. Piccolo, and P. Pinotti. Organized crime, violence, and politics. *The Review of Economic Studies*, 86(2):457–499, 2019.

J. C. Castillo and D. Kronick. The logic of violence in drug war. *American Political Science Review*, 114(3):874–887, 2020.

E. Dal Bó, P. Dal Bó, and R. Di Tella. "plata o plomo?": bribe and punishment in a theory of political influence. *American Political science review*, 100(1):41–53, 2006.

M. Dell. Trafficking networks and the mexican drug war. *American Economic Review*, 105(6): 1738–1779, 2015.

M. Kleiman. Surgical strikes in the drug wars: smarter policies for both sides of the border. *Foreign Aff.*, 90:89, 2011.

M. Kugler, T. Verdier, and Y. Zenou. Organized crime, corruption and punishment. *Journal of Public Economics*, 89(9-10):1639–1663, 2005.

B. Lessing. *Making peace in drug wars: Crackdowns and cartels in Latin America*. Cambridge University Press, 2017.

J. Osorio. The contagion of drug violence: spatiotemporal dynamics of the mexican war on drugs. *Journal of Conflict Resolution*, 59(8):1403–1432, 2015.

Asset confiscation and mafia violence. Unfolding 70 years of interactions between the Italian state and organized crime

Alessio Carrozzo Magli[*†]

Abstract

I develop a model analyzing the interplay between the Italian state and mafias. I demonstrate that targeting criminal profitability reduces conflicts within criminal organizations but increases retaliation against the state, while law enforcement decreases both. Using assassinations of public officers as the dependent variable, I support these findings by exploiting the introduction of Italy's asset forfeiture law and instrumenting confiscations with exogenous variations in US drug demand. This characterizes three major epochs of post-WWII Italian history: the "corrupted state", the "enforcement-retaliation", and the "sinking", identifying the previously proposed short-term electoral violence argument as a special case of the present explanation.

Keywords: Organized crime control strategies, confiscations, high-profile murders, mafia wars, violence "waves".

[*]Dipartimento di Economia, Università di Bologna, Piazza Scaravilli 2, 40126 Bologna, ITALY, e-mail: alessio.carrozzo2@unibo.it

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1 Introduction

The coexistence of modern states with large-scale criminal organizations is a long-term phenomenon (Colajanni, 1900; Salvemini, 1910), documented since several decades ago in the case e.g., of the Mexican drug cartels (Dell, 2015), or even since centuries for Italian mafias as Cosa Nostra[1], 'Ndrangheta and Camorra (CPMS, 1976; Gambetta, 1996; Catino, 2014). Although there is evidence that in some cases criminal or armed groups can supplant weak or failed states in providing "essential functions" for expropriation purposes (Sánchez De La Sierra, 2020), large-scale crime generally has a dramatic economic impact, (Dixit, 2004) including GDP loss (Pinotti, 2015; Mocetti and Rizzica, 2021), public funds' distortion (Barone and Narciso, 2015), expansion of the illegal economy (UNODC, 2011; Savona et al., 2015; Mocetti and Rizzica, 2021) and penetration into the legal one (Mirenda et al., 2022; Daniele and Dipoppa, 2022; Dipoppa, 2022; Le Moglie and Sorrenti, 2022). Not to say about the resulting societal and human lives cost (Alesina et al., 2019), the reduction in the quality of politicians and political life (Acemoglu et al., 2013, 2020; De Feo and De Luca, 2017) and the ensuing disruption of social capital and trust in public institutions (Rolla et al., 2022).

Starting from the main evidences about the post WWII coexistence between the state and organized crime in Italy, this work studies the effects of large-scale economic anti-mafia policies, primarily asset confiscation, on mafia-related violence, especially their role as triggers of lethal attacks against members of the state institutions ("high-profile" murders).

To this end, I propose a novel game-theoretic framework that delves into the mutual influence between a criminal organization, capable of resorting to both violence and bribery, and the state, which can respond with a combination of economic measures and law enforcement. The activity of both the state and the criminal organization are micro-founded by additionally accounting for heterogeneity in the loyalty of institutions' members, distinguishing between honest and corrupt public officers, as well as a multitude of clans which, besides attacking and/or bribing public officers, can also fight against one another, engaging in "mafia wars".

My main theoretical findings are as follows. First, assets confiscation fuels attacks against the state. Second, confiscations reduce within-mafia wars. Notably, the impact on the overall amount of resulting violence remains ambiguous, contingent on which of the two effects predominates. Third, effective law enforcement can refrain clans from launching attacks.

I bring empirical support to the previous theoretical predictions by examining the extent of post WWII mafia violence in the four Italian regions that historically have been most severely afflicted by organized crime. Specifically, I will deal with "Cosa Nostra" (Sicily), "'Ndrangheta" (Calabria), "Camorra" (Campania), and "Sacra Corona Unita" (Apulia). By taking as re-

[1] As a rule we refer to Sicilian mafia as Cosa Nostra, though this name was known to Italian institutions only after the mobster Masino Buscetta, the first whistle blower of Italian organized crime, started to collaborate with the Italian justice.

sponse variable the intensity of high-profile murders, I employ two complementary approaches: firstly, exploiting the introduction of the Italian asset forfeiture law (1982); secondly, instrumenting confiscations with the exogenous variation in the US heroin demand during the 1970s. The analysis provides a robust explanation of the post 1950 interactions between the Italian state and organized crime, primarily Sicilian Mafia (which supplied alone one third of the US heroin market at the time (Falcone and Padovani, 1991)). This allows to go one step forward compared to available results on this topic. In a seminal work, Alesina et al (2019) identified violence cycles in Sicily, Calabria and Campania as a short-term phenomenon whose period is primarily determined by the occurrence of political elections. Instead, by focusing on the role of confiscations, I could show that their electoral violence argument seriously underestimates the volume of mafia-related murders. In particular, I show that their election-violence cycle is indeed a dominant trait of the post WWII relationship between the Italian state and mafias (Catanzaro, 1992; Catino, 2014) but only in an initial phase characterized by a non-belligerent collusion. I term this phase, which is effectively explained by Acemoglu et al (2020)'s weak state hypothesis (Besley et al., 2015; Couttenier et al., 2017), as the *corrupted state*. This initial phase is followed by a blow-up of violence (1977-83) after a small group of brave Sicilian prosecutors broke the corrupted state *status quo* and launched for the first time an epoch of serious economic response, by confiscating mafia assets and threatening the legal impunity of its mobsters. This culminates into the big mafia war against the Italian state (1992-93). The ensuing state response, both military and economic, yielded to the subsequent *sinking* of Sicilian mafia. Overall, this shapes the post 1950 history of the interrelationship between Sicilian mafia and the Italian state into a complex multi-phasic dynamics.

We can broadly identify two main literature strains focusing on the coexistence between the state and organized crime. The first one, initiated by the seminal works of Dal Bó et al (2003; 2006), investigates the lobbying power of criminal organizations, examining how they influence public policies by strategically employing violence (Alesina et al., 2019; Daniele and Dipoppa, 2017; Daniele, 2019) and/or providing electoral support (Buonanno et al., 2016) to colluded parties (De Feo and De Luca, 2017; Acemoglu et al., 2013). I contribute to this research strand by analysing instead how states strategically tailor anti-mafia policies, accounting for organized crime's violent retaliation. The second one focuses on the effects of law enforcement on mafia-related violence. The related findings on violence within (Dell, 2015; Calderón et al., 2015; Atuesta and Ponce, 2017; Lessing, 2015) and outside (Abadie et al., 2014; Lessing, 2017) criminal organizations (i.e., mafia wars vs attacks against the state and its representatives) are still debated and no univocal consensus has been reached (Snyder and Duran-Martinez, 2009; Kleiman, 2011; Castillo and Kronick, 2020).

In contrast, the effects of economic response to the power of organized crime, including violence, have been poorly investigated. So far, scholars have primarily focused on the effects of seizing illegal goods (Becker et al., 2006; Castillo and Kronick, 2020; Castillo et al., 2020) and on policies addressing the distortion of market competition to obtain public funds (Daniele and Dipoppa, 2022). Instead, this works analyses how mafia-related violence is affected by asset confiscation, a policy that, despite representing the main economic response to crime (Cheng, 2021; Frigerio, 2009), has been only marginally studied (Osorio, 2015), mostly as evidence of the criminal presence in a given territory (Dell, 2015; Buonanno et al., 2016).

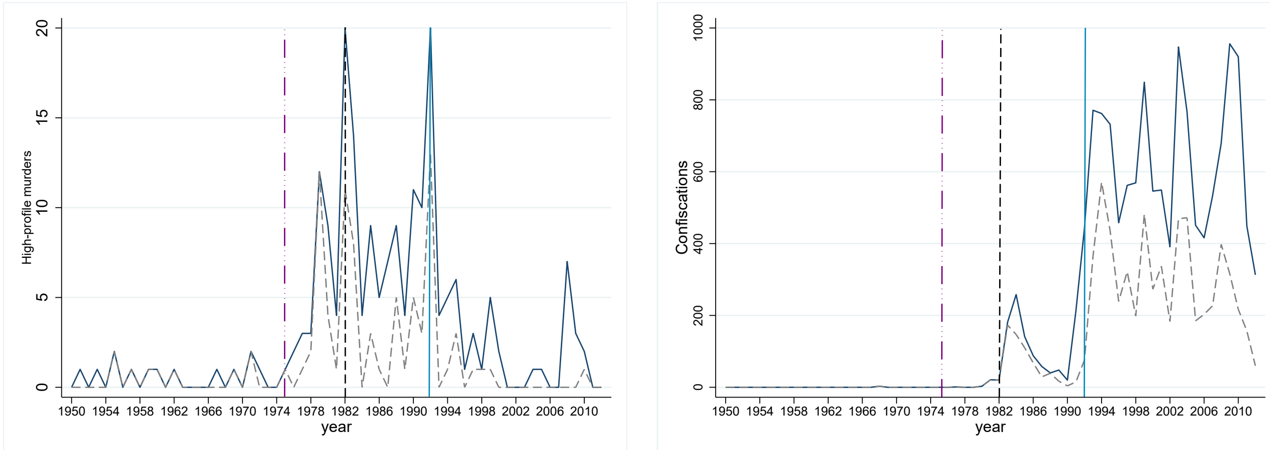
The rest of the article presents: a historical overview on anti-mafia policies and organized crime-related violence in the Italian context, highlighting the importance of asset confiscation and the main results of the paper in a nutshell including the reconciliation with Alesina et al (2019)'s work (section 2); the theoretical model (section 3); data and the empirical strategy (section 4); empirical results (section 5). Concluding remarks follow.

2 Mafias and the State in Italy after WWII: our results in a nutshell

As pointed out in the introduction, in this section I summarize the post-WWII relationship between the Italian state and the four major Italian criminal organizations, with special focus on Cosa Nostra, by far the best documented one. In doing so, I will present the key data of my analysis and my main hypotheses with the aim to briefly introduce the key findings of this work on the long-term phases of this interaction. This will allow to set the present results within the previous literature, in particular to appropriately identify Alesina et al (2019)'s election-violence cycle as the first phase of this long-term interaction. Unlike other works, my analysis considers the period 1950-2012, i.e., after the full establishment of the Italian Republic (1948). This avoids the complications due to the unreliable data from the Fascist period (1922-1943) and the transitional violence phase (e.g., the systematic elimination of trade unionists (Catanzaro, 1992)) before the full onset of the Republic and the establishment of the Christian Democracy leadership in Sicily.

Much of the motivations of the present analyses on the interplay between the Italian state and mafias is summarized by Figures 1 and 2. In particular, panel a) of Figure 1 reports the time series of total murders among members of Italian institutions (prosecutors, politicians, policemen), for simplicity termed high-profile (HP) murders since now on, while panel b) reports the total number of real estates confiscated to mafias in those regions[2]. Specifically, the two

[2]NNotably, the confiscations exhibit a cyclical trend, influenced by the legal procedures required for the definitive confiscation of assets. Such procedures mandate a final sentence within two to three years from the initial seizure. Given that trials involving mafia affiliations often bring dozens of mobsters to court simultaneously, these verdicts can lead to bursts in confiscations. Interestingly, this cyclical pattern of confiscations appears unrelated to electoral cycles. For instance, confiscations were on an increasing trend before the national elections of 1983, 1992, 1994, and 2008, while showing a decline (or even an undefined path), before the elections



(a) Total (solid) and Sicily (dotted)

(b) Total (solid) and Sicily (dotted)

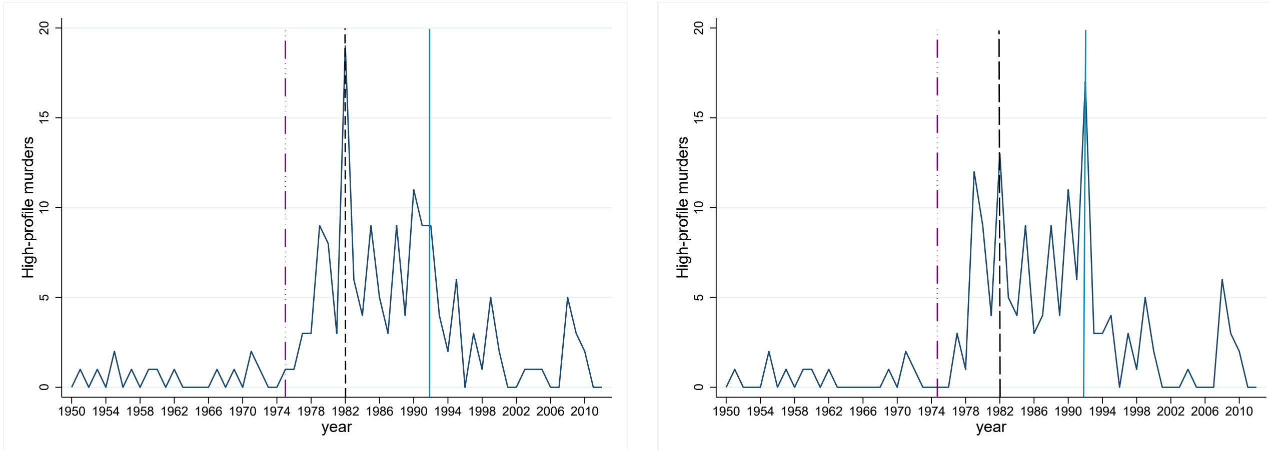
Figure 1: High-profile murders and confiscations in Sicily, Calabria, Campania and Apulia.

Notes: The dash-dotted line denotes the onset of the heroin market boom. The dotted line denotes the introduction of asset confiscation, whereas the solid line denotes the introduction of harsh imprisonment regime.

panels of Figure 1 depict aggregate trends of the four regions considered as well as that of Sicily only, consistently with our focus on Cosa Nostra. Furthermore, panel a) of Figure 2 illustrates HP murders excluding those occurred within the three months before and after national elections, whereas panel b) excludes those occurred within the twelve months before national elections, following Alesina et al (2019)'s definition of the pre-electoral period.

Figure 1 (panel a) shows an initial prolonged epoch (1950-1980) where the intensity of HP murders is steadily very low combined with (panel b) a full lack of economic response, as mirrored by the absence of confiscations. This is only seemingly paradoxical: this is indeed a *denial* epoch, where both the Sicilian and national governments, both dominated by Christian Democracy (that governed Sicily continuously till 1994), denied the existence itself of organized crime, thereby preventing any serious preventive or repressive action. Inspired by previous studies on the concept of weak state, e.g., La Ferrara & Bates (2001) and especially Acemoglu et al (2020) who convincingly argued that all Southern Italy regions severely afflicted by organized crime shared the characteristics of weak states, we term this period as the *corrupted state* epoch. Indeed, though Italy ranked amongst the top five industrialized countries during 1960-90, organized crime was the main tool through which Christian Democracy was able to steadily control the regional elections until its implosion in 1994 (De Feo and De Luca, 2017). This was allowed by well documented large-scale corruption through which Sicilian mafia i.e., Cosa Nostra, gained "substantial economic advantages" as the counterpart for electoral support to Christian Democracy candidates (De Feo and De Luca, 2017). Such economic advantages were

of 1987, 1996, 2001, and 2006.



(a) Dropping 3 months pre/post national elections (b) Dropping 12 months pre national elections

Figure 2: High-profile murders far from elections in Sicily, Calabria, Campania and Apulia.

Notes: The dash-dotted line denotes the onset of the heroin market boom. The dotted line denotes the introduction of asset confiscation, whereas the solid line denotes the introduction of harsh imprisonment regime.

made possible after WWII by the financial flows to Christian Democracy from the Marshall plan and the US Central Intelligence Agency (CIA) to prevent the Communist Party could reach the power as well as by the National government, through the huge transfers to Southern regions - the so called *Cassa per il Mezzogiorno* - aiming in principle to fight the dramatic levels of economic depression and unemployment prevailing therein (Graziani, 1978). This state of affairs ensured a robust political equilibrium, where mafia enjoyed - besides dramatic economic benefits - full legal and economic impunity, lasting at least until the end of the Seventies. The seminal work by Alesina et al (2019), relying on total homicides rather than HP ones, convincingly argued that this equilibrium was ensured by waves of homicides systematically enacted prior to elections, clearly aiming to direct votes. The corrupted state epoch was broken by a combination of events that dramatically altered this long-standing "collusive" equilibrium. These included the heroin market boom in the late 1970s, that raised in the mafias a new awareness of its economic and lobbying power (CPMS, 1987), as well as the emergence of a cohort of honest, brave, investigative and institutional components that finally broke the mafia economic and legal impunity. The "follow the money" strategy, aiming to trace and disrupt organized crime's illicit affairs, proposed by the Italian deputy Pio La Torre in 1979, for the first time seriously threatened mafias' economic power. La Torre strongly advocated the importance of targeting mafias' economic wealth and confiscating their assets (Catanzaro, 1992). His pledge, culminated in 1982 with the approval, after his brutal homicide by Cosa Nostra, of a law (the 'Rognoni-La Torre' law) which finally introduced in the Italian Penal law the crime of "mafia" affiliation. Among other, this enabled the state to confiscate the assets derived from or used in activities of criminal organizations and allowed to launch the first epoch of serious economic response to mafias' power, as apparent by the first confiscation wave in the early 1980s (Figure 1 panel b). The impact of this threat was dramatic because, due to the system of internal values and norms of large scale criminal organizations, confiscations were perceived by apical Cosa Nostra figures as dramatically more threatening than e.g., life imprisoning, given the trust in the possibility to recover impunity in the corrupted state regime[3].

The extent of this State response, seriously threatening mafia's economic power for the first time, led Cosa Nostra to an unprecedented response, which we term the *big retaliation* epoch (Figure 1), against institutional figures[4].

This epoch of massive military attack - compared to the fully "quiet" previous phase - by Cosa Nostra to the State, lasted about 15 years[5] and showed two main peaks: (i) the "intimidation" peak during the so-called "Palermo maxi trial", that for the first time led to massive convictions of Cosa Nostra bosses, aiming to scare the entire anti-mafia team including the popular jury; (ii) the "apical retaliation" phase, which was triggered by the confirmation in the court of appeal of the sanctions sentenced to mafia bosses in the Palermo maxi trial. This culminated in the killing (early 1992) of the top representative of Christian Democracy in Sicily (and also its major link with Cosa Nostra) and the subsequent mass murders of Capaci and Via D'Amelio, that involved the two dominant figures of the state response to mafia, namely judges Falcone and Borsellino (May and July 1992). The two last events finally mounted a wave of widespread public disdain against mafia at the national level that finally brought the Italian State to respond to the retaliation epoch. As a first response, the state cancelled the *impunity* insurance, through the introduction of the so-called article 41-bis into the Italian penal law (harsh imprisonment regime for mobsters), by capturing soon the "boss of bosses" Totò Riina - the major promoter of the retaliation epoch - and finally implementing the threat of confiscations, as showed by their dramatic uprise immediately after 1993 (Figure 1, panel b). This strong reaction by the Italian state led to the last major epoch identified by the present analysis. Since 1993 onward, parallel to mass confiscations finally becoming reality, Cosa Nostra ceased fire and, possibly, completely changed its strategy, entering what we term the "sinking" phase. Surprisingly,

[3]For example, Francesco Inzerillo, a prominent Sicilian mobster emigrated in the US, said: *"There is nothing worse than asset confiscation"*. It's better to go to jail or to be even killed than losing "the things"(*la roba*), i.e., the wealth illegally accumulated (Frigerio, 2009).

[4]It is not then surprising that a major condition set forth by Cosa Nostra in Riina's *papello* (a list of requests from the "boss of bosses" in exchange for his command to Cosa Nostra to cease fire) is the modification of the Rognoni-La Torre Law (Torrealta, 2010). In Riina's words, *"you make war to make peace"*.

[5]As discussed in subsequent sections, there is a time lag of two to three years from the seizure of goods to their final confiscation. Consequently, Figure 1 (panel b) presents a lagged time-series of the Italian state's economic response to mafia activities. Unfortunately, data on seizures are not publicly available, preventing the display of the non-lagged time series. Remarkably, the escalation of mafia violence against the state is closely linked to the murders of Giuseppe Russo in 1977 and Boris Giuliano in 1979. Notably, they were among the first police officers to adopt the follow the money strategy, focusing on the massive flow of funds from the US heroin trade.

this phase remains largely unknown. In terms of political alliances, following the collapse of Christian Democracy at the national level due to Italy's largest corruption trial[6], Cosa Nostra began seeking new allies locally. This shift is evidenced by its documented electoral support for Silvio Berlusconi's party, Forza Italia (Buonanno et al., 2016). On the economic side, it started seeking new markets, especially international ones, where to reinvest and launder its massive capitals, possibly only marginally affected by confiscations (EIIR, 2023). Finally, at the top political level, apical Cosa Nostra members started a secret negotiation with top figures of the Italian State through an independent initiative (*La Trattativa*) conducted by the highest level of the *Arma dei Carabinieri*, seemingly in the absence of any control of the State. The goal was to negotiate the rollback of anti-mafia laws in exchange for a reduction in violence. (Bodrero, 2013). Surely, after 1993-1995 boom, mass confiscations in Sicily started declining[7] (Figure 1, panel b) and returned to a very low level by the end of the period (2012). The theoretical model correctly predicts that reducing violence and switching to different activities is one of the possible options of organized crime to face robust state responses.

To sum up, the present analysis focusing on the relationship between and confiscations and high-profile murders attributable to large scale organized crime, instead of total murders as in the seminal work by Alesina et al (2019), shows that their violence-election cycle is only a part of the story. Indeed, the present analysis suggests that the violence-election cycle was just noise superimposed to a broader, more complicated, longer-term dynamics dominated by the three aforementioned epochs: the *corrupted state* epoch, ensuring full impunity to Cosa Nostra, the *big retaliation* epoch, the *sinking epoch*.

In the forthcoming sections, I try to demonstrate the present claims by developing a theoretical framework and reporting its empirical findings. In particular, I will show that these results unsurprisingly extend also to the other Italian regions plagued by the presence of large scale crime and more exposed to the influence and power of the Christian Democracy, also in light of the possibility to resort to the *Cassa per il Mezzogiorno*.

3 The model

3.1 Model setup

Consider a criminal organization formed by n symmetric[8] clans. Each clan i controls an illegal market of size π but can undertake an extra military investment x_i to attack the others and

[6] The so-called "Mani Pulite" maxi trial debuted in February 1992 in Milan, the same month of the killing of Salvo Lima, the main political interface between Sicilian Christian Democracy and Cosa Nostra.

[7] However, they remained fairly stable in Campania, Calabria, and Apulia.

[8] The effect of state repression on the balance of power between asymmetric clans (Ríos, 2013; Dell, 2015) does not alter the results of the model, though it surely represents an interesting extension.

contest their wealth[9] *à la Tullock* (Tullock, 1980). Moreover, all clans interact with a state consisting of a central government and a mass of h honest public officers and $1-h$ corruptible ones[10] (Dal Bó et al., 2006). The government aims at minimizing the wealth of the criminal group, thereby increasing the probability that it will leave the market (Dal Bó et al., 2006). To this purpose, it can invest into economic response (a) and/or law enforcement (g). The first policy empowers public officers to confiscate illegal profits, whereas the second employs direct force to undermine clans. Law enforcement can be interpreted as encompassing any military or judicial action designed to increase the costs for clans to exert violence, thereby indirectly safeguarding public officers from retaliatory attacks. Specifically, public officers derive benefit from the fraction of illegal profit that they confiscate (because of e.g., higher wages and/or top positions in the public office), but their effort is costly. Each clan i can increase this cost by violently harassing (m_i) honest public officers. Pairwise, it can increase the opportunity cost of confiscation for corrupt public officers by offering bribes (b_i) decreasing in their effort. The timing of the game[11] is the following[12]:

1. The government chooses the intensity of its economic response (a) and the level of law enforcement (g);

2. Clans belonging to the organization choose their individual level of bribe expenditure (b_i) and violence (m_i) to reduce confiscation. Simultaneously, they also chose their level of military investment x_i against one another.

3. Public officers decide their individual effort devoted to confiscation.

The loss function of the government is defined as follows:

$$S = -\sum_{i=1}^{n}[1 - hY_i - (1-h)Z_i]\frac{x_i}{\sum_{i=1}^{n} x_i}\pi - dg - ea \tag{1}$$

With a slight abuse of notation, I will interchangeably refer to d and e as relative strength between organized crime and the state (such that weak states are those characterized by high values of these parameters) and as (inverse) measures of popular support for the state.

Throughout the analysis, I take those parameters as exogenous. However, in Appendix A, I will suggest how making them endogenous may lead to multiple equilibria in the main game

[9] Notably, in this setup a higher n implies a higher internal fragmentation of the criminal group.

[10] One can interpret h as the probability that a honest public officer is extracted to interact with clan i. Alternatively, h and $(1-h)$ an be interpreted as the frequency of interactions with honest (corrupt respectively) public officers.

[11] In Appendix A, I solve the game removing the sequential ordering, i.e., considering a state and a criminal organization who move simultaneously.

[12] Figure 3 plots the game solution for the simplified game with $n = h = 1$, thereby focusing on the key ingredients of the model: economic response (a), law enforcement (g) and violence against the state (m).

between the state and the criminal organization.
The payoff function of the generic clan i is the following:

$$W_i = [1 - hY_i - (1-h)Z_i]\frac{x_i}{\sum_{i=1}^{n} x_i}\pi - (m_i + x_i)(g+1) - qb_i \tag{2}$$

The parameter q in equation (2) captures institutional and technological factors influencing the cost of delivering bribes (e.g., quality of law enforcement (Dal Bó et al., 2006)), In contrast, the cost of clans' violence is increasing in the level of government's military investment.
Denoting by Y_i^j (Z_i^j) the fraction of asset confiscated by the honest (corrupt) public officer j to clan i, her payoff function U_j^H (U_j^C) is defined as follows:

$$\begin{cases} U_j^H = \sum_{i=1}^{n} \left[ln(Y_j) - Y_i^j \frac{(m_i+1)}{\frac{a}{a+1}} \right] \\ U_j^C = \sum_{i=1}^{n} \left[ln(Z_i^j) + b_i(1 - Z_i^j) - Z_i^j \right] \end{cases} \tag{3}$$

In Appendix A, I show that results are preserved substituting:

- $\frac{a}{a+1}$ with any increasing and concave function G bounded between 0 and 1[13](so that the cost of confiscation is decreasing and convex in a, yielding an increasing and concave benefit from confiscation effort for the government);

- $m_i + 1$ with any increasing and concave function F such that its inverse $H = \frac{1}{F}$ is a decreasing and convex function bounded between 0 and 1[5] (so that the cost of confiscation is decreasing and convex in m_i, yielding an increasing and concave benefit from violence)

- b_i with any non-linear decreasing function of b_i, such that the optimal Z_i resulting from the maximization of the second equation (3) is overall decreasing and convex in b_i

Note that, neglecting violence m_i and bribery b_i, corrupt officers pay a lower cost for confiscation, although higher investment in economic investigations from the government (a) decreases this gap. This is based on the assumption that colluded officers have access to better information on criminal activities, and their behaviour is also loosely bounded by laws and regulations. The implication is that a corrupt state is able to eliminate minor criminals that are not strong enough to pay for their immunity, but it is less able to (if not completely unable) to fight mighty criminal organizations. Anecdotal evidence supporting this hypotheses comes from the fascist repression of Sicilian mafia. In 1925, Cesare Mori was appointed prefect of Palermo, with the aim of eradicating mafia. Here the telegram of Mussolini (Petacco, 2004):
"Your excellence, you have carte blanche. The state's authority must be absolutely -I repeat, absolutely- restored in Sicily. If current laws hamper you, no problem, we'll make new laws".

[13]In Appendix A, I also show that results are unaffected reinterpreting fractions in absolute terms.

"Being more mafioso than mafiosi" (Catanzaro, 1992), the "iron prefect" Mori conducted an aggressive campaign against mafia, resulting in the conviction of all low ranks mobsters. However, when he started targeting high ranks white collars colluded with the fascist political power, he was immediately dismissed (Catanzaro, 1992).
Clan's outside option is $u \geq 0$. The solution concept is sub-game perfect Nash equilibrium (SPNE) and the game is solved by backward induction.

3.2 Game solution: stage three

Simultaneous maximization of equations (3) yields the fraction of confiscated asset from honest and corrupt public officers:

$$\begin{cases} Y_j(a, m_i) = Y(a, m_i) = \frac{a}{(a+1)(m_i+1)} \\ Z_j(b_i) = Z(b_i) = \frac{1}{b_i+1} \end{cases} \tag{4}$$

Note that, in the simplified case where $h = n = 1$ (absence of corruption and mafia wars), the substitution of the first equation (4) into the payoff function of the state and the criminal organization gives rise to a sequential game analogous to previous tax evasion models (Bayer and Cowell, 2009; Besfamille et al., 2009). This becomes evident reinterpreting (i) confiscations of illegal profits as taxation of legal ones, (ii) violent retaliation from the criminal group as tax evasion and (iii) law enforcement as the expected fine (which increases the cost of evading).

3.3 Game solution: stage two

Substituting equations (4) into (2) and maximizing with respect to m_i, b_i and x_i, one gets:

$$\begin{cases} \hat{m}_i = \sqrt{\frac{ah}{n(a+1)(g+1)}\pi} - 1 \\ \hat{b}_i = \sqrt{\frac{(1-h)}{qn}\pi} - 1 \\ \hat{x}_i = \left[1 - h\frac{a}{(a+1)(m_i+1)} - (1-h)\frac{1}{b_i+1}\right] \frac{n-1}{(g+1)n^2}\pi \end{cases} \tag{5}$$

Simple inspection of equations (5) allows to derive the following Proposition.

Proposition 1. *Given the level of government's activity: (i) violence external to the criminal organization is increasing in profit, confiscation and the fraction of honest public officers, whereas it is decreasing in internal fragmentation*[14] *and the level of law enforcement; (ii) corrup-*

[14]Although outside the scope of the paper, it is important to remark that, if clans' economic and military power were asymmetric, the degree of internal fragmentation does not necessarily relate to the number of clans.

tion is increasing in profit and in the fraction of corrupt public officers, whereas it is decreasing in law enforcement and internal fragmentation; (iii) violence internal to the organization is increasing in profit and internal fragmentation and decreasing in confiscation and law enforcement; (iv) clans' propensity to bribe relative to use violence ($\frac{\hat{b}_i}{\hat{m}_i}$) increases in law enforcement and in the efficiency of the bribe technology relative to clans' military strength, whereas it decreases in the state's confiscation effort and honesty of public officers.

On the one hand, law enforcement increases the costs associated with both internal and external violence, thereby having a negative relationship with each. On the other hand, confiscations reduce the revenues of the organization. This creates an incentive to external violence (attacking public officers to reduce confiscation). Moreover, by reducing the net wealth contested by clans, asset confiscation deters conflicts internal to the organization (Sobrino, 2019; Castillo and Kronick, 2020) i.e., it "compacts" clans against the state. Last, a higher number of clans implies higher internal conflict intensity and therefore lower final profit, thereby reducing the incentive to bribe public officers and the ensuing extent of bribery. Overall, equations (5) show that profit booms trigger the surge in corruption as well as internal and external violence. Finally, replacing $a = 0$ into equations (5) allows to derive an important corollary.

Corollary 1. $a = 0 \implies \hat{m} = 0$

Corollary 1 states that in absence of confiscation, the criminal group does not attack the state (even with positive law enforcement), though clans continue to engage internal struggles.

3.4 Game solution: stage one

Substituting equations (5) into equation (1), maximizing with respect to a and g and substituting back into equations (5), one gets the following:

$$\begin{cases} a^* = \sqrt{\frac{nh\pi}{4ed}} - 1 \\ g^* = \frac{nh\pi}{4d^2} - \frac{\sqrt{neh\pi}}{2d\sqrt{d}} - 1 \\ m_i^* = \frac{2d}{n} - 1 \\ b_i^* = \sqrt{\frac{(1-h)\pi}{qn}} - 1 \\ x_i^* = 2d\frac{n-1}{n^2}\left[\frac{\pi - \sqrt{(1-h)qn\pi}}{\frac{nh\pi}{2d} - \frac{\sqrt{neh\pi}}{\sqrt{d}}} - 1\right] \end{cases} \tag{6}$$

Simple inspection of equations (6) allows to derive the following Proposition.

Proposition 2. *When the government's reaction is endogenous: (i) confiscation and law enforcement are increasing in profit and internal fragmentation; (ii) bribe expenditure is increasing in profit and decreasing in internal fragmentation; (iii) violence external to the criminal organization is decreasing in popular support and internal fragmentation; (iv) violence internal to the organization is decreasing in profit, popular support and internal fragmentation; (v) clans' propensity to bribe relative to use violence ($\frac{b_i^*}{m_i^*}$) increases in profit and in the efficiency of the bribe technology relative to clans' military strength, while it decreases in public officers' honesty.*

Notably, whereas (given the strength and size of the players) external violence becomes constant, internal violence is now decreasing in profit, thereby still being negatively related to confiscation. Moreover, while equations (5) indicate that violence increases with the fraction of honest officers in the presence of a weak state, equations (6) show that this is not the case for a strong state capable of eliminating the trade-off between confiscation and violence (i.e., when the RHS of the first two equations (6) are positive). Here, higher fractions of honest public officers result in a decrease in corruption without causing an increase in violence.
Conversely, given the levels of q, corruption increases with the profit level even after state intervention. This implies that, in the presence of a weak state, periods of high profits are associated with elevated levels of both corruption and violence. In contrast, with a strong state, law enforcement effectively enables an increase in confiscation while deterring violence, leading the criminal organization to increasingly rely on bribery.
Note that (Proposition 1) prior to the implementation of law enforcement (e.g., when the RHS of the second equation (6) is not positive), more fragmented organizations are subject to more mafia wars (Catino, 2014). However (Proposition 2), when facing a significant threat of law enforcement, the opposite holds. The intuition is that a strong state exhibits greater efficacy in countering a less cohesive organization. Consequently, clans belonging to more fragmented organizations experience higher military costs and compete for a lower net wealth, leading to a reduced incentive for internal struggles. Instead, both Propositions suggest that fragmented criminal organizations are less aggressive towards the state (Catino, 2014). The following Lemma illustrates the corner solutions of the game, assuming, without loss of generality, the absence of mafia wars and corruption ($h = n = 1$).

Lemma 1. *For low profit (and popular support), optimal confiscation and law enforcement are zero. As profit (and/or the relative strength) increases, the optimal a^* becomes positive, while g^* remains zero. Further increases lead to a positive optimal g^*.*
Proof. Appendix A.

In other words, $g^* > 0 \implies a^* > 0$ but the vice-versa does not necessarily hold.

Notably, if the state is bounded to the corner solution with no anti-mafia policy, $m = 0$ and $W = \pi$, i.e., the criminal organization does not attack the state (though it will engage mafia wars if $n > 1$) and its wealth is maximized. Lemma 1 allows to derive the following Proposition.

Proposition 3. *(i) For intermediate values of profit (and/or popular support), the government may set $a > 0$ and $g = 0$, triggering violent retaliation from the criminal organization. (ii) Only for sufficiently large values of profit (and/or popular support), such that $g^* > 0$, the government intervenes with both confiscation and law enforcement, at the same time preventing an escalation of retaliating violence.*
Proof. Appendix A.

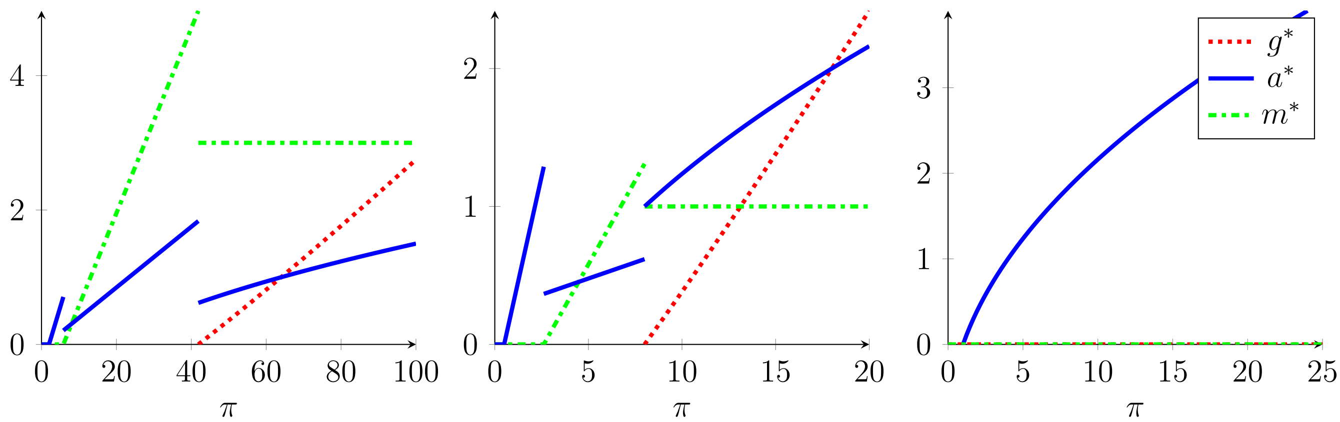
The next corollary shows that mighty states discourage any attack from the criminal organization, thereby achieving the maximum confiscation levels.

Corollary 2. $2d < 1 \implies m = 0 \implies g = 0 \implies \bar{a} = \sqrt{\frac{\pi}{e}} - 1 > a^*$.
Proof. Appendix A.

The intuition behind Proposition 3 and Corollary 2 is illustrated in Figure 3, where I depict the game solution across various values of the cost parameters and profit levels. Specifically, Figure 3 demonstrates that g^* becomes positive after a^* regardless of the assigned values for the cost parameters. Panel (a) of Figure 3 (with $d = e = 2$) reveals that as profit increases, confiscation also rises. However, in order to reduce confiscation, the criminal group eventually becomes more aggressive towards the state, resulting in a sudden decline in confiscation once violent retaliation becomes positive. Violence continues to escalate, ultimately compelling the state to employ law enforcement. As profit further rises, economic and law enforcement continue to increase, but mafia violence stabilizes at a lower level determined by the relative strength ratio between the state and the criminal group. Panel (b) (with $e = \frac{1}{2}$, $d = 1$) shows that stronger states' anti-mafia policies are harsher, whereas mafia retaliation is lower. Finally, Panel (c) shows that very mighty states ($e = 1$, $d = \frac{1}{2}$) discourage violence, enabling the state to focus solely on economic response. Note that weaker states are inactive for higher ranges of profit values, essentially colluding with organized crime, which in turn refrains from attacking.

4 Data and empirical strategy

The model presented in section 3 yields a wealth of theoretical predictions, some of which present serious challenges in terms of their testability. Specifically, the rest of the paper is primarily devoted to an extensive test of the main testable prediction:



(a) $d = e = 2$

(b) $d = 1,\ e = \frac{1}{2}$

(c) $d = \frac{1}{2},\ e = 1$

Figure 3: Game solution for different strength levels of the state.

Notes: a^*, g^*, m^* respectively denote the optimal economic and military anti-mafia policies and organized crime violent retaliation. π is the profit level.

- H1: in the absence of law enforcement, confiscations increase external violence;

Additionally, a wealth of correlations will be provided to support the secondary predictions of the model:

- H2: confiscations decrease internal violence;
- H3: law enforcement reduces and stabilizes external violence;
- H4: confiscations increase corruption.

Due to data availability, the rest of the paper is mainly devoted to the test of H1 and to a brief test of H2, whereas suggestive correlations in favour of H3 and H4 are presented in Appendix B.

Note that H1 and H3 respectively correspond to testing the drivers of the second and third main epochs described in subsection 2, whereas the driver of the first main epoch, namely the absence of economic response, is documented in Figure 1 by the very low intensity of high-profile murders occurred before the heroin market boom and the ensuing political debate in favour of the introduction of asset confiscation.

To the best of my knowledge, the model presented in Section 3 provides the first theoretical framework to explain the impact of different state response strategies, namely law enforcement vs confiscations (Osorio, 2015), on various forms of mafia-related violence i.e., mafia wars vs direct attacks against the state and its representatives (Abadie et al., 2014).

For all testable hypotheses, the analysis is focused on Sicily, Calabria, Campania, and Apulia—four Italian regions historically plagued by powerful criminal organizations[15]. Concerns about selection bias are addressed in Appendix B, where I demonstrate that results hold expanding the analysis to the whole country[16].

Since (i) criminal clans extend their control beyond a single (on average very small in Italy) municipality and (ii) murders outside the organization often require the authorization of the "provincial commission" (Catanzaro, 1992), in the main text, I adopt my preferred specification, disaggregating data at the provincial[17] level (summary statistics in Table 1) for the years between 1950 and 2012, focusing on different temporal intervals depending on the characteristics of each theoretical prediction. Nonetheless, in Appendix C I replicate the main analysis at the municipal level, correcting also for spillovers across neighbouring municipalities. Remarkably, the results align with the presented anecdotal evidence on the geography of mafias' decision-making process: whereas I find that confiscations in neighbouring municipalities (defined as municipalities within 10 km distance) positively affect the likelihood of observing a high-profile murder in the considered municipality, this is not the case when the province is the unit of analysis . Neither confiscations nor violence in neighbouring provinces (defined as contiguous provinces) affect high-profile murders in the considered province (see Table C4).

4.1 H1: confiscation increases external violence

I test H1 on the years before the introduction of harsh imprisonment regime (1950-92).

I adopt both a specific and a generic measure of external violence, namely the count of high-profile murders (*HP murders*) and innocent victims (*Innocent victims*) of criminal organizations. The latter is the sum between HP murders and murders of civilians[18].

Though my preferred variable is high-profile murders, I believe that the complementary use of innocent victims adds further robustness to my results. Indeed, judicial evidence (Lodato, 2012) has extensively documented that Cosa Nostra intentionally targeted civilians in 1992-1993 to blackmail the Italian State and obtain a looser application of the novel repressive policies introduced from the approval of the Rognoni-La Torre law onwards.

Data on high-profile murders (Figures 1 and 4) and innocent victims (Figure 4 and 5) are obtained from "Libera" (Libera), a popular non-profit association aimed at increasing awareness and knowledge about organized crime. Additional data is sourced from "wiki-mafia" (Wikimafia), an association that maintains an online database listing all innocent people killed by organized crime in Italy, specifying their profession, year, and municipality of the murders.

[15]It is noteworthy that these regions account for approximately 75% of national confiscations.

[16]Note that organized crime has penetrated also the North of Italy in the last decades (Mocetti and Rizzica, 2021).

[17]A province corresponds to the NUTS 3 Eurostat level of territorial delimitation.

[18]Results with the use of murdered civilians alone is reported in Appendix B.

I then employ the number of confiscated real estates (Figures 1, panel b) and 4) (*Confiscation*), taken from the Italian "National Agency for the Management and Destination of Assets Seized and Confiscated from Organized Crime" (ANBSC). The database provides disaggregated data at various levels (national, regional, provincial, municipal). I use data on confiscated assets that have already been destined back to the civil society (around 20,000 out of 45,000), since information of the year of confiscation are unavailable for the not yet destined ones. This justifies the choice of 2012 as end year of the panel data, given that these 25,000 confiscated assets, which have not yet been destined (meaning that their locations are known, but not the year of confiscation), predominantly represent the most recent confiscations. Including them would thus result in a significant underestimation of the volume of confiscations in the most recent years[19]. Figures 1, 4 and 5 show that both confiscation and external violence are affected by a marked spatial and temporal heterogeneity. For instance, Palermo, Naples, and Reggio Calabria alone account for around 40% of national confiscation and 66 (58)% of high-profile murders (innocent victims). In Appendix B, I show that results are substantiated when using a wider measure of confiscation (which I label *Total confiscation*), encompassing both real estates and firms[20].

Finally, I include a set of socio-demographic and economic indicators, obtained from ISTAT censuses (ISTAT, a), interpolating data when missing.

To test the prediction H1 on the effects of confiscation on external violence in absence of law enforcement, I adopt the following empirical strategy:

$$External\ violence_{i,t} = \beta\ confiscation_{i,t} + \gamma X_{i,t} + \alpha_i + \varepsilon_t + u_{i,t}, \tag{7}$$

where $X_{i,t}$ is the set of control variables, α_i controls for provincial fixed effects, ε_t is a set of year dummies and $u_{i,t}$ is the standardized error term clustered at the provincial level. The coefficient of interest is β, which captures the change in the number of high profile murders due to a change in the level of economic response to organized crime (i.e., confiscation).

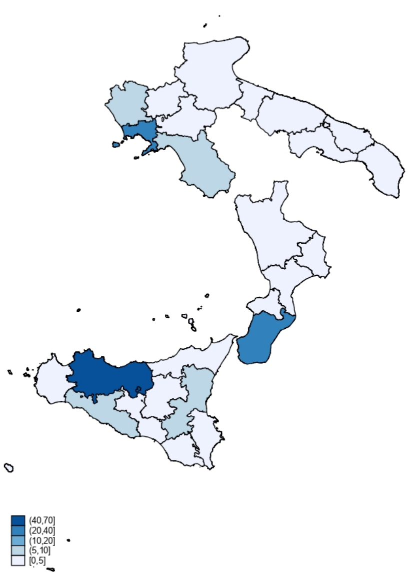
Notably, equation (7) may be subject to a significant concern of reverse causality. For instance, the state might choose to intensify repression in areas where organized crime is already more violent. Conversely, as the theory suggests, the threat of asset confiscation might provoke the mafia to increase their violence in an attempt to intimidate and eliminate honest public officers. To address this concern, I adopt several approaches. First, I consider different lagged values of the explanatory variable. In particular, whereas a good can only be confiscated after the

[19] Additionally, since almost all (if not all) not yet destined assets have been confiscated after 1992, this does not pose a problem for the causal identification required to test H1.

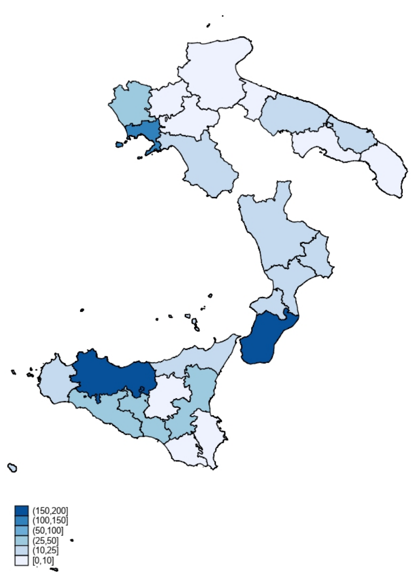
[20] I use only real estates as the baseline since confiscations of firms is not as widespread as that of real estates (see Table 1) and since the lack of information on the economic value of the confiscated firms raises severe concerns of measurement errors, possibly making the confiscation of real estates and firms not immediately comparable.

VARIABLES	N	mean	sd	min	max
MAIN VARIABLES					
Confiscation	1,575	8.991	31.827	0	527
High-profile murders	1575	.125	.633	0	11
Profit (Access to ports*overdoses/1000000)	1575	17.049	40.048	.0138	397.435
Mafia war	676	8.752	19.969	0	169
Detainees at harsh imprisonment regime (Art. 41bis)	1575	7.03	18.29	0	123
Fake profit (Access to major Italian cities*overdoses/1000)	1575	2.612	6.627	.009	38.388
Low-profile murders per 100,000 inhabitants	1386	3.050	2.989	0	34.355
Reported crimes of mafia affiliation (Art. 416bis)	1485	50.692	113.058	0	980
Confiscation value (millions)	1,575	.969	6.698	0	180.918
Innocent victims	1,575	.538	1.603	0	20
City council dissolution	550	.140	.655	0	9
Total confiscation	1575	9.703	33.631	0	541
SOCIO-DEMOGRAPHIC CONTROLS					
Share of population under 25	1575	.4	.075	.242	.568
Share of illiterate population	1575	.09	.065	.012	.316
Share of population with university degree	1575	.031	.026	.005	.115
Log(population)	1575	13.134	.642	11.844	14.935
Mafia	1575	.64	.48	0	1
ECONOMIC CONTROLS					
Share of labour force in building sector	1575	.109	.045	.027	.269
Share of male labour force searching first occupation	1575	.038	.061	0	.212

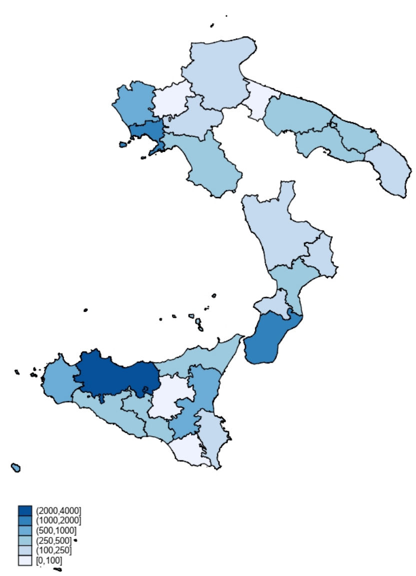
Table 1: Summary statistics for Sicilian, Calabrian, Campanian and Apulian provinces, 1950-2012.



(a) High-profile murders



(b) Innocent victims



(c) Confiscations

Figure 4: Provincial distribution of high-profile murders, innocent victims and confiscations.

final sentence of a trial, its actual seizure from the mobster's ownership occurs before the trial as a precautionary measure. Therefore, the moment when the good is removed from the mobster's possession is the seizure itself. Since the confiscation of the good must take place within one and a half years from the seizure, and the deadline can be extended up to three years, confiscations at time t (i.e., the measure of economic response to crime that I use in my preferred specification, although I also perform a wealth of robustness checks using confiscations at time t and $t+1$) reflect seizures occurred between time $t-2$ and $t-3$. It is therefore extremely unlikely that a confiscations at time t (i.e., seizures at time $t-3$) reflected state retaliation against organized-crime related violent event occurred at time t. Second, I exploit the staggered Difference-in-Differences (DID) approach (Guerra-Cujar et al., 2023; Callaway and Sant'Anna, 2021). Specifically, I estimate the following equation:

$$Externalviolence_{i,t} = \beta T_{i,t} + \gamma X_{i,t} + \alpha_i + \varepsilon_t + u_{i,t}, \tag{8}$$

where $T_{i,t}$ is a dummy variable that takes the value one if province i has been treated at time t. The baseline definition of treatment is a dummy variable set to one from the first year an asset was confiscated in province i, and zero otherwise. Additionally, I employ a different set of continuous treatments in a standard Difference-in-Differences (DID) framework, supplemented by robustness checks and falsification tests that will be detailed in the next sections. Specifically, I explore the interaction betwee a dummy (*post 1982*) taking the value one from 1982 onward (i.e., since the introduction of the Rognoni-La Torre law) and two alternative sources of cross-sectional variation. The first is a dummy variable for provinces in the top tertile for mafia-related murders of innocents between 1950 and 1975, according to Libera and Wiki-Mafia's databases (Libera; Wikimafia). This strategy assumes that only powerful criminal organizations engage in high-profile murders, which generally attract unwanted attention and are less efficient than the "secrecy of bribery" (Trejo and Ley, 2021). The second is a measure of port access, discussed further in subsequent paragraphs (equation (9)), which indicates a province's access to the illicit cash flows from the drug trade with the US. Specifically, as a third approach to address endogeneity concerns, I exploit an exogenous trade shock (Dal Bó and Dal Bó, 2011; Autor et al., 2020) in the drug market to instrument confiscations. Unlike the first approach based on lagged values of seizures, the instrumental variable (IV) allows to tackle the omitted variable bias and the measurement error bias inherent in the uncertain time lag between seizures and confiscations. In particular, I construct a measure of drug profit by interacting an indirect proxy for drug demand, which is the number of deaths from overdose in the United States (NCHS) with a municipal index (which I also aggregate at the provincial level) of access to ports, as drug traffics mostly occurs by sea (UNODC, 2011). Notably, the US drug market was heavily supplied, among the others, by mobsters belonging to Cosa Nostra, 'Ndrangheta, Camorra and

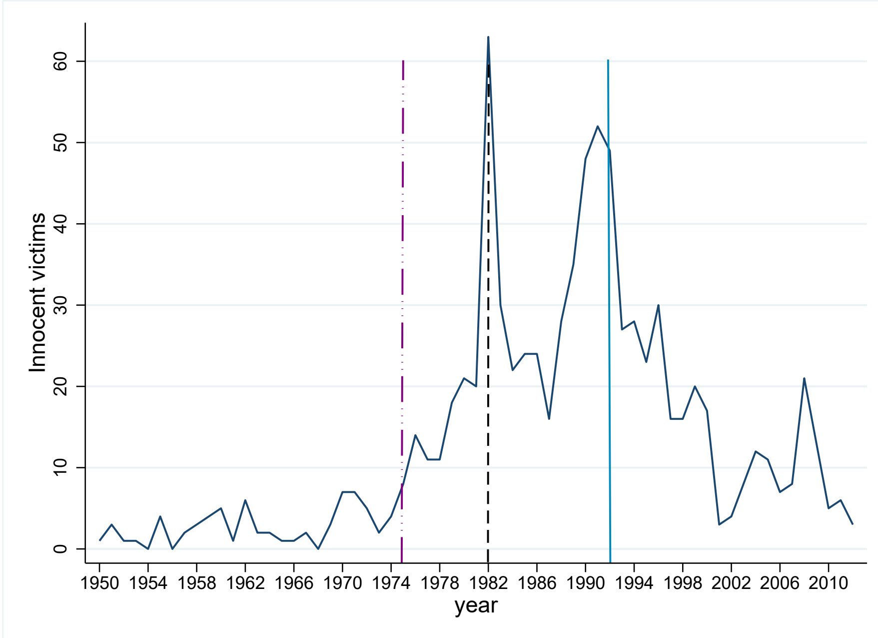


Figure 5: Time series of innocent victims.

Notes: The dash-dotted line denotes the onset of the heroin market boom. The dotted line denotes the introduction of asset confiscation, whereas the solid line denotes the introduction of harsh imprisonment regime.

Sacra Corona Unita (DIA), especially in the Seventies and Eighties when Cosa Nostra alone supplied one third of the US heroin market (Falcone and Padovani, 1991).

Two simultaneous events played a crucial role in the immediate surge in drug profits for Italian mafias. First, the crackdown of the Marseillaise mafia carried on by the French and US police forces allowed Italy, and in particular Sicily, to emerge as the preferred location for refining heroin (Blakey, 1982). Second, the consumption of drugs boosted starting from the Seventies, initially in the US and then in the rest of the advanced economies (Blakey, 1982).

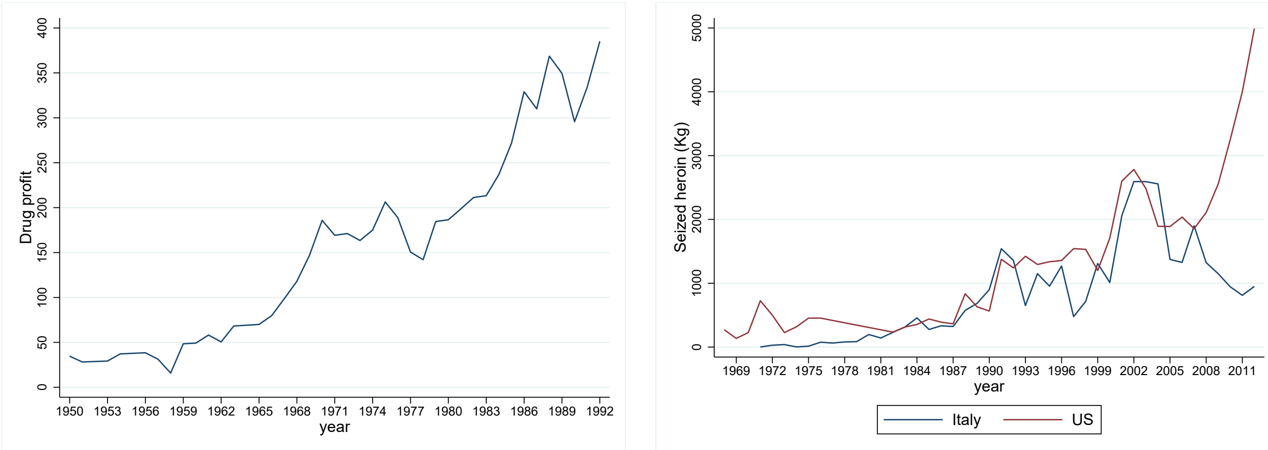
Denoting by B_j the berths of all port(s) in municipality j and by d_{ij} the distance between the 26 (25 + the $i-th$ municipality itself) closest municipalities (i) and j I define ports access as follows:

$$Ports_i = \sum_{j=1}^{n_i} \frac{B_j}{d_{ij}+1} \tag{9}$$

My IV (*profit*) is the product between deaths for overdose and ports access (Figure 6, panel a):

$$profit_{i,t} = Ports_i * Overdose_t \tag{10}$$

The credibility of my results is further supported in Section 5.3, where I demonstrate that the relationship between US drug profits and confiscations significantly varies over time. Specifically, a strong correlation between these two variables is evident up to the early Nineties, particularly



(a) Drug profit in Southern Italy

(b) Heroin seizures (Kg).

Figure 6: Time series of drug profit in Sicily, Calabria, Campania and Apulia, 1950-1992 and heroin seizures in Italy and US.

Notes: Data on heroin seizures from 1990 to 2012 come from the Annual Drug Seizures database (UNODC). Data on prior years are sourced by the Ministry of interior (Ministero dell'Interno, 2007) for Italy and by (Staats, 1977) and (McPhail, 1992) for US.

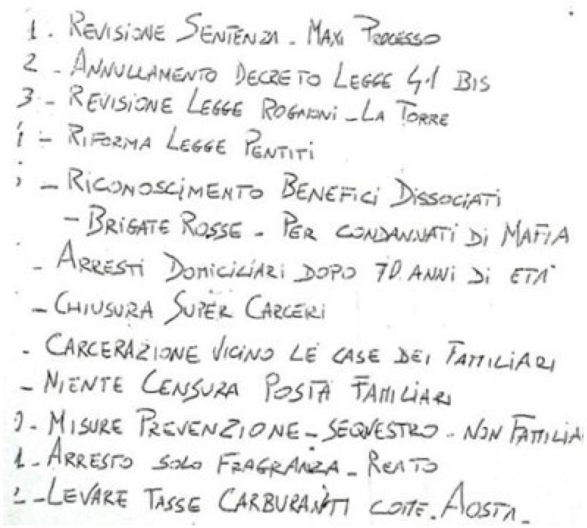
from 1972 to 1992. However, this relationship disappears from 1993 onward. Remarkably, the Italian-American operations 'Pizza Connection' and 'Iron Tower' in the late Eighties significantly diminished Sicily's role in the international drug trade. By the early Nineties, these operations had reduced Cosa Nostra's share of the US heroin market from 30% to just 5%, with the remaining 95% taken over by Chinese, Kurdish, and Puerto Rican syndicates (Falcone and Padovani, 1991). Notably, as shown in Figure 6 (panel b), heroin seizures in Italy and the US exhibited a common trend and magnitude up to 1992, but thereafter began to follow divergent paths and levels.

Further tests are reported in Appendix B, where I utilize the number of overdose deaths on the East Coast instead of the entire US, given that heroin from Sicily primarily crossed the Atlantic Ocean. Additionally, in Appendix B, I further corroborate these results by employing the synthetic control method (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Pinotti, 2015; Mirenda et al., 2022). Finally, in Section 5.3, I present a placebo test (Van Kippersluis and Rietveld, 2018) supporting the hypothesis that variations in drug profits (instrument) affect high-profile murders (outcome) solely through confiscation (endogenous variable).

4.1.1 Exclusion restriction: discussion

Notably, it is exceedingly difficult, if not impossible, to completely isolate all factors other than confiscation that may influence high-profile murders. However, in the following discussion, I outline the main concerns regarding my identification strategy and explain why they should not undermine the validity of the analysis. Neglecting the electoral violence argument discussed and mostly rejected in section 2, the first concern is the potential influence of proximity to ports on economic development (Ferrari et al., 2012; Bakker et al., 2021) which, in turn, could affect the degree of mafia penetration even within regions and provinces already under significant criminal control. As mentioned in the previous section, I address this issue by including a comprehensive set of socio-demographic and economic controls. Additionally, the DID results strongly suggest that the spike in high-profile murders predominantly occurred in provinces already dominated by mafias prior to the heroin market boom. The concern represented by economic development and other omitted factors linked to network infrastructures is further mitigated in Appendix B, where I show that the instrument becomes unambiguously weak when substituting the inverse distance to ports described by equation (9) with the inverse distance to the 14 major Italian cities (the so-called *Aree metropolitane*). I label the interaction between access to the major cities and deaths for overdose in the US *Fake profit*. The second concern pertains to the possibility that booms in illegal profits may affect high-profile violence through channels other than confiscation. While my IV is not suited for the test of H2 given the direct link between profit booms and mafia wars (Sobrino, 2019; Castillo and Kronick, 2020), it is more challenging to argue that this holds true for conflicts with the state. In "normal circumstances", organized crime prefers collusive secret agreements with political powers rather than drawing unwanted attention through high-profile criminal violence (Trejo and Ley, 2021). Engaging in attacks against institutions may gather public attention and enhance government repression, which seems completely counter-productive in presence of a colluded state not threatening organized crime. In other words, attacking a colluded state seems counter-productive i.e., the most plausible way in which variations in profits may affect variations in high-profile murders is through changes in state repression (Lessing, 2015). This claim is supported (Figure 7) by the infamous *papello* (Corriere della Sera, 2009), a list of requests written by the "boss of bosses" *Totò Riina* to the Italian state in 1992-1993 in exchange of the end of the mass murders perpetrated by Sicilian mafia[21]. Except for the last request, the *papello* offers compelling evidence that the state's response to mafia is the primary, if not the sole, determinant of high-profile murders. Conditions 5-11 required more lenient convictions that would allow mobsters to maintain communication with the outside world and continue issuing orders. Importantly, this was the norm before the introduction of the harsh imprisonment regime (article 41 bis) in late 1992, whose abrogation is indeed the second request. However, the harsh imprisonment regime could not have caused the wave of lethal attacks against the state that occurred between 1977 and 1993 because it was introduced only in late 1992. Hence, requests 5-11 were not crucial in initiating the war against the state, as they were already fulfilled before 1993. The same conclusion holds for requests 1 and 4, as they refer to events occurred in 1992 and 1991, respectively. The same applies to

[21]The mightiest and most violent criminal organization at the time.



1. Revisione Sentenza - Maxi Processo
2 - Annullamento Decreto Legge 41 Bis
3 - Revisione Legge Rognoni - La Torre
4 - Riforma Legge Pentiti
5 - Riconoscimento Benefici Dissociati
- Brigate Rosse - Per condannati di Mafia
- Arresti Domiciliari dopo 70 anni di età
- Chiusura Super Carceri
- Carcerazione vicino le case dei familiari
- Niente censura posta familiari
0 - Misure prevenzione - sequestro - non familia
1 - Arresto solo fragranza - reato
2 - Levare tasse carburanti come Aosta

(a) Hand-written in Italian.

1. Maxi Trial sentence revision
2. Art. 41 bis abrogation
3. **Rognoni-La Torre Law revision**
4. Whistle blowers Law reform
5. Benefits recognition for mafia dissociated
6. House detention for over 70s
7. Elimination of super prison
8. Conviction to jail close to relatives
9. No censored mails to relatives
10. No precautionary seizure for relatives
11. Arrest only in *flagrante delicto*
12. Gasoline fees removal

(b) English translation.

Figure 7: Riina's *papello*.

the law introducing the crime of criminal organization aimed at drug trafficking, which was enacted in late 1990 and is not even mentioned in the *papello*. In contrast, the Rognoni-La Torre law (request 3) was under discussion since the late 1970s and was introduced in 1982 with threefold implications: (i) recognizing mafia as a crime (article 416 bis); (ii) eliminating bank secrecy; and (iii) authorizing the systematic use of confiscation as an additional penalty for mafia-related crimes.

Implication (i) alone has unlikely caused the escalation in violence. As previously mentioned, convicted mobsters were not isolated from the rest of the prison population and could communicate with the outside world. Essentially, their conditions in prison were similar to previous years when they were convicted for homicides or other crimes without the recognition of being affiliated with a criminal organization. As Italian anti-mafia prosecutor Nino Di Matteo stated (Di Matteo, 2023): *"Mobsters do not fear the jail, they do fear 41 bis"*.

Implication (ii) was more an instrument than an objective. The removal of bank secrecy allows prosecutors to trace illegal money flows stemming from criminal activities. However, without the possibility of attacking the wealth of the organization through judicial investigations, this is fruitless, as mobsters had always accounted for the possibility of being convicted for minor crimes before the Rognoni-La Torre law. In the words of Italian prosecutor Nicola Gratteri (Gratteri, 2022): *"Mobsters are exemplary detainees: they are the ones who leave the jail first"*.

Hence, I argue that implication (iii) is the key novelty that triggered the decision to directly attack the state. The extensive use of confiscation severely damages the wealth of a criminal organization, unlike article 416 bis and the elimination of bank secrecy which are primarily instruments that enable the systematic implementation of asset confiscation, that, in turn, is likely the ultimate trigger for the war against the state.

Other drivers of high-profile murders not related to anti-mafia policy are discussed (for the Mexican case) in Trejo and Ley (2021): (i) clans may attack local authorities in search of protection or rents or (ii) to conquer local governments, populations and territories, exploiting political polarization to attack subnational authorities who are unprotected by their federal partisan rivals.

Although they cannot be excluded *a priori*, motivations (i) (which lead to a severe underestimation of high-profile violence according to the same authors) and (ii) are somewhat unsuited to explain the Italian case until 1992, characterized by a stable (national and local) leadership of the Christian Democracy which has continuously provided economic concessions (De Feo and De Luca, 2017) and protection (Catanzaro, 1992; Lodato, 2012) to clans.

4.1.2 External validity: The Colombian and Mexican case

On the one hand, the opaque decision-making processes within criminal organizations necessitate an exogenous shock that is very localized in order to credibly suggest a causal relationship between confiscations and high-profile murders. On the other hand, the discussion of the exclusion restriction hypothesis in Section 4.1.1 relies heavily on the specific context of Italy, which may raise concerns about the external validity of the results presented in subsequent sections. Accordingly, while the main text focuses on a specific period of Italian history—from the seventies to the nineties—to isolate the effect of confiscations (exploiting the fact that other anti-mafia policies were implemented no earlier than the Nineties), Appendix C adapts the proposed identification strategy to the Mexican context. Specifically, I demonstrate a positive relationship between asset forfeiture and high-profile murders outside Italy. The positive correlations observed in OLS estimations are corroborated by employing the staggered DID approach as well as instrumenting confiscations with an estimate of drug profits[22].

Unlike the Italian case, the IV used in the Mexican context leverages the (inverse) distance from the US (Dell, 2015) instead of access to ports. Although the specific features of the Mexican case preclude establishing a definitive causal link, Appendix C presents a wealth of correlations supporting the hypothesis that the state's economic responses to crime may have unintended violent consequences. This evidence is complemented by observations of spikes in violence following the enactment of three asset forfeiture laws in Colombia (1980, 1986, 1997) and during the initial period (1999-2005) of "Plan Colombia", which included the aerial spraying of illegal crop fields to hamper cocaine production (Abadie et al., 2014).

[22]Notably, Mexican drug cartels gradually took the lead over Colombian ones in the 1990s and early 2000s as the primary suppliers of the US drug market (Trejo and Ley, 2021).

4.2 H2: confiscation decrease internal violence

As dependent variable, I adopt two different measures of internal violence.
the count of innocent victims from the total number of voluntary murders, as reported in ISTAT's judicial statistics (ISTAT, 1953, 1974, b). By definition, this variable encompasses the sum of: (i) victims of terrorism, (ii) murders related to theft, (iii) passion crimes, (iv) residual homicides with motives unrelated to criminal organizations, and (v) victims of conflicts among mobsters within mafia wars.
To compute the rates of low-profile murders per 100,000 inhabitants (*LP-murders rate*), I aggregate municipal data on innocent victims across 22 provinces. This aggregation involves incorporating Vibo Valentia and Crotone into the larger province of Catanzaro and dividing the province of Barletta-Andria-Trani between Bari and Foggia, aligning with the historical administrative boundaries used by ISTAT to compute total murders prior to 2004[23].
Notably, there is a non-negligible amount of noise in this variable, necessitating the assumption that voluntary murders unrelated to the mafia are not influenced by our variable of interest (Alesina et al., 2019). To address this concern, I also employ a refined measure of internal violence. Specifically, I calculate the number[24] of mobsters killed by other mobsters (*Mafia war*) by subtracting the number of innocent victims from the total number of mafia-related murders, according to data published by the Ministry of Interior (Ministero dell'Interno).
Overall, the empirical strategy to test H2 is the following:

$$Internal\ violence_{i,t} = \beta\ confiscation_{i,t} + \gamma X_{i,t} + \alpha_i + \varepsilon_t + u_{i,t}, \tag{11}$$

The coefficient β captures the impact of confiscation on internal violence. The OLS results are further corroborated by the Synthetic Control Method (Appendix B).

5 Empirical results

5.1 H1: confiscation increases external violence

5.1.1 OLS results

The OLS estimations of equation (7) are presented in Table 2. In column 1, I regress high-profile murders on confiscations (for the period 1950-1992) with time and province fixed effects only. Column 2 follows the approach of Alesina et al (2019) by controlling for the log of pop-

[23]In Appendix B, I demonstrate that using the old administrative boundaries does not alter the results concerning external violence.

[24]Unlike low-profile murders, this measure is better suited to being treated as a count variable, although I will also demonstrate its robustness when expressed as a rate per 100,000 inhabitants.

y=	HP murders				Innocent victims			
	Absolute number			Dummy	Absolute number			Dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confiscation	.017**	.016**	.015**	.152*	.050*	.050**	.046*	.102
	(.007)	(.006)	(.007)	(.082)	(.026)	(.023)	(.026)	(.074)
GDP and Pop controls		✓	✓	✓		✓	✓	✓
Other controls			✓	✓			✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075	1075	1075
R-squared	.15	.15	.17	.18	.29	.29	.32	.34
Provinces	25	25	25	25	25	25	25	25

Table 2: The impact of confiscation on high-profile murders and innoccent victims-OLS results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

ulation and using a proxy for GDP per capita. As provincial-level GDP data is unavailable, I utilize the rate of young male unemployment, which also provides information on social factors beyond production levels. Expanding on Alesina et al (2019), column 3 includes additional socio-demographic and economic controls (illiteracy rate, tertiary education rate, fraction of population under 25, share of labor force employed in the construction sector) which may affect mafia activity (De Feo and De Luca, 2017).

Across all columns, the coefficient of interest, which captures the impact of confiscations on high-profile murders, is positive and statistically significant. The magnitude of the impact, consistently observed across all specifications, is far from negligible: every 60-65 confiscated assets are associated with an additional high-profile murder. As around 20,000 assets have been confiscated and destined, this translates into an estimated total of over 300 high-profile murders.

To address zero inflation, column 4 replicates the analysis of column 3 by replacing the dependent and explanatory variables with dummies taking value one in presence of positive values of high-profile murders and confiscations, respectively.

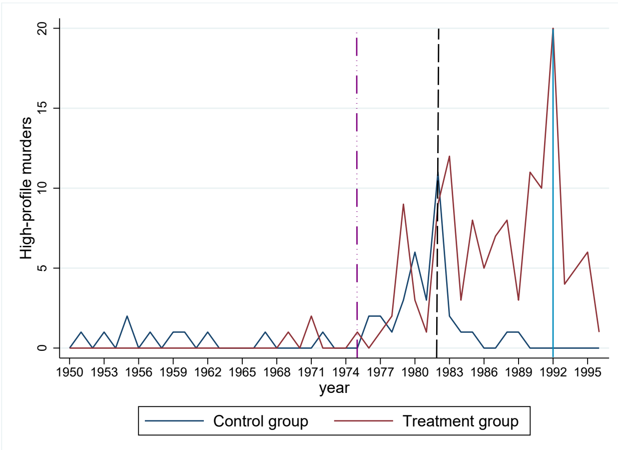
In the last four columns, I replace high-profile murders with innocent victims (public officers + civilians) as the dependent variable. While high-profile murders remain the primary variable of interest due to its lower likelihood of violating the exclusion restriction hypothesis in the instrumental variable (IV) analysis detailed later, incorporating innocent victims captures a broader spectrum of external violence. All columns, except the last — which is marginally insignificant with a p-value of 0.182 — show statistically significant coefficients. The diminished statistical significance of the final set of regressions, which will be addressed by DID and IV strategies, aligns with the hypothesis that OLS endogeneity issues are exacerbated when using a less direct indicator of external violence. For example, the number of civilians killed by organized crime may be more affected by omitted variable bias, including cases such as entrepreneurs murdered for refusing to pay extortion fees.

Additional robustness checks are presented in Appendix B, where I employ alternative measures of the explanatory (value of confiscations and confiscations spanning over the last years) and dependent variables (rates per 100,000 inhabitants, respectively) and also estimate non-linear (Poisson) models (Chen and Roth, 2023). To address the low number of clusters (25 provinces), in Appendix B I use bootstrap standard errors and I also expand the panel to all Italian provinces. Finally, in subsections 5.1.2 and 5.1.3, I address endogeneity concerns by conducting a series of DID estimations and by instrumenting confiscations using drug profits, respectively.

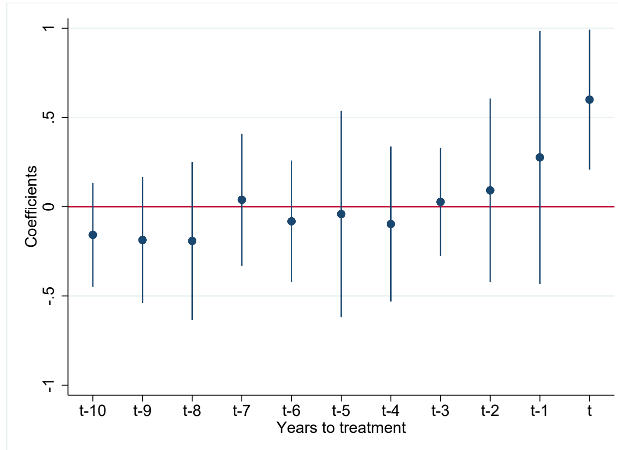
5.1.2 Staggered DID results

In this section I exploit the staggered implementation of confiscations within Italian provinces. Specifically, although the national law that introduced asset confiscation dates back to 1982, Figures 1 (nale b) and 4 (panel c) show that the actual implementation of confiscations is substantially heterogeneous across time and space, with some provinces (such as Palermo and Naples) which have been treated several years before others (such as the Apulian provinces). My explanatory variable is a dummy ($First\ treatement_{it}$) taking value 1 from the first year a confiscation occurred in province i. The control group is represented by the not yet treated units (Guerra-Cujar et al., 2023; Callaway and Sant'Anna, 2021).Concerns may arise due to the early spike in violence in 1979 (Figure 1, panel a), coinciding with the first proposal of the Rognoni-La Torre Law to the Italian Parliament. To satisfy the parallel trends assumption, this spike should represent a temporal shock affecting all provinces uniformly, whereas the actual implementation of mass confiscations starting in 1982 should have caused differentiated effects on high-profile murders, depending on whether a province was treated or not. This issue is addressed in Figure 8. First, panel a) demonstrates that the control and treated groups exhibited parallel trends in high-profile murders up to the introduction of the Rognoni-La Torre Law, immediately diverging thereafter in both level and trend, and then converging again following the introduction of the harsh imprisonment regime in 1992. Second, I estimate a dynamic version of the main specification (Roth et al., 2023; Guerra-Cujar et al., 2023) by interacting $first_treatment$ with ten year dummies corresponding to the ten years before the treatment, and regressing high-profile murders on these interactions with the inclusion of time and province fixed effects. As shown in panel b), the coefficient for $first_treatment$ is positive and statistically significant; however, none of the interactions with the lead year dummies show statistical significance.

The estimations of equation (8) are shown in Table 3 (the analysis is replicated at the municipal level in Appendix C), where I replicate the analysis of Table 2. All coefficients are positive



(a) Parallel trends in high-profile murders.



(b) Dynamic difference in differences.

Figure 8: Parallel trends and dynamic difference in differences in high-profile murders.

Notes: The dash-dotted line denotes the onset of the heroin market boom. The dotted line denotes the introduction of asset confiscation, whereas the solid line denotes the introduction of harsh imprisonment regime.

y=	HP murders				Innocent victims			
	Absolute Value			Dummy	Absolute Value			Dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First treatment	.492**	.463**	.347**	.158**	1.09***	1.04**	.657**	.218***
	(.210)	(.196)	(.150)	(.061)	(.368)	(.409)	(.262)	(.063)
GDP and Pop controls		✓	✓	✓		✓	✓	✓
Other controls			✓	✓			✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075	1075	1075
R-squared	.13	.13	.14	.18	.23	.23	.27	.35
Provinces	25	25	25	25	25	25	25	25

Table 3: The impact of the staggered introduction of confiscations on high-profile murders and innocent victims-OLS (DID) results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

and statistically significant, substantiating the hypothesis that asset confiscation has triggered mafia's violent retaliation against both public officers and civilians.

Table 4 conducts a series of robustness checks and falsification exercises, with all regressions including the full set of controls. In column 1, I replace *First treatment* with an interaction between a dummy variable (*Post 1982*)—which takes the value 1 from 1982 onward, coinciding with the introduction of the Rognoni-La Torre law—and port access (see equation (9)). This continuous treatment addresses concerns about reverse causality that might affect confiscations. In column 2, I create an interaction between *Post 1982* and a new dummy variable, *Murders pre-heroin*, assigned a value of one for provinces with the highest number of murders outside the criminal organization from 1950 to 1975 i.e., before the heroin market boom. IDuring this period, 12 out of 25 provinces recorded no innocent victims, with another 5 provinces reporting only one each. For these provinces, *Murders pre-heroin* is set to zero, while t is set to one for the remaining 32% of the provinces. Both regressions display positive and statistically significant coefficients. However, there remains a concern that the increase in high-profile murders could be directly influenced by the mid-Seventies heroin boom rather than solely by the enactment of the Rognoni-La Torre law in 1982. Columns 3 and 4 conduct falsification exercises to address this concern. In particular, I substitute *Post 1982* with a dummy (*Years 1975-81*), which takes the value one from 1975 to 1981—during the heroin boom but before the asset forfeiture law—and zero otherwise. These regressions do not yield statistically significant coefficients, supporting the hypothesis that the heroin market boom, in the absence of confiscations, did not incite an increase in lethal attacks against public officers. The analysis is replicated in the last four columns using innocent victims as the dependent variable, yielding similar results.

5.1.3 IV results

Table 5 reproduces the analysis from Table 2 using the IV approach. All coefficients are positive and highly significant, substantiating the OLS results: between 1950 and 1992, confiscations have contributed to the escalation of high-profile murders in Southern Italy. The Kleibergen-Paap F-statistics suggests that the instrument is not weak.

Notably, the higher magnitude of the IV results appears to support the notion that the OLS estimation was affected by endogeneity concerns. The OLS downward bias aligns with the theoretical prediction that increases in violence triggered by asset confiscation would eventually reduce it.

5.1.4 Robustness checks

In this section, I conduct one set of robustness checks and two falsification exercises.

The robustness check (Table 6) refines the instrumental variable strategy by restricting the

y=	HP murders				Innocent victims			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ports × post 1982	114*				.263**			
	(.062)				(.121)			
Murders pre-heroin × post 1982		.730**				1.856**		
		(.313)				(.807)		
Ports × Years 1975-81			0.000				.000	
			(.000)				(.000)	
Murders pre-heroin × Years 1975-81				.102				.119
				(.118)				(.193)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075	1075	1075
R-squared	.17	.18	.13	.13	.29	.32	.26	.26
Provinces	25	25	25	25	25	25	25	25

Table 4: The impact of the introduction of the Rognoni-La Torre law on high-profile murders and innocent victims for provinces with better access to ports and/or higher mafia penetration-OLS (DID) results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable Ports is divided by 1000.

y=	HP murders				Innocent victims			
	Absolute number			Dummy	Absolute number			Dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confiscation	0.056***	0.053***	0.051***	1.765***	.149***	.152***	.144***	.789***
	(0.020)	(0.019)	(0.018)	(0.542)	(.056)	(.055)	(.051)	(.070)
GDP and Pop controls		✓	✓	✓		✓	✓	✓
Other controls			✓	✓			✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075	1075	1075
R-squared	-.22	-.17	-.14	-.15	-.30	-.32	-.23	-.19
Provinces	25	25	25	25	25	25	25	25
Kleibergen-Paap F statistics	45.44	44.80	54.99	24.12	45.44	44.80	54.99	24.12

Table 5: The impact of confiscation on high-profile murders and innoccent victims-IV results.
Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

analysis to the period between 1972 and 1992 (ten years before and after the introduction of the Rognoni-La Torre law), i.e. dropping the observations before the heroin boom, where both drug profits and confiscations were low and displayed little variability. In column 1, I control for young male unemployment and population, whereas the full set of controls is included in column 2. The Kleibergen-Paap statistics shows a remarkable increase, outperforming the results in columns 3-4, where I reexamine the years 1950-92 by interacting drug profits with and a dummy taking value one from 1972 onwards. The same pattern is observed when considering innocent victims as dependent variable, as shown in columns 5-8.

Then, I present a falsification exercise (Table 7) which serves as a placebo test to assess the validity of the exclusion restriction assumption, thereby enhancing the robustness of the identification strategy. Following van Kippersluis and Rietveld (2018), I regress the outcome variable (high-profile murders) on the instrument (drug profit) and the full set of controls for sub-samples characterized by stable levels of confiscation. Specifically, I divide the sample into two subsets: observations with no confiscation (column 1) and observations with positive confiscation (column 2). As additional check, in columns 3-4 I replicate the analysis on two different sub-samples, namely those with 0 and positive confiscations between time t and t+1. This second approach accounts for the lag between seizures and confiscations[25]. All coefficients are insignificant, suggesting that drug profits have likely influenced high-profile murders only through variations in confiscations. This is especially true in columns 1 and 3, where confiscations are invariant and equal to zero (the most common value in the data). Note that the reduced form presented in column 5 shows that (when confiscation is not kept fixed) there is indeed a positive correlation between drug profits and high-profile murders.

The last falsification exercise shows that the relation between US drug profits and confiscations in Southern Italy ceased from the 1990s onward. As detailed in Section 4.1, operations "Pizza Connection" and "Iron Tower" precipitated a steep decline in the share of the US heroin market controlled by Cosa Nostra—from 30% in the late Eighties to just 5% by the early Nineties (Falcone and Padovani, 1991). This shift is supported by the findings in Table 8, where I replicate the IV regressions from Table 5 using the sub-sample covering the years between 1993 and 2012. Since my object of interest here is the (absence of) correlation between drug profit from the US and confiscations after 1993, I only show the first stage results and the Kleibergen-Paap F statistics, which is indeed almost zero in all specifications. This suggests the absence of correlation between drug profit and confiscations following the significant curtailment of Cosa Nostra's influence area in the US.

[25]In Appendix B I instead show that variations in confiscations caused by variations in profit strongly affect high-profile murders.

y=	High profile murders				Innocent victims			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confiscation	.014***	.020***	.061***	.059***	.064**	.081***	.166***	.160***
	(.005)	(.005)	(.021)	(.020)	(.026)	(.032)	(.058)	(.055)
GDP and Pop controls	✓	✓	✓	✓	✓	✓	✓	✓
Other controls		✓		✓		✓		✓
Period	1971-92	1971-92	1950-92	1950-92	1971-92	1971-92	1950-92	1950-92
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	525	525	1075	1075	525	525	1075	1075
R-squared	.01	-.01	-.28	-.25	-.01	-.07	-.44	-.36
Provinces	25	25	25	25	25	25	25	25
Kleibergen-Paap F statistics	84.59	62.48	38.78	48.09	84.59	62.48	38.78	48.09

Table 6: The impact of confiscation on high-profile murders and innocent victims: 1972-1992-IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

y=HP murders	(1)	(2)	(3)	(4)	(5)
(6)					
Profit	.010	.096	.004	.040	.015**
	(.009)	(.091)	(.003)	(.055)	(.007)
Confiscation	$= 0$	> 0			
Confiscation^T			$= 0$	> 0	
Full set of controls	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓
Observations	985	90	941	134	1075
R-squared	.11	.41	.10	.42	.15
Provinces	25	24	25	24	25

Table 7: Placebo test and reduced form. The impact of drug profit on high-profile murders.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. Confiscation^T denotes the number of asset confiscated at time t and $t + 1$. The variable profit is divided by 10^6.

y=Confiscation	Number of asset			Dummy
	(1)	(2)	(3)	(4)
Profit	-.039	-.040	-.020	-.0003
	(.050)	(.049)	(.033)	(.0004)
GDP and Pop controls		✓	✓	✓
Other controls			✓	✓
Period	1950-92	1950-92	1950-92	1950-92
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	500	500	500	500
R-squared	.05	.13	.14	.10
Provinces	25	25	25	25
Kleibergen-Paap F statistics	.59	.67	.40	.47

Table 8: Falsification exercise. The impact of confiscation on high-profile murders, 1993-2012-IV first stage results

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^6.

Y=	LP murders	Mafia war		
	Rate	Rate	Absolute number	
	(1)	(2)	(3)	(4)
Confiscation	-.008**	-.004*	-.032**	-.232**
	(.006)	(.002)	(.012)	(.111)
Time period	1950-2012	1983-2012	1983-2012	1983-1992
Full set of controls	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1386	676	676	236
R-squared	.46	.33	.25	.29
Provinces	22	22	22	22

Table 9: Impact of confiscation on low-profile murders and mafia wars-OLS results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

5.2 H2: confiscation decreases internal violence

The OLS estimations of equation (11) are presented in Table 9. In all specifications, I employ the full set of controls. The statistically significant coefficients reported in columns 1 and 2 indicate a negative correlation between confiscation and the rate of low-profile murders (in column 1) and mafia war victims (in column 2) over the periods 1950–2012 and 1983–2012, respectively. Column 3 analyzes the count of mafia war victims rather than the rate per 100,000 inhabitants, yielding similar results. Finally, to disentangle the effect of confiscations from that of law enforcement, column 4 replicates the regressions of column 3, excluding the years after 1992. Despite limitations due to data availability, Table 9 provides evidence of a negative effect of confiscations on internal violence, a finding further supported by the synthetic control method used in Appendix B. Notably, the estimations presented in Table 9 serve also as a falsification exercise in favour of the hypothesis that confiscation is not positively associated with any type of murders except for high-profile ones, and possibly murders of civilians.

Conclusions

In this paper, I study the impact of confiscation on mafia-related violence. Employing a sequential game framework, I show that illegal profit booms play a crucial role in prompting a state to employ economic repression and counter organized crime. Asset confiscation acts as a pacifying force within criminal clans but increases retaliatory actions against members of institutions. However, this incentive can be offset by a harsh military crackdown. The level of popular support for the state and the quality of its institutions are crucial factors in effectively deterring violence while still implementing confiscation measures. Building upon the model's predictions, I document the impact of confiscations on high-profile murders in Southern Italy. The findings suggest that the relationship between the Italian state and organized crime post-World War II can be divided into three distinct periods: (i) the economic success/full impunity epoch (1950-1975). The dominant trait of this epoch is Alesina et al.'s (2019) violence-election cycle at very low violence levels, where no confiscations threatened mafia's steady economic advantage allowing it to penetrate dramatically into economic activity (De Feo and De Luca, 2017); (ii) the 1980-1993 mafia war against the Italian state in Sicily. This mafia war was triggered, after the take-off of heroin profits, by the first threat of a serious economic attack to mafia assets (fiercely sustained by Pio La Torre) and the subsequent first wave of large-scale confiscations in parallel with the sudden rupture of the full impunity postulate. The threat of an economic response broke the enduring peace of economic advantages ensured by Christian Democracy; (iii) the dramatic fall of violence after the State response in 1993. These findings suggest that electoral homicides are only a minor component of organized crime external violence, especially that directed against the members of institutions. Notably, these three epochs characterized, albeit with lower intensity compared to other Italian regions plagued by the massive presence of different criminal organizations, namely Camorra, 'Ndrangheta and Sacra Corona Unita. The magnitude of the impact is substantial, as Apulia, Calabria, Campania, and Sicily account for approximately 75% of total confiscations, involving around 15,000 assets. In the absence of a serious military response, my instrumental variable estimations suggest that nearly 700 high-profile murders would have occurred in the past five decades.

The evolving dynamics between the Italian state and organized crime, once confined to poorer regions characterized by weak institutuions, now demand greater scrutiny as these criminal entities extend their reach into the strong institutional frameworks of the world's richest economies (Savona et al., 2015; Dipoppa, 2022).

References

A. Abadie and J. Gardeazabal. The economic costs of conflict: A case study of the Basque Country. *American economic review*, 93(1):113–132, 2003.

A. Abadie, A. Diamond, and J. Hainmueller. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American statistical Association*, 105(490):493–505, 2010.

A. Abadie, M. C. Acevedo, M. Kugler, and J. Vargas. *Inside the war on drugs: Effectiveness and unintended consequences of a large illicit crops eradication program in Colombia*. Cambridge, MA: Harvard University. Unpublished Manuscript, 2014.

D. Acemoglu, J. A. Robinson, and R. J. Santos. The monopoly of violence: Evidence from Colombia. *Journal of the European Economic Association*, 11(S1):5–44, 2013.

D. Acemoglu, G. De Feo, and G. D. De Luca. Weak states: Causes and consequences of the Sicilian Mafia. *The Review of Economic Studies*, 87(2):537–581, 2020.

A. Alesina, S. Piccolo, and P. Pinotti. Organized crime, violence, and politics. *The Review of Economic Studies*, 86(2):457–499, 2019.

ANBSC. Agenzia Nazionale per l'amministrazione e la destinazione dei beni sequestrati e confiscati alla criminalità organizzata.

Archivio Antimafia.

L. H. Atuesta and A. F. Ponce. Meet the narco: Increased competition among criminal organisations and the explosion of violence in Mexico. *Global Crime*, 18(4):375–402, 2017.

D. Autor, D. Dorn, G. Hanson, and K. Majlesi. Importing political polarization? The electoral consequences of rising trade exposure. *American Economic Review*, 110(10):3139–3183, 2020.

J. D. Bakker, S. Maurer, J.-S. Pischke, and F. Rauch. Of mice and merchants: Connectedness and the location of economic activity in the Iron Age. *Review of Economics and Statistics*, 103(4):652–665, 2021.

G. Barone and G. Narciso. Organized crime and business subsidies: Where does the money go? *Journal of Urban Economics*, 86:98–110, 2015.

R. Bayer and F. Cowell. Tax compliance and firms' strategic interdependence. *Journal of Public Economics*, 93(11-12):1131–1143, 2009.

G. S. Becker, K. M. Murphy, and M. Grossman. The market for illegal goods: The case of drugs. *Journal of Political Economy*, 114(1):38–60, 2006.

M. Besfamille, P. De Donder, J.-M. Lozachmeur, et al. Tax enforcement may decrease government revenue. *Economics Bulletin*, 29(4):2665–2672, 2009.

T. Besley, T. Fetzer, and H. Mueller. The welfare cost of lawlessness: Evidence from Somali piracy. *Journal of the European Economic Association*, 13(2):203–239, 2015.

G. Blakey. Organized crime in the United states: A review of the public record, 1982.

L. Bodrero. Italian trial looks at mafia-state pact, 2013.

G. E. Box and D. R. Cox. An analysis of transformations. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 26(2):211–243, 1964.

P. Buonanno, G. Prarolo, and P. Vanin. Organized crime and electoral outcomes. Evidence from Sicily at the turn of the XXI century. *European Journal of Political Economy*, 41: 61–74, 2016.

G. Calderón, G. Robles, A. Díaz-Cayeros, and B. Magaloni. The beheading of criminal organizations and the dynamics of violence in Mexico. *Journal of Conflict Resolution*, 59(8): 1455–1485, 2015.

B. Callaway and P. H. Sant'Anna. Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2):200–230, 2021.

J. C. Castillo and D. Kronick. The logic of violence in drug war. *American Political Science Review*, 114(3):874–887, 2020.

J. C. Castillo, D. Mejía, and P. Restrepo. Scarcity without leviathan: The violent effects of cocaine supply shortages in the mexican drug war. *Review of Economics and Statistics*, 102 (2):269–286, 2020.

R. Catanzaro. Il delitto come impresa. Storia sociale della mafia. 1992.

M. Catino. How Do Mafias Organize?: Conflict and Violence in Three Mafia Organizations. *European Journal of Sociology/Archives Européennes de Sociologie*, 55(2):177–220, 2014.

J. Chen and J. Roth. Logs with zeros? some problems and solutions. *Quarterly Journal of Economics*, 2023. doi: 10.48550/arXiv.2212.06080. Forthcoming.

D. Cheng. The potential of asset forfeiture for countering extortion in Central America. 2021.

CIA. Combating communism in Italy, 1953-1956.

N. Colajanni. *Nel Regno della Mafia, dai Borboni ai Sabaudi*. Rivista Popolare, Roma, 1900.

Corriere della Sera, 2009. corriere.it/cronache/cards/strage-capaci-papello-caso-moricosa-sa-trattativa-stato-mafia/giallo-papello.shtml.

M. Couttenier, P. Grosjean, and M. Sangnier. The wild west is wild: The homicide resource curse. *Journal of the European Economic Association*, 15(3):558–585, 2017.

CPMS. Commissione parlamentare sul fenomeno della mafia in Sicilia-La genesi della mafia, 1976. Backup Publisher: Archivio Pio La Torre http://archiviopiolatorre.camera.it/img-repo/DOCUMENTAZIONE/Antimafia/03/_rel.pdf.

CPMS. Commissione parlamentare di inchiesta sul fenomeno della criminalità organizzata mafiosa o similare, IX Legislatura, 1987.

E. Dal Bó and P. Dal Bó. Workers, warriors, and criminals: Social conflict in general equilibrium. *Journal of the European Economic Association*, 9(4):646–677, 2011.

E. Dal Bó and R. Di Tella. Capture by threat. *Journal of Political Economy*, 111(5):1123–1154, 2003.

E. Dal Bó, P. Dal Bó, and R. Di Tella. "Plata o Plomo?": Bribe and punishment in a theory of political influence. *American Political Science Review*, 100(1):41–53, 2006.

G. Daniele. Strike one to educate one hundred: Organized crime, political selection and politicians' ability. *Journal of Economic Behavior & Organization*, 159:650–662, 2019.

G. Daniele and G. Dipoppa. Mafia, elections and violence against politicians. *Journal of Public Economics*, 154:10–33, 2017.

G. Daniele and G. Dipoppa. Fighting organized crime by targeting their revenue: Screening, mafias and public Funds. *BAFFI CAREFIN Centre Research Paper*, (2018-98), 2022.

G. De Feo and G. D. De Luca. Mafia in the ballot box. *American Economic Journal: Economic Policy*, 9(3):134–167, 2017.

M. Dell. Trafficking networks and the Mexican drug war. *American Economic Review*, 105(6): 1738–1779, 2015.

M. Di Cataldo and N. Mastrorocco. Organized crime, captured politicians, and the allocation of public resources. *The Journal of Law, Economics, and Organization*, 38(3):774–839, 2022.

A. Di Matteo. Interview, 2023.

G. Dipoppa. How criminal organizations expand to strong states: Migrant exploitation and political brokerage in Northern Italy. 2022.

Direzione investigativa antimafia. Relazione semestrale, Various issues.

A. K. Dixit. *Lawlessness and economics: Alternative modes of governance*, volume 5. Princeton University Press, 2004.

G. Falcone and M. Padovani. Cose di Cosa nostra. *Milano, Rizzoli*, 1991.

C. Ferrari, O. Merk, A. Bottasso, M. Conti, and A. Tei. Ports and regional development: A European perspective. 2012.

N. C. for Health Statistics.

L. Frigerio. La confisca dei beni alle mafie. 2009. URL https://www.legalite.net/archivio/formazione/beni%20confiscati/La%20confisca%20dei%20beni%20alle%20mafie.pdf.

D. Gambetta. *The Sicilian Mafia: The business of private protection*. Harvard University Press, 1996.

N. Gratteri. Interview, 2022.

A. Graziani. The Mezzogiorno in the Italian economy. *Cambridge Journal of Economics*, 2(4): 355–372, 1978.

M. E. Guerra-Cujar, M. Prem, P. A. Rodríguez-Lesmes, and J. F. Vargas. A peace baby boom? Evidence from Colombia's peace agreement, 2023.

INEGI. Censo de población y vivienda, Various issues.

ISTAT. Censimento generale della popolazione, Various issues, a.

ISTAT. Statistiche giudiziarie, Various issues, b.

ISTAT. *Cause di morte, Anni 1949-1950*, volume 3(2). 1953.

ISTAT. *Annuario di statistiche provinciali*, volume 1-13. 1974.

M. Kleiman. Surgical strikes in the drug wars: Smarter policies for both sides of the border. *Foreign Aff.*, 90:89, 2011.

M. Kugler, T. Verdier, and Y. Zenou. Organized crime, corruption and punishment. *Journal of Public Economics*, 89(9-10):1639–1663, 2005.

E. La Ferrara and R. H. Bates. Political competition in weak states. *Economics & Politics*, 13 (2):159–184, 2001.

M. Le Moglie and G. Sorrenti. Revealing "mafia inc."? Financial crisis, organized crime, and the birth of new enterprises. *Review of Economics and Statistics*, 104(1):142–156, 2022.

B. Lessing. Logics of violence in criminal war. *Journal of Conflict Resolution*, 59(8):1486–1516, 2015.

B. Lessing. *Making peace in drug wars: Crackdowns and cartels in Latin America*. Cambridge University Press, 2017.

Libera. Associazioni, nomi e numeri contro le mafie.

W. Lin and J. M. Wooldridge. Testing and correcting for endogeneity in nonlinear unobserved effects models. In *Panel data econometrics*, pages 21–43. Elsevier, 2019.

S. Lodato. *Quarant'anni di mafia*. Bur, 2012.

W. McPhail. War on drugs: Heroin price, purity, and quantities seized over the past 10 years, 1992.

Ministero dell'Interno. Dipartimento della Pubblica Sicurezza. Banca Dati Interforze - SSD - Mod. StatDel2, Various issues.

Ministero dell'Interno. Rapporto sulla criminalità in Italia. Analisi, prevenzione, contrasto., 2007.

L. Mirenda, S. Mocetti, and L. Rizzica. The economic effects of mafia: Firm level evidence. *American Economic Review*, 112(8):2748–2773, 2022.

S. Mocetti and L. Rizzica. La criminalità organizzata in Italia: Un'analisi economica (Organized crime in Italy: An economic analysis). *Bank of Italy Occasional Paper*, (661), 2021.

J. Osorio. The contagion of drug violence: spatiotemporal dynamics of the Mexican war on drugs. *Journal of Conflict Resolution*, 59(8):1403–1432, 2015.

A. Petacco. *L'uomo della provvidenza: Mussolini, ascesa e caduta di un mito*. Edizioni Mondadori, 2004.

P. Pinotti. The economic costs of organised crime: Evidence from Southern Italy. *The Economic Journal*, 125(586):F203–F232, 2015.

V. Ríos. Why did Mexico become so violent? A self-reinforcing violent equilibrium caused by competition and enforcement. *Trends in organized crime*, 16:138–155, 2013.

P. Rolla, P. Justino, et al. *The social consequences of organized crime in Italy*. United Nations University World Institute for Development Economics Research, 2022.

J. Roth, P. H. Sant'Anna, A. Bilinski, and J. Poe. What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244, 2023.

G. Salvemini. *Il ministro della mala vita: Notizie e documenti sulle elezioni giolittiane nell'Italia meridionale*. Edizioni della Voce, Firenze, 1910.

R. Sánchez De La Sierra. On the origins of the state: Stationary bandits and taxation in eastern congo. *Journal of Political Economy*, 128(1):000–000, 2020.

E. U. Savona, M. Riccardi, et al. *From illegal markets to legitimate businesses: The portfolio of organised crime in Europe-Final report of project OCP organized crime portfolio*. Transcrime–Università degli Studi di Trento, 2015.

R. Snyder and A. Duran-Martinez. Does illegality breed violence? Drug trafficking and state-sponsored protection rackets. *Crime, law and social change*, 52:253–273, 2009.

F. Sobrino. Mexican cartel wars: Fighting for the US opioid market. 2019.

E. B. Staats. Drugs, Firearms, Currency, and Other Property Seized by Law Enforcement Agencies: Too Much Held Too Long, 1977.

The European Institute for International Law and International Relations (EIIR). How mafia is changing, 2023.

The New York Times, 2009.

M. Torrealta. *La trattativa*. Bur, 2010.

G. Trejo and S. Ley. High-profile criminal violence: Why drug cartels murder government officials and party candidates in Mexico. *British Journal of Political Science*, 51(1):203–229, 2021.

G. Tullock. Efficient rent seeking. *In Buchanan, James M and Tollison, Robert D and Tullock, Gordon: Toward a theory of the rent-seeking society*, pages 97–112, 1980.

UNODC. Annual drug seizures. URL https://dataunodc.un.org/drugs/seizures.

UNODC. World drug report, 2011.

H. Van Kippersluis and C. A. Rietveld. Beyond plausibly exogenous. *The Econometrics Journal*, 21(3):316–331, 2018.

Wikimafia. https://www.wikimafia.it/wiki/Categoria:Vittime

Appendix A

In this section I derive the proofs and generalizations of my theoretical results.

General functional form for G, H and Z

In this subsection, I solve the baseline game of section 3 using the generic equations (1) and (2), i.e., without specifying the functional form of $H(m)$, $G(a)$ and $Z(b)$ emerging from the third stage of the game. To simplify, I neglect mafia wars from the analysis by assuming $n = 1$.

Game solution: stage two

First, rewrite equations (1) and (2) as follows:

$$\begin{cases} S = -[1 - hG(a)H(m) - (1-h)Z(b)]\pi - dg - ea \\ W = [1 - hG(a)H(m) - (1-h)Z(b)]\pi - qb - m(g+1) \end{cases} \tag{A.1}$$

Maximization of the second equation (A.1) with respect to b and m yields the following:

$$\begin{cases} \hat{m} = (-H')^{-1}(\frac{g+1}{hG(a)\pi}) \\ \hat{b} = (-Z')^{-1}(\frac{q}{(1-h)\pi}) \end{cases} \tag{A.2}$$

Notably, given convexity of H and Z, both $(-H')^{-1}$ and $(-Z')^{-1}$ are decreasing functions. Therefore, $\hat{m}$ is increasing in π, h and in $G(a)$ (and therefore, also in a, whereas decreasing in $g+1$. Pairwise, $\hat{b}$ is increasing in π and $1-h$ and decreasing in q. In other words, Proposition 1 holds irrespective of the adopted functional forms, provided that H and Z are decreasing and convex (so that $-H$ and $-Z$ are increasing and concave).

Game solution: stage one

Substituting (A.2) into the first equation (A.1), one gets:

$$S = -[1 - hG(a)H((-H')^{-1}(\frac{g+1}{hG(a)\pi})) - (1-h)Z((-Z')^{-1}(\frac{q}{(1-h)\pi}))]\pi - dg - ea \tag{A.3}$$

Maximizing equation (A.3) with respect to g and a and rearranging terms, one gets the following first order conditions:

$$\begin{cases} hG'(a)\pi[H((-H')^{-1}(\frac{g+1}{hG(a)\pi})) - (\frac{g+1}{hG(a)\pi})^2 \frac{1}{H''((-H')^{-1}(\frac{g+1}{hG(a)\pi}))}] = e \\ \frac{g+1}{hG(a)\pi} \frac{1}{H''((-H')^{-1}(\frac{g+1}{hG(a)\pi}))} = d \end{cases} \tag{A.4}$$

Let us start from the second equation (A.4). We will exploit the following lemma.

Lemma A1. *The inverse of a strictly decreasing and convex function is (i) strictly decreasing* *and (ii) convex.*

Proof. (i) I first prove that the inverse of a strictly decreasing function is strictly decreasing. Let f be a real function such that $f' > 0$. Then, by definition:

$$x < y \leftrightarrow f(x) > f(y)$$

Thus:

$$f^{-1}(x) < f^{-1}(y) \leftrightarrow f^{-1}(f(x)) > f^{-1}(f(y))$$

Simplifying the last expression:

$$f^{-1}(x) < f^{-1}(y) \leftrightarrow x > y$$

(ii) Now, I prove that if $f'' > 0$, then $(f'')^{-}1 > 0$. By definition, if f is convex it shall hold:

$$f(ax + by) \leq af(x) + bf(y), \forall a, b \in R : a + b = 1$$

Exploiting the results proven in part (i), I can write:

$$af^{-1}(f(x)) + bf^{-1}(f(y)) = ax + by \leq f^{-1}(af(x) + bf(y))$$

Thus, f^{-1} is convex. ■

Let $x = \frac{g+1}{hG(a)\pi}$ and $f(x) = H''(H')^{-1}(x)$. Then, the LHS of the second equation (A.4) can be rewritten as $N(x) = \frac{x}{f(x)}$. Then, the following Lemma holds.

Lemma A2. (i) *$f(x)$ is (i) increasing but (ii) $N(x) = \frac{x}{f(x)}$ is decreasing.*

Proof. (i) Since by hypothesis $H''' < 0$, $-H'$ is decreasing and convex, Lemma A1 ensures that $(-H')^{-}1$ is decreasing and convex. Since H'' is a decreasing function, then $H''((-H')^{-}1)$ is an increasing function.
(ii) From equations (A.3) and (A.4) one can see that $\frac{x}{f(x)}$ is the marginal benefit from investing in law enforcement from the state. Therefore, since the cost is linear, any well defined optimization problem would require an increasing and concave function of g. Any increasing and concave function has a first order derivative which is positive and decreasing. Since $\frac{x}{f(x)}$ is exactly the first order derivative of the state revenue function, i.e. the marginal benefit, it shall be positive and decreasing. ■

Therefore, the denominator of the second factor of the LHS of second equation (A.4) is increasing in π, h and $G(a)$ and decreasing in $g + 1$. Thus, on the LHS of the second equation (A.4) there is a ratio between two functions increasing and decreasing in the same arguments. Finally, exploiting Lemma A1 and Lemma A2, I can derive the following Proposition.

Proposition A1. *Given a positive and increasing $f(x)$, $N(x) = \frac{x}{f(x)}$ is decreasing and concave only if $f(x)$ is convex.*

Proof. Differentiate $\frac{x}{f(x)}$ with respect to x to get the following expression:

$$\frac{f(x) - xf'(x)}{(f(x))^2}$$

The denominator is always positive and increasing in x. As for the numerator, recall that $f(x) = H''^{-1}(\frac{g+1}{hG(a)\pi})$.
Thus, $f(0)$ requires that $\pi \to \infty$. From equations (A.1), one can see that if $\pi \to \infty$ then the marginal benefit of m goes to infinity and so will the optimal value as of equations (A.2). In other words, $(H')^{-1}(\frac{g+1}{hG(a)\pi})$ would go to infinity, so that $H''(\infty) = f(0) = 0$. Differentiating the numerator of the first order derivative, one gets $-xf''(x)$. Notably, if $-xf''(x) > 0$ then also the first order derivative would be positive, i.e. $\frac{x}{f(x)}$ would be increasing. This holds because the numerator of the first order derivative evaluated in zero is zero, i.e. $f(0) = H''(\infty) = 0$. Therefore, $-xf''(x) < 0$ (i.e., a convex $f(x)$) is a necessary condition for $\frac{x}{f(x)}$ to be decreasing. Moreover, if $f(x)$ is convex, $\frac{x}{f(x)}$ is also concave, because $-xf''(x) < 0$ would imply a first order derivative characterized by a negative and always decreasing numerator and a positive and always increasing denominator, thereby yielding an overall ratio always negative and decreasing. ■

Summing up, part (ii) of Lemma A2 implies that $N(x) = \frac{x}{f(x)}$ is decreasing. From this, in Proposition A1 I can conclude that, since $\frac{x}{f(x)}$ is decreasing and $f(0) = 0$, then $f(x)$ is convex and most important $\frac{x}{f(x)}$ is concave.
Therefore, I can rewrite the second equation (A.4) as $N(\frac{g+1}{hG(a)\pi}) = d$. Solving for $g + 1$:

$$g + 1 = N^{-1}(d)hG(a)\pi \tag{A.5}$$

Given Lemma A1, I can state that $N^{-1}(d)$ is decreasing and concave, since it is the inverse of a decreasing and concave function. Substituting equation (A.5) into the first equation (A.2), one gets:

$$m^* = (-H')^{-1}(N^{-1}(d)) \tag{A.6}$$

In other words, the optimal m when law enforcement is endogenous is a decreasing function of a decreasing function of d, i.e. it is simply increasing in the cost of law enforcement d.

Now, substituting equation (A.5) into the first equation (A.4), one gets the following:

$$hG'(a)\pi[H((-H')^{-1}(N^{-1}(d)) - (N^{-1}(d))^2 \frac{1}{H''((-H')^{-1}(N^{-1}(d))}] = e \tag{A.7}$$

Notice that the last term on the LHS of equation (A.7) can be rewritten as:

$$N^{-1}(d)*N^{-1}(d)*\frac{1}{H''((-H')^{-1}(N^{-1}(d))} = N^{-1}(d)*\frac{(N^{-1}(d))}{f(N^{-1}(d))} = N^{-1}(d)*N(N^{-1}(d)) = dN^{-1}(d)$$

Substituting the last expression into equation (A.7) and solving for a, one gets:

$$a^* = (G')^{-1}(\frac{e}{[H((-H')^{-1}(N^{-1}(d)) - dN^{-1}(d)]h\pi}) \tag{A.8}$$

Since G is an increasing and concave function, by Lemma A1 G'^{-1} is decreasing in $\frac{e}{h\pi}$, i.e., it is increasing in π and h and decreasing in e. Finally, to be decreasing in d, the expression in square bracket shall be decreasing. Differentiating it with respect to d and imposing the derivative lower than 0, one gets:

$$-\frac{H'((-H')^{-1}(N^{-1}(d))}{H''((-H')^{-1}(N^{-1}(d)) * N'(N^{-1}(d))} - N^{-1}d - \frac{d}{N'(N^{-1}(d))}$$

Notably, the numerator of the first term in the LHS of the last expression is simply $N^{-1}(d)$, which can therefore be rewritten as:

$$\frac{N^{-1}(d)}{H''((-H')^{-1}(N^{-1}(d)))} * \frac{1}{N'(N^{-1}(d))} = N(N^{-1}(d) * \frac{1}{N'(N^{-1}(d))} = \frac{d}{N'(N^{-1}(d))}$$

Overall, the derivative simplifies to:

$$\frac{d}{N'(N^{-1}(d))} - N^{-1}d - \frac{d}{N'(N^{-1}(d))} = -N^{-1}d < 0$$

Since the decreasing function of d enters into the denominator in square bracket of the RHS of (A.8), the square bracket is overall increasing in d, because the reciprocal of a decreasing function is increasing. Summing up, a^* is a decreasing function of $\frac{e}{h\pi}$, i.e., it is decreasing in e and increasing in $h\pi$. Moreover, a^* is a decreasing function of an increasing function of d, i.e., it is decreasing in d. Finally, substituting equation (A.8) into (A.5), I get the optimal g^*:

$$g^* = N^{-1}(d)h\pi G(G^{-1}(\frac{e}{[H((-H')^{-1}(N^{-1}(d)) - dN^{-1}(d)]h\pi})) - 1 \tag{A.9}$$

The first term of equation (A.9) ($N^{-1}(d)h\pi$) is decreasing in d and increasing in h and π. The second term is an increasing function of a decreasing function, i.e it is decreasing in e and d and increasing in h and π. Since the product between two increasing functions is increasing, g^* is increasing in h and π. Pairwise, since the product between two decreasing function is decreasing, g^* is decreasing in e and d. In other words, Proposition 2 holds. Moreover, in line with Lemma 1 and Proposition 3, for low $h\pi$ (and/or high d and e), law enforcement is zero, becoming positive only for high enough values of $h\pi$ (with respect to e and d).

Different hypotheses on the confiscation function Y

In this subsection I show that results are qualitatively unaffected if I relax the hypothesis that Y is bounded between 0 and 1, thereby representing the intensity of confiscation rather than the fraction of confiscated asset. Then, keeping this hypothesis, I make the confiscation function also depend on g. Relaxing both hypothesis at once allows to preserve the close form solution. However, the main qualitative results would clearly hold considering a model where g enters into the confiscation function and the confiscation function is bounded between 0 and 1.

Unbounded confiscation function

I adopt a convenient functional form for the new payoff functions, choosing $G(a) = \sqrt{a}$:

$$\begin{cases} S = -[r - h\frac{\sqrt{a}}{m+1} - \frac{1-h}{b+1}]\pi - dg - ea \\ W = [r - h\frac{\sqrt{a}}{m+1} - \frac{1-h}{b+1}]\pi - qb - (g+1)m \end{cases} \tag{A.10}$$

Notably, $r\pi$ is total illegal profit and $r > 0$. In the second stage, the maximization of the second equation (A.10) with respect to m and b yields the following first order conditions:

$$\begin{cases} \hat{m} = \sqrt{\frac{\sqrt{a}}{g+1}h\pi} - 1 \\ \hat{b} = \sqrt{\frac{(1-h)\pi}{q}} \end{cases} \tag{A.11}$$

Equations (A.11) confirms the validity of Proposition 1. Substituting equations (A.11) into the first equation (A.10), maximizing with respect to g and a and substituting back into the first equation (A.11), one gets the first stage equilibrium levels of a, g, m and b:

$$\begin{cases} a^* = (\frac{\pi}{8ed})^2 \\ g^* = \frac{\pi^2}{32ed^3} - 1 \\ m^* = 2d - 1 \\ b^* = \sqrt{\frac{(1-h)\pi}{q}} \end{cases} \tag{A.12}$$

Results from Proposition 2 are confirmed. Moreover, law enforcement can be zero in presence of positive economic response, in line with Lemma 1 and Proposition 3.

Confiscation depending also upon law enforcement

I modify equations (A.10) as follows:

$$\begin{cases} S = -[r - h\frac{\sqrt{a}(g+1)^{\gamma}}{m+1} - \frac{1-h}{b+1}]\pi - dg - ea \\ W = [r - h\frac{\sqrt{a}(g+1)^{\gamma}}{m+1} - \frac{1-h}{b+1}]\pi - qb - (g+1)m \end{cases} \tag{A.13}$$

Notably, the first equation (A.13) reflects the (intuitive) hypothesis that, whereas confiscation is 0 if $a = 0$, it can be positive when $g = 0$. To have decreasing return to scale, I also assume $\gamma < \frac{1}{2}$. These two hypotheses imply that law enforcement is less effective than economic response in determining the actual confiscation level. If this were not the case, there would be little room for a.

I now solve the game. In the second stage, the maximization of the second equation (A.13) yields the following first order conditions:

$$\begin{cases} \hat{m} = \sqrt{\frac{\sqrt{a}}{(g+1)^{1-\gamma}}h\pi} - 1 \\ \hat{b} = \sqrt{\frac{(1-h)\pi}{q}} \end{cases} \tag{A.14}$$

Substituting equations (A.14) into the first equation (A.13), maximizing with respect to a and g and substituting back into equations (A.14), one gets the equilibrium levels of a, g, m and b:

$$\begin{cases} a^* = [(\frac{\gamma+1}{d})^{\gamma+1}(\frac{e^{\gamma-1}}{2^{3-\gamma}})]^{\frac{2}{1-2\gamma}}(h\pi)^{\frac{1}{1-2\gamma}} \\ g^* = [(\frac{(\gamma+1)^3}{d^3 2^5 e})^{1-\gamma}(h\pi)^{\frac{3-4\gamma}{2}}]^{\frac{1}{(1-\gamma)(1-2\gamma)}} - 1 \\ m^* = \frac{2d}{\gamma+1} - 1 \\ b^* = \sqrt{\frac{(1-h)\pi}{q}} \end{cases} \tag{A.15}$$

Once again, Propositions 1 and 2 hold. Moreover, law enforcement can be zero in presence of positive economic response, in line with Lemma 1 and Proposition 3.

The simultaneous game

In the previous subsection I proved that the sequential game yields the same results irrespective of whether or not (i) g directly enters into the confiscation function and (ii) the confiscation function is expressed in absolute terms rather than as the fraction of confiscated asset.

Notably, in the simultaneous game results would change if g does not directly determine confiscation, because g would not have any positive impact on the revenue function of the state and therefore would be optimally set to zero. In particular, the game solution would yield similar results to those found in the proof of Proposition 3.

That is why for the simultaneous game I shall relax the simplifying assumption that g has no impact on confiscation. Formally, I will solve the simultaneous game with payoff functions given by equations (A.13). Then, the first order conditions for the criminal organization are given by equations (A.14).

As for the state, maximization of the first equation (A.13) yields the following first order conditions:

$$\begin{cases} \frac{(g+1)^\gamma}{2\sqrt{a}(m+1)} h\pi = e \\ \gamma \frac{\sqrt{a}(g+1)^{\gamma-1}}{m+1} h\pi = d \end{cases} \tag{A.16}$$

Substituting the first equation (A.14) into equations (A.16) and solving the ensuing system, one gets the following optimal levels of a, g, m and b:

$$\begin{cases} a^* = [(\frac{1}{2d})^{1-\gamma}(\frac{\gamma}{d})^{1+\gamma} h\pi]^{\frac{2}{1-2\gamma}} \\ g^* = [\frac{\gamma^3 (h\pi)^2}{2ed^3}]^{\frac{1}{1-2\gamma}} - 1 \\ m^* = \frac{d}{\gamma} - 1 \\ b^* = \sqrt{\frac{(1-h)\pi}{q}} \end{cases} \tag{A.17}$$

Equations (A.14) and (A.17) confirms again the results of Propositions 1 and 2. Moreover, law enforcement can be zero in presence of positive economic response, in line with Lemma 1 and Proposition 3.

Proof of Lemma 1

Let $\sqrt{\pi} = z$ and impose the first equation (6) greater than 0:

$$a^* > 0 \leftrightarrow z = \sqrt{\pi} > 2\sqrt{ed} \tag{A.18}$$

Imposing also the second equation (6) greater than 0, one gets:

$$g^* > 0 \leftrightarrow z^2 - 2\sqrt{ed}z - 4d^2 > 0$$

The solution of the above expression is given by:

$$g^* > 0 \leftrightarrow z > \sqrt{ed} + \sqrt{ed + 4d^2} = \sqrt{ed}\left(1 + \sqrt{1 + \frac{4d}{e}}\right) \tag{A.19}$$

Notably, the term in brackets is greater than 2. Therefore, the threshold for a positive g^* is greater than that for a positive a^*.

Proof of Proposition 3

If the positive a^* was based on an optimal negative g^*, the fact that g is constrained to 0 means that $a(g = 0) < a(g = g^*)$. Only if $a(g = 0) > 0$ there is a range of value the parameters such that optimal confiscation is positive but law enforcement is nil. In this case, the first equation (5) would change as follows

$$\hat{m} = \sqrt{\frac{a\pi}{a+1}} - 1$$

Substituting this expression into the first equation (4), on gets the new state payoff function:

$$S = -\pi + \sqrt{\frac{a\pi}{a+1}} - ea$$

Maximizing the above expression with respect to a, one gets:

$$a(a+1)^3 = \frac{\pi}{4e^2}$$

The above equation shows that even with a nil law enforcement, economic response is positive in the optimum. Since proving the exact range of existence of the region characterized by $a(g) > 0, g < 0$ would be cumbersome, I only provide the simplest numerical example that supports my claim. Let $\frac{\pi}{4e^2} = 54$ so that $a^* = 2$. Then, $m^* = 12e - 1$ (which is meaningful only if $12e > 1$).

I am left to prove that the value I chose for π (i.e., $\pi = 216e^2$) is compatible with the conditions stated in Lemma 1 for a positive optimal a and a non positive optimal g, i.e. inequalities (A.18) and (A.19). Summing up, the three conditions form the following system:

$$\begin{cases} \pi = 216e^2 \\ \sqrt{\pi} > 2\sqrt{ed}\sqrt{\pi} < \sqrt{ed}(1 + \sqrt{1 + \frac{4d}{e}} \end{cases}$$

The above system originates the following chain of inequalities:

$$2\sqrt{ed} < 6\sqrt{6}e < \sqrt{ed}(1 + \sqrt{1 + \frac{4d}{e}}$$

The above inequalities are satisfied, e.g., for $e = \frac{1}{8}$ and $d = 2$. In this case, the state will intervene with positive confiscation and no law enforcement, and the criminal organization would react with both bribes and violence.

Proof of Corollary 2

Simple inspection of the third equation (3) shows that if $d < \frac{1}{2}$, then $m^* = 0$. Since $m = 0$, the state objective function becomes:

$$S = -\pi + \frac{a\pi}{a+1} - ea - dg$$

The maximization with respect to g clearly implies $g = 0$. In contrast, maximizing the above expression with respect to a yields the following:

$$\bar{a} = \sqrt{\frac{\pi}{e}} - 1$$

Intuitively, $\bar{a}$ is higher than the equilibrium value of a in presence of violence -as given by the first equation (6). Indeed, comparing the two values, one get that $\bar{a} > a^*$ provided that $d > \frac{1}{4}$. This condition must be fulfilled to have a positive level of violence in equilibrium.

Extension: popular support and multiple equilibria

In what follows, I derive an intuitive and simple extension of the presented model to show that, *coeteris paribus*, different levels popular support and trust in the institutions may yield completely different strategic interactions between governments and public officers.

Assume that the criminal organization asks a payment from each private agent, trying to punish those who refuse to pay. Such payment can be either monetary or "moral" (or both). Examples of moral cost for the population is the *code of omertà*. In what follows, I will focus on moral cost only, knowing that the generalization to monetary payments would be straightforward.

Formally, inhabitant i shall choose between paying a moral cost M_i (which is agent specific) and supporting mafia or rebelling (refusing to pay) and face a punishment[26] L from the criminal organization. Let the punishment be successful with probability $\rho(p)$, where p is the fraction of rebels (i.e., of state supporters). In particular, I assume[27] that the punishment probability is increasing in the diffusion of *omertà*, or, equivalently, decreasing in the fraction of state supporters, according to the following expression:

$$\rho(p) = 1 - \beta p \tag{A.20}$$

Define $R_i = \frac{M_i}{L}$ and assume that R_i is uniformly distributed in the interval $[0, \bar{R}]$. For clarity of the exposition, I rank players such that higher i are associated with higher values of R_i. Then,

[26]results would clearly hold assuming that the punishment perception is individual-specific.

[27]Notably, allowing the strategic interactions between state and organized crime to influence the popular support game would represent an interesting and fascinating extension of this model.

the equilibria of the popular support game are obtained by finding the player(s) indifferent between rebelling or not, given that the individuals with higher moral values have already rebelled[28]. Formally, it shall hold:

$$R_i = 1 - \beta p \tag{A.21}$$

Notably, players with very high moral values ($R_i > 1$) are always state supporters regardless of the others' behaviour. Pairwise, those with very low moral values ($R_i < 1 - \beta$) will never rebel to organized crime.

Exploiting the fact that $R_i = \bar{R}(1 - i)$ and the last rebel is such that $p = i$, I can rewrite condition (A.21) as follows:

$$\bar{R}(1 - i) = 1 - \beta i$$

The solution to the above equation is:

$$i^* = \frac{\bar{R} - 1}{\bar{R} - \beta} \tag{A.22}$$

(Only) players with a $R_i > R_{i^*}$ will rebel. Moreover, simple inspection of equation (A.22) shows that the closer i^* get to 1 $(1 - \beta)$, the lower (higher) the fraction of state supporters.

The value of $\bar{R}$ determines also the possible emergence of multiple equilibria. In particular, if $\bar{R} > 1$, then there will be players always rebelling. Given the uniform distribution, their rebellion will motivate other players with the highest $R_i < 1$ to rebel, up to the equilibrium threshold (A.22). Pairwise, if $\bar{R} < 1$, then no one will rebel. In contrast, if $\bar{R} < 1$, no player will rebel alone, but it will if a sufficient fraction of the population rebels. In this case, the game has a coordinative nature, where the two stable equilibria are given by (A.22) and by $p = 0$.

Then, when a shock -or a smooth change- pushes down (up) the value of i^*, there may be a sudden jump from a state-supporting to a mafia supporting equilibrium or vice-versa. Such a shock may affect either $\bar{R}$ (the trade-off between rebelling or not to organized crime) or β (the ability of rebels to protect each other) or both.

For instance, a high-profile murder that shocks the population can trigger a sudden transition towards a state supporting equilibrium, whereas a prolonged period of sinking from the organization can reduce popular support for harsh repression and favour a transition towards high values of *omertà*.

Now, if one assumes that the cost function of the is such that $d = d(p), d'(p) < 0$ and $e = e(p), e'(p) < 0$ -i.e., the relative strength of the state is increasing in popular support- then equations (6) will modify accordingly, i.e. violence will go down, whereas confiscation will go up. Law enforcement may go up since d will go down, but if $d < \frac{n}{2}$, then $m^* = 0$ without

[28] Rebels know that agents with higher R_i already rebelled because, if it is convenient for them to rebel, then it is also for those with higher moral values.

the need of law enforcement[29].
The implication of the popular support game is far from irrelevant. If the population is stuck in a mafia supporting equilibrium, the profit threshold triggering state intervention will be higher i.e., state intervention will be delayed [30].
If those shocks occur frequently (more in general, if popular support is quite volatile), there may be sudden switch from mild to harsh policies against organized crime (and vice-versa) as well as wave of organized crime related violence followed by periods of sinking.
As a final remark, notice that if the value of R_i is equal for all i, then only corner solution exists. In particular, if $R_i > 1$, equation (A.21) shows that all players will rebel to the criminal organization. Pairwise, if $R_i < 1-\beta$, no player will rebel. Finally, for $1-\beta < R_i < 1$, equation (A.21) defines a coordination game with $p^* = 0$ and $p^* = 1$ as stable corner equilibria, and an unstable equilibrium where $p^* = \frac{1-R_i}{\beta}$. Notably, the lower the unstable equilibrium, the higher the basin of attraction of the good equilibrium with $p^* = 1$.

Appendix B

This appendix is organized as follows. In section B1 I perform some further robustness checks for the empirical analysis presented in the main text. In section B2 I present the results of the Synthetic Control Method. In section B3 I present the data and empirical strategy for the empirical test of H3 and H4, whereas the empirical results are shown in section B4.

B.1 Further robustness checks

First, I show that the empirical results on H1 are unaffected when using the old administrative boundaries that are necessary to test H2. Specifically, the analysis presented in Table 2 of the main text is replicated (Table B1) collapsing the municipalities of the province of Barletta-Andria-Trani into Bari and Foggia and collapsing the provinces of Crotone and Vibo Valentia into Catanzaro. To account for the low number of clusters at the provincial level, in the second test, I run some regressions with bootstrap standard errors. The first four columns replicate the OLS analysis presented in Table 2, whereas the IV regressions of Table 5 are replicated in the last four columns. The estimations (Table B2) further corroborate the OLS and IV results obtained in the main text with clustered standard errors. All coefficients are positive and statistically significant. In all cases the number of bootstrap samples is 1000. Still to tackle the low number of clusters and to mitigate any potential selection bias, in Table B3 perform a set of

[29] This stems from the fact that the state does not derive any direct benefit from reducing struggles internal to criminal organizations. Changing accordingly the state payoff function would possibly imply a positive law enforcement even with $m^* = 0$ provided that $X^* > 0$.

[30] and/or may be limited to confiscation if the conditions in Lemma 1 hold.

y=HP murders	Absolute number			Dummy
	(1)	(2)	(3)	(4)
Confiscation	.019***	.018***	.017***	.143*
	(.005)	(.004)	(.005)	(.073)
GDP and Pop controls		✓	✓	✓
Other controls			✓	✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	946	946	946	946
R-squared	.16	.16	.18	.19
Provinces	22	22	22	22

Table B1: The impact of confiscation on high-profile murders (old administrative boundaries)-OLS results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

y=HP murders	Absolute number			Dummy	Absolute number			Dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Confiscation	.017**	.017**	.016**	.151*	.057**	.053*	.051*	.682***
	(.007)	(.007)	(.007)	(.082)	(.028)	(.031)	(.031)	(.227)
GDP and Pop controls		✓	✓		✓	✓		
Other controls			✓	✓			✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075	1075	1075
R-squared	.15	.15	.17	.18	-.10	-.06	-.03	-.03
Provinces	25	25	25	25	25	25	25	25
Kleibergen-Paap F statistics					13.80	13.00	11.68	32.72

Table B2: The impact of confiscation on high-profile murders-OLS and IV results.

Notes: Bootstrap standard error in parentheses. In all columns the number of bootstrap samples is 1000. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

OLS and IV regressions expanding the panel to all Italian provinces.The first column estimates equation (7) with the inclusion of a set of controls slightly different from that used in the most demanding specification of Table 2. Specifically, due to the limited digitalization of the national census prior to 1991, I use the information provided by 8000census, an ISTAT database containing synthetic indicators of each municipalities with the old administrative boundaries. To stick as close as possible to the set of controls used in the main text, I use (Table B4) the log of population, the occupation rate, the fraction of workers employed in the secondary sector, the illiteracy and tertiary education rate (out of the population over 6) and the fraction of under 15 (over the active population). Turning to the extensive margin, the second column adds an interaction term between the variable confiscation and a dummy taking value one for the four Italian regions used in the main analysis (Sicily, Calabria, Campania and Apulia) and zero otherwise. The estimated coefficient aligns with that of the previous regression, suggesting that the positive relation between confiscations and high-profile murders is almost entirely driven by the regions plagued the most by organized crime. Building on the results of the first two columns, in the third one I instrument confiscations with the interaction between drug profit and the dummy taking value one in Sicily, Calabria, Campania and Apulia, where the interaction reflects the low (although not nil) degree of mafia penetration in the North of the country up to the Nineties such that access to ports and drug demand from the US should have a negligible impact on confiscation[31]. The IV coefficient is statistically significant and slightly more than double the OLS one, substantiating the hypothesis of a severe downward bias of the latter. In the last three columns I replace the dependent and independent variables with dummies, obtaining results in line with those of the previous regressions. In the fourth test, I substitute the number of confiscated asset with an estimate of their value (in hundred thousands euros) as main explanatory variable. Specifically, for each year I divide the total value of confiscation by the total number of confiscated asset to get the average value of one confiscated asset in Italy, and then I multiply this value by the number of asset confiscated in each province (or municipality). Results are shown in Table B5, where I essentially replicate the analysis of Table 2. In column 1, I estimate the effect of confiscation (value) on high profile murders with time and province fixed effects only. In column 2 I control for GDP and log of population, whereas the remaining socio-demographic and economic controls are added in column 3. In all specification results are line with those of Table 2, displaying an even higher statistical significance. Then, I use confiscations occurring at time t and t+1 (which I label as Confiscation^T) as explanatory variable. As stated in section 4.1, confiscations at time t and $t+1$ roughly reflects seizures at time $t-3$ and $t-2$, thereby being a more recent indicator of past seizures. Results are presented in Table B6. In columns 1 and 2 I respectively report the

[31]Indeed, confiscations in the Center-North were almost zero before 1992. In the last decades, instead, confiscations in some Northern regions is comparable to those in Sicily.

y=HP murders	Absolute number			Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV	OLS	OLS	IV
Confiscation	.018**	-.003	.041***	.107**	-.023**	.556***
	(.007)	(.002)	(.009)	(.048)	(.011)	(.136)
Confiscation * Mafia regions		.021***			.196***	
		(.006)			(.061)	
Full set of controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Observations	4730	4730	4730	4730	4730	4730
R-squared	.12	.12	-.03	.09	.10	-.20
Provinces	110	110	110	110	110	110
Kleibergen-Paap F-statistics			15.84			14.06

Table B3: The impact of confiscation on high-profile murders in Italy-OLS and IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

VARIABLES	N	mean	sd	min	max
MAIN VARIABLES					
Confiscation	6,930	2.656	16.677	0	527
high-profile murders	6,930	0.028	0.280	0	12
Profit (Access to ports*overdoses/1000000)	6,930	3.678	18.252	0	345.435
SOCIO-DEMOGRAPHIC CONTROLS					
Percentage of under 15 out of active population	6,930	29.241	9.344	14.163	62.671
Percentage of illiterate population	6,930	5.732	6.532	0.108	38.014
Percentage of over 6 population with university degree	6,930	13.252	11.248	1.103	46.676
Log(population)	6,930	12.821	0.714	10.813	15.209
ECONOMIC CONTROLS					
Share of labour force in secondary sector	6,930	35.864	11.609	10.891	77.619
Employment rate	6,930	44.807	6.593	26.985	63.977

Table B4: Summary statistics for all Italian provinces, 1950-2012.

y=HP murders	(1)	(2)	(3)
Confiscation value	.016***	.015***	.014***
	(.003)	(.002)	(.002)
GDP and Pop controls		✓	✓
Other controls			✓
Time FE	✓	✓	✓
Province FE	✓	✓	✓
Observations	1075	1075	1075
R-squared	.16	.16	.18
Provinces	25	25	25

Table B5: The impact of confiscation (value) on high-profile murders-OLS results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

y=HP murders	Absolute number				Dummy	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Confiscation^T	.016***	.025***	.016***	.024***	.126*	.781**
	(.005)	(.006)	(.005)	(.006)	(.066)	(.360)
GDP and Pop controls	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075
R-squared	.29	.15	.30	.17	.17	-.37
Provinces	25	25	25	25	25	25
Kleibergen-Paap F statistics		19.2		22.11		19.62

Table B6: The impact of two years confiscation on high-profile murders-OLS and IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. Confiscation^T denotes the number of asset confiscated at time t and $t + 1$. First stage results are reported in Appendix D.

y=HP murders rate				
Confiscation=	Absolute number	2 years	Value	Dummy
	(1)	(2)	(3)	(4)
Confiscation	.012*	.013**	.012***	.455
	(.007)	(.005)	(.003)	(.277)
Full set of controls	✓	✓	✓	✓
Period	1950-92	1950-92	1950-92	1950-92
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1075	1075	1075	1075
R-squared	.15	.20	.17	.15
Provinces	25	25	25	25

Table B7: The impact of confiscation on high-profile murders rate-OLS results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

OLS and IV estimations, controlling for population and young male unemployment. Columns 3 and 4 include the full set of controls. The last two columns replicate the analysis of columns 3 and 4, substituting both the dependent and explanatory variables with dummies. Across all specifications, the coefficients are positive and statistically significant. Note that this broader definition of confiscation increases the significance of the correlation, though at the expense of a lower (still acceptable) Kleibergen-Paap F statistics in the IV regressions. Furthermore, the downward bias of the OLS estimations (now much closer to the IV ones) is remarkably lower, possibly because of a partial mitigation of the measurement error emerging when considering just one year of confiscations.

Next, in Table B7 I use high-profile murders rate per 100,000 inhabitants as dependent variable. In column 1, I use confiscation at time t as explanatory variable, whereas in column 2 I consider

y=HP murders	PPML			IVPPML		
	(1)	(2)	(3)	(4)	(5)	(6)
Confiscation	.023***	.010**	.008**	.214***	.152***	.128***
	(.004)	(.005)	(.004)	(.018)	(.028)	(.028)
GDP and Pop controls		✓	✓		✓	✓
Other controls			✓			✓
Time FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Observations	725	725	725	725	725	725
Pseudo R-squared	.20	.37	.41	.41	.42	.44
Provinces	25	25	25	25	25	25

Table B8: The impact of confiscation on high-profile murders-PPML and IV PPML results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

confiscation at time t and t+1. Finally, in columns 3 and 4 I respectively use the estimated value of confiscation and a dummy taking value one if at least one asset has been confiscated at time t. Results are positive and statistically significant in all specification except the last one, where the coefficient is barely insignificant (with a p-value of .105).

In the seventh test (Table B8) I conduct a series of Poisson Pseudo Maximum Likelihood (PPML) estimations. First, I estimate equation (7) with only time and province fixed effects. I gradually introduce the control variables in the following two columns, following the logic of Table 2. In the last three columns, I re-run the first three Poisson regressions, instrumenting confiscation[32]. For the IV estimations, I adopt the strategy outlined in Lin Wooldridge (2019). In accordance with the previous results, all coefficients are positive and statistically significant, still with remarkably higher estimates from the IV regressions.

In the next test (Table B9), I replicate (neglecting the two basic regressions without controls) and confirm the analysis of Tables 2 and 5 substituting innocent victims with the count of civilians murdered by organized crime. All coefficients are positive and statistically significant. Then, to account for different levels of mafia penetration across provinces, in Table B10, I create a dummy variable (*mafia*) taking value one for provinces with a mafia penetration index ranking within the first quartile according to the index elaborated by Transcrime (2015), and zero otherwise. This variable is interacted with confiscation in the OLS estimation. However, since the mafia index is potentially endogenous (though it is computed based on information from the first decade of the 2000s), I restrict the IV regressions on provinces with mafia=1. This entails dropping the interaction term (although, for the sake of clarity, the coefficients are still reported in the row *confiscation*mafia*, to highlight the focus on mafia provinces) and avoiding a direct confrontation with provinces with mafia=0.

The OLS and IV estimates with full set of controls are presented in columns 1 and 2, whereas

[32] The IV strategy is described in subsection 5.2.

y=Murdered civilians	Absolute number				Dummy	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Confiscation	.033*	.099***	.046*	.144***	.078	.735***
	(.018)	(.038)	(.026)	(.051)	(.064)	(.184)
GDP and Pop controls	✓	✓	✓	✓	✓	✓
Other controls			✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075
R-squared	.26	-.23	.32	-.23	.29	-.18
Provinces	25	25	25	25	25	25
Kleibergen-Paap F statistics		44.80		54.99		24.12

Table B9: The impact of confiscations on murders of civilians-OLS and IV results.

Notes: Robust standard error clustered ad the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

y=	High-profile murders				Innocent victims			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confiscation	-.045*		-.035		-.086		-.056	
	(.023)		(.022)		(.058)		(.060)	
Confiscation*mafia	.060**	.046**	.042*	.021***	.131**	.128**	.084	.075*
	(.025)	(.022)	(.024)	(.008)	(.049)	(.064)	(.057)	(.042)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Period	1950-92	1950-92	1972-92	1972-92	1950-92	1950-92	1972-92	1972-92
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1075	731	525	357	1075	731	525	357
R-squared	.17	-.08	.10	-.01	.33	-.14	.24	-.04
Provinces	25	17	25	17	25	17	25	17
Kleibergen-Paap F statistics		38.08		63.78		38.08		63.78

Table B10: Accounting for different levels of mafia penetration- OLS and IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

in columns 3 and 4 I restrict the sample to the period 1972-1992. In columns 5-8 I replicate the analysis using innocent victims as dependent variable. Notice that provinces with mafia=0 display a negative (sometimes significant) relation between confiscation and high-profile murders, unlike those with mafia=1, whose positive and statistically significant (apart from column 7 where it is barely insignificant) coefficient is obviously strongly inflated. In the tenth set of robustness checks (Table B11), I substantiate the OLS and IV results of the main text using the sum of confiscated real estates and firms as explanatory variable (*Total confiscation*). Specifically, columns 1-2, 3-4 and 5-6 respectively replicate the OLS and IV regressions shown in columns 2,3 and 4 of Tables 2 and 5 respectively. Finally, I present two additional tests (complementary to those presented in Table 7 and 8) to further corroborate the IV strategy

y=HP murders	Absolute number				Dummy	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Total Confiscation	.017***	.052***	.015**	.050***	.386*	.682**
	(.005)	(.017)	(.006)	(.017)	(.203)	(.272)
GDP and Pop controls	✓	✓	✓	✓	✓	✓
Other controls			✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075
R-squared	.15	-.17	.17	-.14	.15	-.18
Provinces	25	25	25	25	25	25
Kleibergen-Paap F statistics		41.7		51.07		24.12

Table B11: The impact of confiscation of real estates and firms on high-profile murders-OLS and IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. Total confiscation denotes the number of real estates and firms confiscated at time t. First stage results are reported in Appendix D.

described in the main text. First, I modify equation (10) replacing the number of deaths for overdose in the US with the number of deaths for overdose in the East coast, which clearly served as the primary entry point for ships coming from Italy. All regressions in Table B12 include the full set of controls. The first column considers the number of deaths for overdose in the 14 US states that have access to the Atlantic Ocean, whereas the second column further restricts the number of overdoses to those occurred in the US counties that have a direct access to the Atlantic Ocean. Columns 3 and 4 use the same instrument but substitute high-profile murders and confiscations with dummy variables. The last four regressions replicate the analysis of columns 1-4 using innocent victims as dependent variable. All regressions display positive and statistically significant results. Furthermore, the use of more precise data on deaths for overdose leads to a higher strength of the instrument in almost all regressions, as well as to a lower difference between the OLS and IV coefficients, although the OLS downward bias is still high. Second (Table B13), I replicate the analysis of Table 5 substituting the measure of access to ports defined in equation (9) with the same definition of inverse distance from the 14 major Italian cities. Since my object of interest here is the correlation between my "fake" instrument and confiscations, I only show the first stage results and the Kleibergen-Paap F statistics, which indeed witnesses a striking contraction. This suggests that network infrastructures *per sé* are a poor predictor of confiscations.

B.2 Synthetic control

To bolster the credibility of my identification strategy, I employ the Synthetic Control Method (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Pinotti, 2015; Mirenda et al., 2022).

y=	HP murders				Innocent victims			
	Absolute Value		Dummy		Absolute Value		Dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Confiscation	.034***	.041***	.374**	.393**	.087***	.094***	.287***	.307***
	(.011)	(.014)	(.170)	(.168)	(.033)	(.036)	(.110)	(.103)
East coast territories	States	Counties	States	Counties	States	Counties	States	Counties
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1075	1075	1075	1075	1075	1075	1075	1075
R-squared	-.08	-.15	-.05	-.07	-.04	-.08	-.01	-.01
Provinces	25	25	25	25	25	25	25	25
Kleibergen-Paap F statistics	52.81	46.19	64.59	94.09	52.81	46.19	64.59	94.09

Table B12: The impact of confiscations on high-profile murders and innocent victims-alternative IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

y=Confiscation	Number of asset			Dummy
	(1)	(2)	(3)	(4)
Fake profit	0.213**	.210**	.198*	.056**
	(.967)	(.949)	(.982)	(.024)
GDP and Pop controls		✓	✓	✓
Other controls			✓	✓
Period	1950-92	1950-92	1950-92	1950-92
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1075	1075	1075	1075
R-squared	.20	.20	.21	.43
Provinces	25	25	25	25
Kleibergen-Paap F statistics	4.85	4.89	4.08	5.65

Table B13: Falsification exercise: The impact of confiscations on high-profile-murders exploiting differences in access to the major Italian cities-IV first stage results

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable Fake profit is divided by 10^3.

Specifically, I designate the heroin market boom (and the subsequent introduction of asset confiscation) as the treatment in my event study framework.
It is noteworthy that a significant portion, approximately 20% of national confiscation (and 33% of high-profile murders), occurred in Palermo, with another 20% taking place in Naples and Reggio Calabria. The remaining 60% is distributed among the other Italian provinces, although none of them reaches a significant level of confiscation. Consequently, following Pinotti (2015), I include all other units in the control group, even though they experienced minor, albeit non-zero, levels of confiscation[33].

Variables	Treated	Synthetic		
		(high profile)	(innocent)	(low profile)
MODEL 1 (y=Counts)				
High-profile murders	.689	.125		
Innocent murders	1.906		.257	
Low-profile murders	117.848			
Male share searching 1st empl	.083	.063	.058	
Illiterate share	.107	.131	.135	
Young share	.451	.450	.437	
Tertiary educated share	.020	.018	.012	
Building sector's workers share	.127	.125	.139	
Ln(pop)	13.921	13.724	13.112	
MODEL 2 (y=rates per 100,000 inhabitants)				
High-profile murders rate	.059	.013		
Innocent murders rate	.167		.065	
Low-profile murders rate	4.160			4.129
Male share searching 1st empl	.083	.063	.063	.050
Illiterate share	.107	.131	.136	.119
Young share	.451	.450	.433	.421
Tertiary educated share	.020	.018	.011	.014
Building sector's workers share	.127	.125	.141	.122
Ln(pop)	13.921	13.724	12.967	12.904

Table B14: Pre-treatement characteristics of Palermo and the synthetic controls over the period 1950-1981.

Then, I construct a synthetic Palermo serving as a counterfactual to predict high-profile murders, murders of innocent people (both in absolute terms and per 100,000 inhabitants) and the rate of low-profile murders. The employed predictors encompass the full set of control variables used to estimate equations (7) and (11), namely population (in log), illiteracy rate, tertiary education rate, fraction of young population, young unemployment, and the share of workers employed in the building sector. The weights assigned in the synthetic control model aim to minimize the mean square predictor error for each type of murder (high-profile murders, mur-

[33]It should be noted that in Pinotti's study, regions with low mafia penetration were considered "mafia-free".

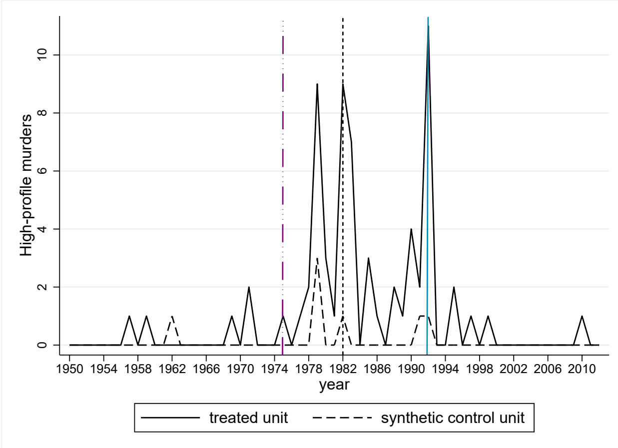
ders of innocent people and low-profile murders) and the other predictors during the period from 1950 to 1981.

The algorithm assigns positive weights to the following provinces: Agrigento (0.362), Catania (0.174), and Trapani (0.465) for murders of innocent people; Catania (1) for high-profile murders.

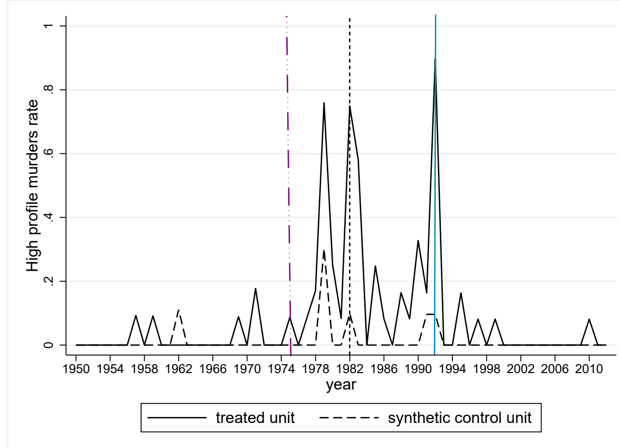
Similarly, the algorithm assigns positive weights to: Ragusa (0.111), Taranto (0.118) and Trapani (0.771) for low-profile murders rate; Agrigento (0.427) and Trapani (0.573) for innocent people murders rate; Catania (1) for high-profile murders rate. The treated and synthetic Palermo are compared in Table B14. The results are depicted in Figure B1. For high-profile murders (panels a and b), both the synthetic and actual Palermo exhibit a similar pattern characterized by a minimal level of high-profile violence. However, a notable deviation between the two occurs after the heroin boom (represented by the dot-dashed purple line) and the subsequent political campaign led by Pio La Torre, which resulted in the enactment of the Rognoni-La Torre Law. During this period, the actual Palermo experiences a significant increase in high-profile murders, while the synthetic Palermo remains at a low level.

From 1992 (represented by the blue solid line), which coincides with the introduction of article 41bis and the wave of public outrage following the mass murders of judges Falcone and Borsellino, the actual and synthetic Palermo converge once again, indicating a decline in high-profile murders. Given the low number of high-profile murders, the results for innocent victims (panels c and d) offer more informative insights. Again, the algorithm initially predicts low but positive homicides of innocent victims, aligning with the actual Palermo. However, a significant divergence occurs after the heroin market boom and the implementation of the Rognoni-La Torre law. Subsequently, the synthetic and actual Palermo converge again following the introduction of harsh imprisonment regime. Focusing on low-profile murders (panel e), consistent with my theoretical predictions and the empirical findings discussed in subsection 5.2, the synthetic control method (which closely predicts homicides prior to the treatment) overestimates the number of low-profile murders in Palermo from the early 1980s to the early 1990s, despite capturing the correct declining trend.

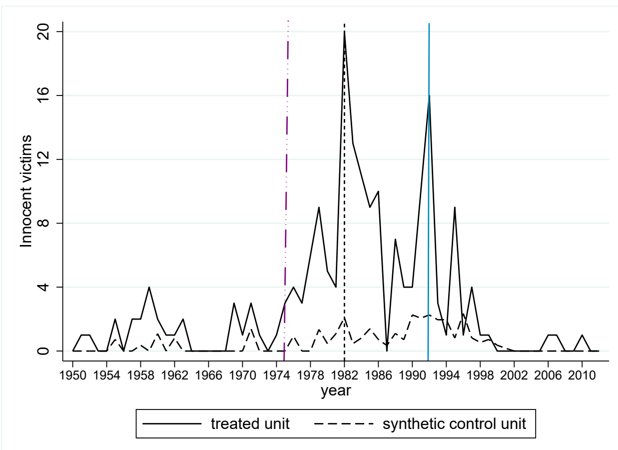
As a placebo test (Abadie et al., 2010; Pinotti, 2015), I replicate the synthetic control exercise for the other provinces. Figure B2 illustrates the difference between the actual and synthetic provinces, both in absolute terms and every 100,000 inhabitants. Remarkably, between the mid-1970s and early 1990s, Palermo (bold solid orange line) experiences the highest increases and peaks (especially in absolute terms) for high-profile murders and murders of innocent victims. Simultaneously, Palermo shows the sharpest decline in low-profile murders. Another province undergoing a similar surge in high-profile murders and murders of innocent victims is Reggio Calabria. Consistent with the theory, Reggio Calabria ranks among the top three provinces for asset confiscation, accounting for 10% of national confiscation alone. Finally, in Figure B3 I



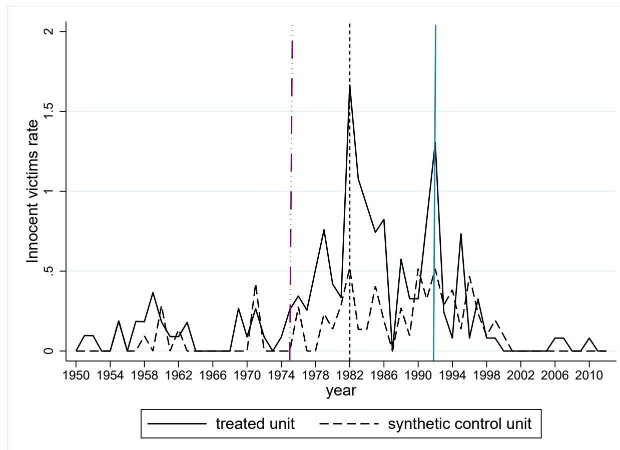
(a) High-profile murders



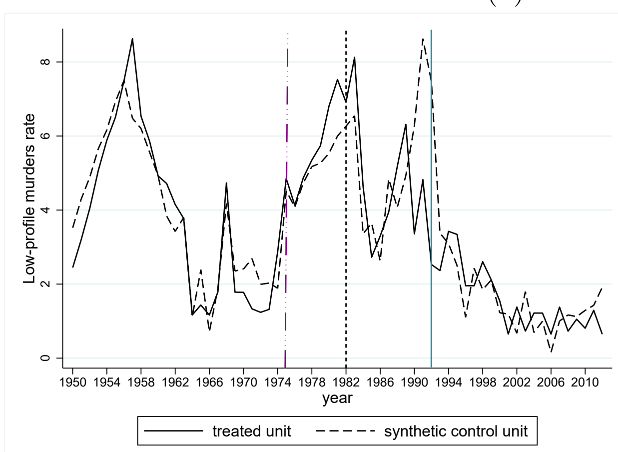
(b) High-profile murders rate



(c) Innocent victims



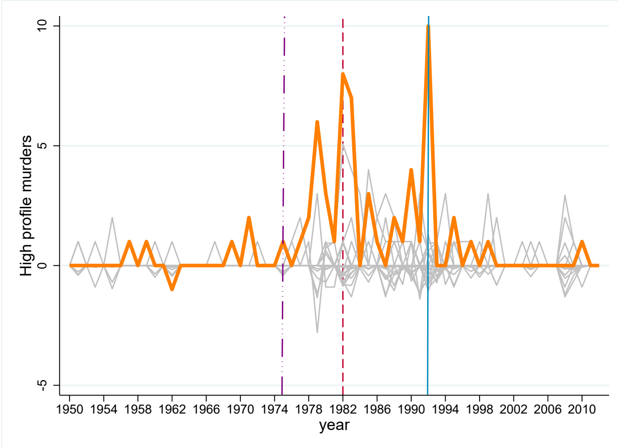
(d) Innocent victims rate



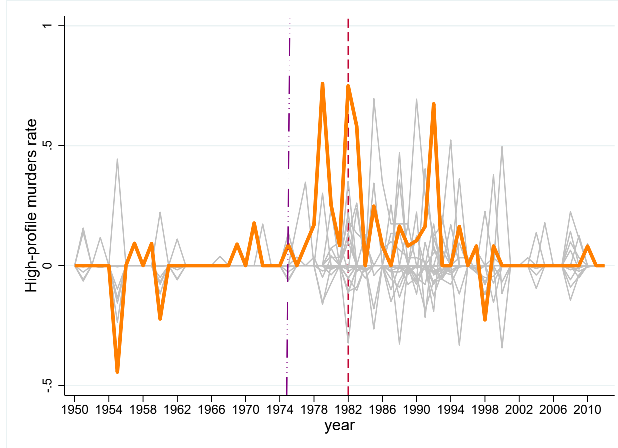
(e) Low-profile murders rate

Figure B1: High profile murders, innocent murders and low profile murders in Palermo and synthetic unit.

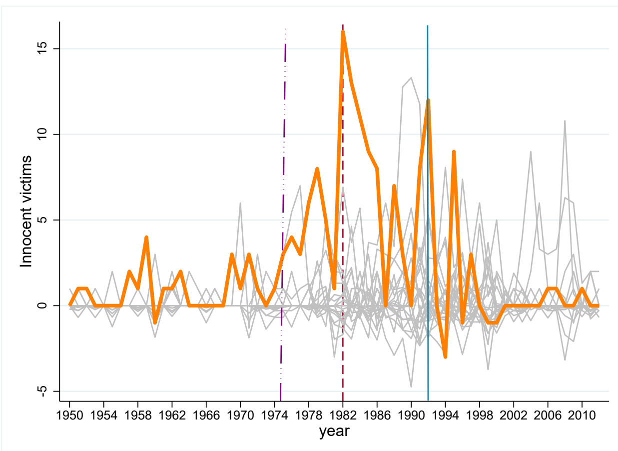
Notes: The weights used to construct the synthetic control are chosen to minimise distance with Palermo in terms of high profile murders and some economic and socio-demographic predictors listed in Table B14 during the period 1950-1981. Panels a) and c) refer to absolute quantities, whereas the rates per 100,000 inhabitants are respectively depicted in panels b), d) and e). The solid blue line denotes the introduction of harsh imprisonment regime, whereas the dot dashed purple line denotes the approximate onset of the heroin market boom and the ensuing adoption of the follow the money strategy at the end of the Seventies (dashed line).



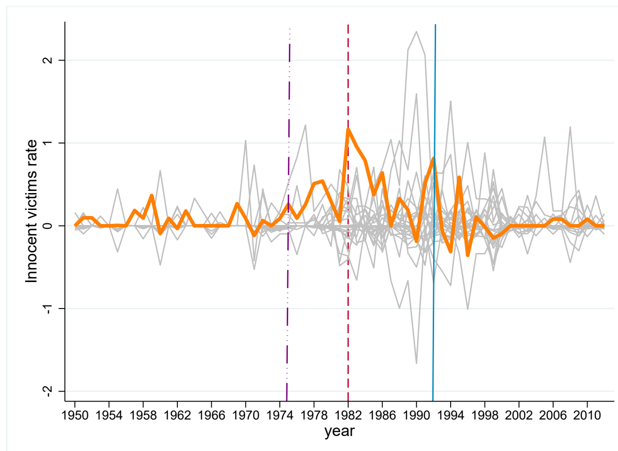
(a) High-profile murders



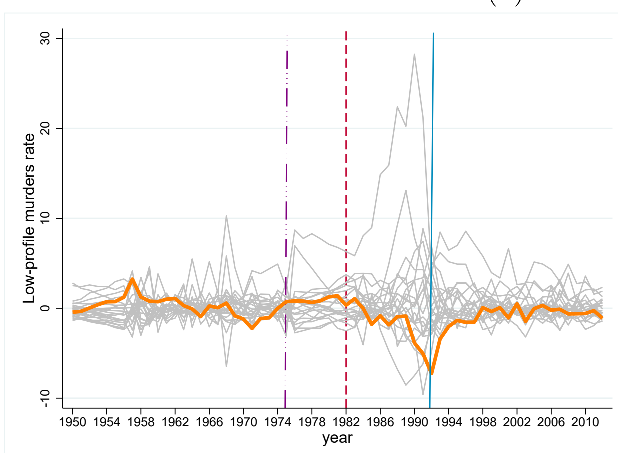
(b) High-profile murders rate



(c) Innocent victims



(d) Innocent victims rate



(e) Low-profile murders rate

Figure B2: Difference between treated and synthetic units in terms of high profile murders, innocent victims and low profile murders.

Notes: Panels a) and c) refer to absolute quantities, whereas the corresponding rates per 100,000 inhabitants are respectively depicted in panels b), d) and e). The bold solid orange line represents Palermo. The solid blue line denotes the introduction of harsh imprisonment regime, whereas the dot dashed purple line denotes the approximate onset of the heroin market boom and the ensuing adoption of the follow the money strategy at the end of the Seventies (dashed line).

report the synthetic control estimations for high profile murders, innocent victims murders (in absolute terms and per 100,000 inhabitants) and the rate of low profile murders for Palermo, using as weights the best predictors minimizing the mean square error for the period 1950-1974.

B.3 Data and empirical strategy for H3 and H4

B.3.1 H3: law enforcement reduces and stabilizes violence

To support H3, I use the number of detainees under the harsh imprisonment regime (*41bis*) as a proxy for law enforcement, sourced from "Anti-mafia Archive" (Archivio Antimafia). Article 41-bis significantly differs from the earlier form of imprisonment for mafia affiliation (established by the Rognoni-La Torre law), as it prevents any communication with the outside world, thereby constituting a concrete elimination of the mobster. It is widely known that, unless isolated, convicted mob bosses continue to issue orders and manage their criminal activities from prison (Lodato, 2012). Notably, the joint adoption of military and economic repressive measures from late 1992[34] onward introduces another endogeneity concern, as the two policies, once both implemented, are obviously correlated. Thus, I will simply show some correlations suggesting that the relation between confiscations and high-profile murders disappears after 1992 and a negative relation between harsh imprisonments and high-profile murders emerges. This is done introducing an interaction term between confiscation and a dummy (d) that takes value one from 1992 onward, as well as restricting the panel to the years between 1992 and 2012. Formally, let $\xi_{i,t} = \gamma X_{i,t} + \alpha_i + \varepsilon_t + u_{i,t}$. Then, I test H3 adopting the following empirical strategy:

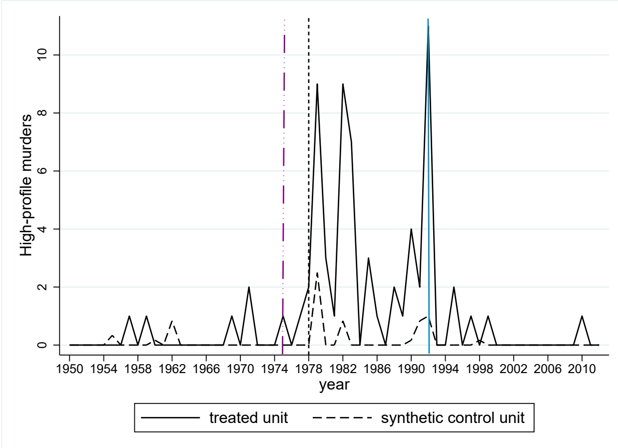
$$External\ violence_{i,t} = \beta confiscation_{i,t} + \delta confiscation_{i,t} * d_t + \eta 41bis_{i,t} + \xi_{i,t} \tag{B.1}$$

The coefficients of interest are δ and η, respectively capturing the impact of one additional confiscation (from 1992 onward) and detainee at harsh imprisonment regime on external violence.

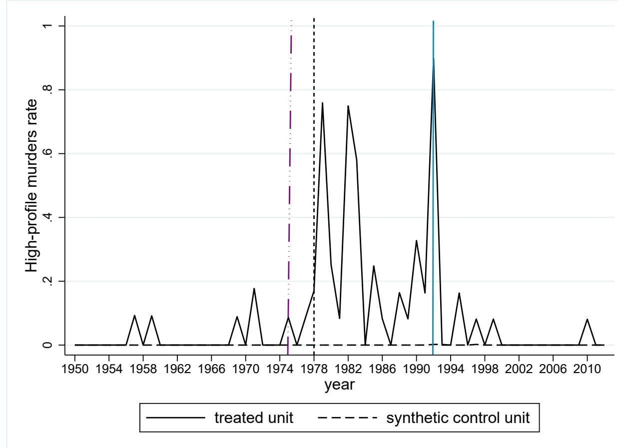
B.3.2 H4: confiscation increases corruption

To support H4, I exploit the Italian Law No.221-1991, allowing the dissolution of a city council for mafia penetration. Specifically, I show that confiscations increase following the dissolution of a city council, suggesting the pre-existence of a corruptive tie aimed at reducing economic attacks. The dissolution of a city council due to mafia infiltration serves as an exogenous event that enhances the likelihood of honest behavior among local public officers (Di Cataldo

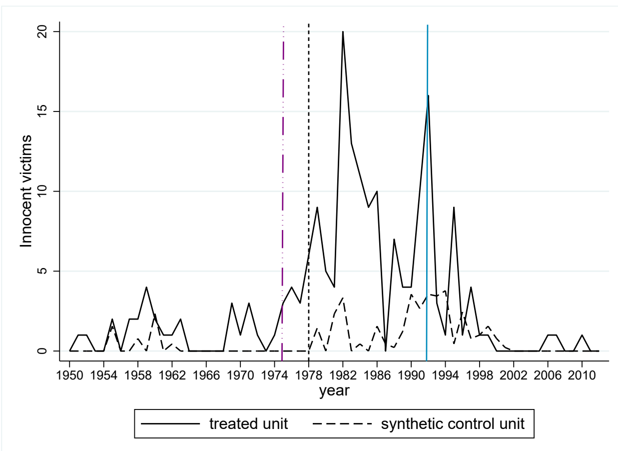
[34]This year is also characterized by many shocks, namely: the dissolution of the Soviet Union, the end of the Italian First Republic due to a major judicial inquiry known as "Mani Pulite" (Clean Hands), the subsequent emergence of new political parties, a wave of public disdain following the murders of Falcone and Borsellino, and the subsequent establishment of the non-profit organization Libera.



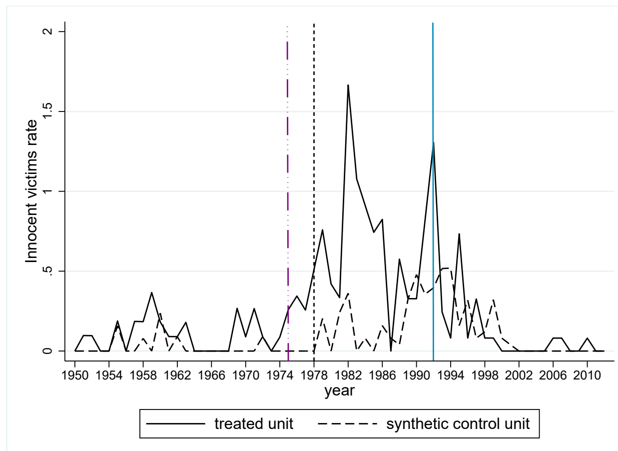
(a) High-profile murders



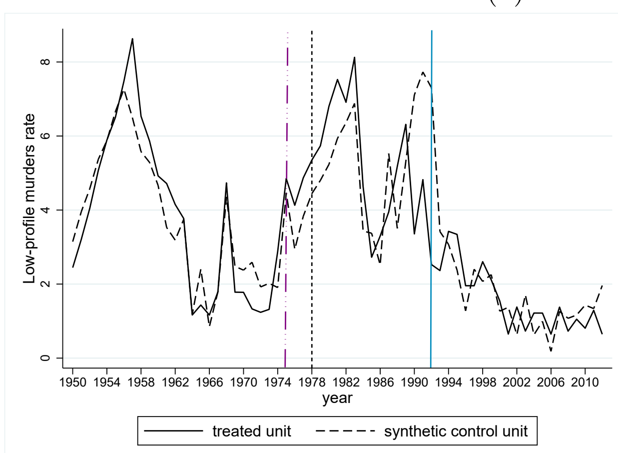
(b) High-profile murders rate



(c) Innocent victims



(d) Innocent victims rate



(e) Low-profile murders rate

Figure B3: High profile murders, innocent murders and low profile murders in Palermo and synthetic unit.

Notes: The weights used to construct the synthetic control are chosen to minimize distance with Palermo in terms of high profile murders and some economic and socio-demographic predictors listed in Table B14 during the period 1950-1974. Panels a) and c) refer to absolute quantities, whereas the corresponding rates per 100,000 inhabitants are respectively depicted in panels b), d) and e). The solid blue line denotes the introduction of harsh imprisonment regime, whereas the dot dashed purple line denotes the approximate onset of the heroin market boom and the ensuing adoption of the follow the money strategy at the end of the Seventies (dashed line).

and Mastrorocco, 2022). This is because the council is replaced by three special administrators selected from judges and public officers. Consequently, one would anticipate lower levels of confiscation prior to the dissolution, indicating the influence of organized crime on council activities. Conversely, higher levels of confiscation are expected following the dissolution, reflecting the shift towards greater integrity and anti-mafia efforts. Since the law has been implemented in 1991, the number of dissolutions (obtained from *Wiki mafia*) presents no variability before that year. Therefore, my preferred specification will focus on the years between 1991 and 2012. Then, I measure the change in confiscation effort (*Delta confiscation*) generating two different variables. The first one is the difference between confiscations at time t+2 and confiscation at time t-1 ($Delta_3\ confiscation$). The second one is the difference between confiscation at time t+2 and confiscation at time t ($Delta_2\ confiscation$). The empirical strategy is the following:

$$Delta\ confiscation_{i,t} = \beta Dissolution_{i,t} + \gamma X_{i,t} + \alpha_i + \varepsilon_t + u_{i,t} \tag{B.2}$$

Intuitively, if many municipalities are dissolved for mafia penetration, I expect an increase in confiscation in the following years. This effect is captured by the coefficient β.

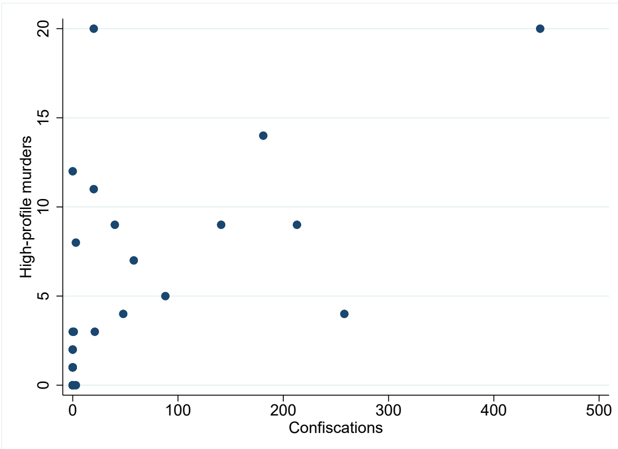
B.4 Empirical results for H3 and H4

B.4.1 H3: law enforcement reduces and stabilizes violence

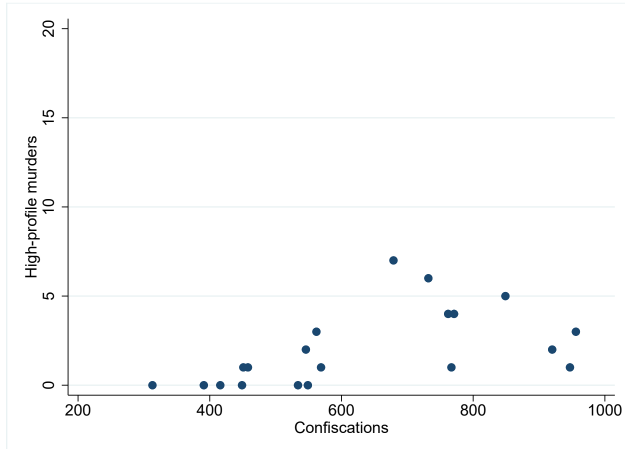
The effect of the introduction of harsh imprisonment is effectively illustrated in Figure B4. The four scatter plots demonstrate that the previously positive correlation between confiscation and high-profile murders significantly weakens, if not entirely disappears, after 1992. Moreover, in Table B15 I present the results of the OLS estimations of equation (B.1). All regressions include the full set of controls. In the first (last) two column2, I use high-profile murders (innocent victims) as dependent variable. In both cases, the coefficients are strongly significant: whereas asset confiscation increases external violence before 1992, the coefficient of the interaction term has same magnitude and opposite sign, suggesting that after 1992 the effect disappears. This is confirmed also by restricting the panel to the years between 1992 and 2012: confiscation has a negative effect on high-profile murders (column 2), and surprisingly, the negative effect is statistically significant at the 1% level of confidence for innocent victims (column 4).

B.4.2 H4: confiscation increases corruption

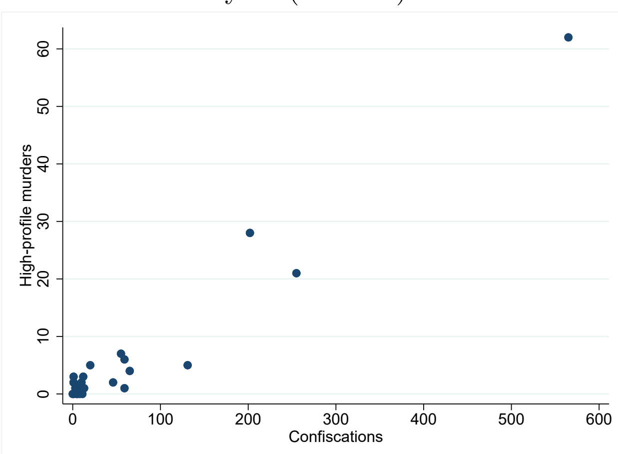
Table B16 presents the results of the OLS estimation of equation (B.2). In the first (last) two columns, the dependent variable is $Delta_3\ confiscation$ ($Delta_2\ confiscation$), i.e., the difference between confiscation at time t+2 and t-1 (t). In columns 1 and 3, I use the extended panel covering the years between 1950 and 2012, whereas in columns 2 and 4, I exclude the



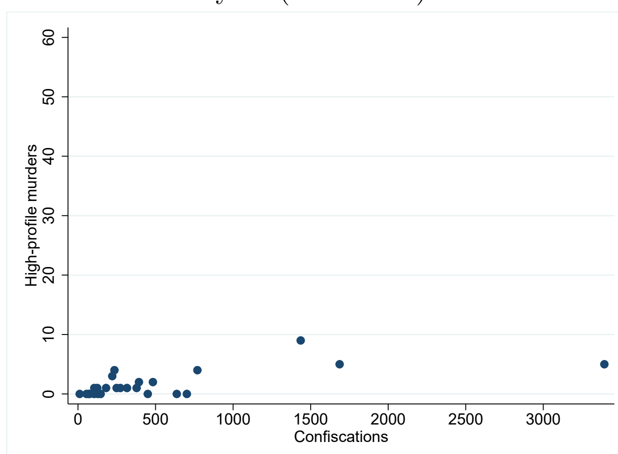
(a) Confiscations and High-profile murders, by year (1950-92)



(b) Confiscations and High-profile murders, by year (1992-2012)



(c) Confiscations and High-profile murders, by province (1950-92)



(d) Confiscations and High-profile murders, by province (1992-2012)

Figure B4: The relation between confiscations and high-profile murders, before (left panel) and after (right panel) the onset of law enforcement.

Notes: In the upper part I depict the annual relation between confiscations and high-profile murders in Southern Italy, before (top left panel) and after (top right panel) the introduction of harsh imprisonment regime (1992). In the bottom part I depict the relation between total confiscations of real estates and total high-profile murders in each province, before (top left panel) and after (top right panel) the introduction of harsh imprisonment regime (1992).

Y=	HP-murders		Innocent victims	
	(1)	(2)	(3)	(4)
Confiscation	.016***	-.003*	.063***	-.005***
	(.003)	(.002)	(.014)	(.001)
Confiscation*d	-.017***		-.062***	
	(.003)		(.013)	
Detainees 41 bis	-.005**	-.099***	-.015**	-.158***
	(.002)	(.024)	(.007)	(.015)
Time period	1950-2012	1992-2012	1950-2012	1992-2012
Full set of controls	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1575	525	1575	525
R-squared	.16	.45	.29	.35
Provinces	25	25	25	25

Table B15: Impact of confiscation and harsh imprisonment regime on high-profile murders and innocent victims-OLS results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

y=	$Delta_3$ confiscation		$Delta_2$ confiscation	
	(1)	(2)	(3)	(4)
Dissolution	6.693*	7.706*	5.562*	7.885*
	(3.371)	(3.811)	(3.341)	(3.966)
Full set of controls	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1575	550	1575	550
R-squared	.10	.14	.08	.10
Provinces	25	25	25	25

Table B16: The impact of confiscation on corruption-OLS results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

years before the introduction of the law on the dissolution of city councils for mafia penetration (1991). In all regressions, I employ the full set of economic and socio-demographic controls. All coefficients are positive and statistically significant, suggesting a positive correlation between the dissolution of a city council and the subsequent increase in confiscations. Note that these results also provide suggestive evidence in favor of the theoretical claim (Kugler et al., 2005) that harsher anti-mafia policies can generate higher crime rates as a result of mobsters' increased corruptive effort to avoid harsher forms of punishment (such as confiscations).

VARIABLES	N	mean	sd	min	max
MAIN VARIABLES					
Confiscation	98217	0.1496	2.9891	0	445
High-profile murders	98217	0.0018	0.0640	0	7
Detainees at harsh imprisonment regime (Art. 41bis)	98217	0.0701	1.3569	0	70
Profit (Access to ports*overdoses/1000000)	98217	.2734	1.401	0	78.673
Confiscation value (ten thousands)	98217	1.6415	63.658	0	10314.01
Innocent victims	98,217	.009	.1487	0	17
SOCIO-DEMOGRAPHIC CONTROLS					
Share of population under 25	98217	0.386	0.087	0.054	0.669
Share of illiterate population	98217	0.1009	0.0732	0.0004	0.5729
Share of population with university degree	98217	0.0227	0.0252	0.0001	0.5558
Log(population)	98217	8.4046	1.0950	5.1417	13.9978
ECONOMIC CONTROLS					
Share of labour force in building sector	98217	0.115	0.070	0	0.743
Share of male labour force searching first occupation	98217	0.023	0.056	0.000	0.849

Table C1: Summary statistics for the municipal panel.

y=HP murders	Absolute number			Dummy
	(1)	(2)	(3)	(4)
Confiscation	.015*	.015*	.015*	.033
	(.008)	(.008)	(.008)	(.022)
GDP and Pop controls		✓	✓	✓
Other controls			✓	✓
Time FE	✓	✓	✓	✓
Municipality FE	✓	✓	✓	✓
Observations	67037	67037	67037	67037
R-squared	.04	.04	.04	.01
Municipalities	1559	1559	1559	1559

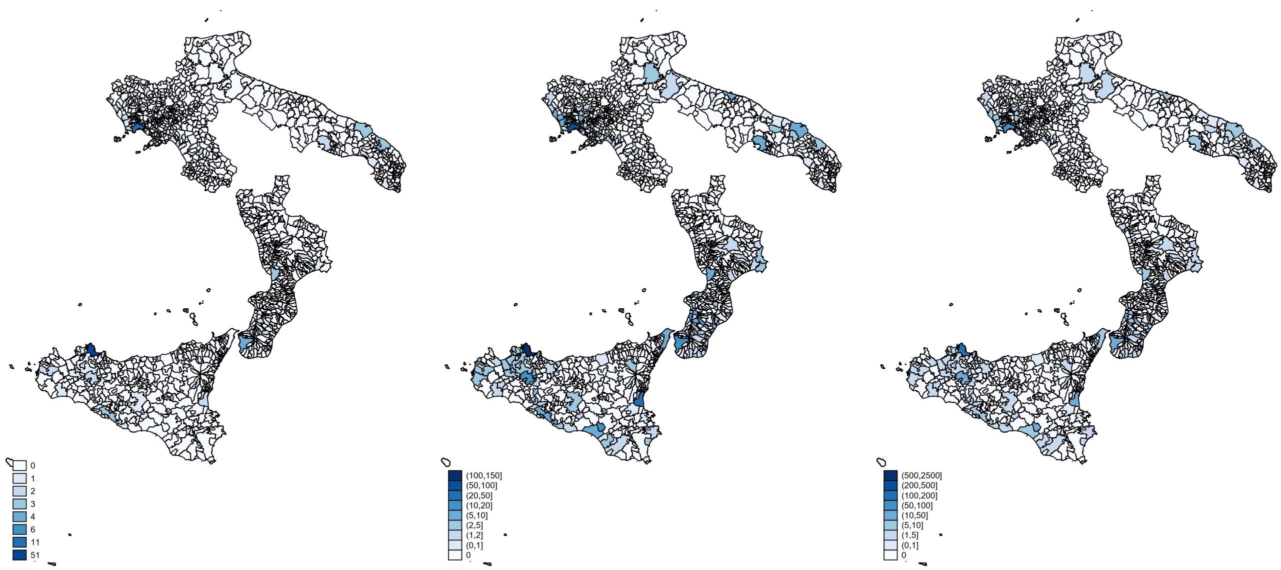
Table C2: The impact of confiscation on high-profile murders-OLS results.

Notes: Robust standard errors clustered at the municipal level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

Appendix C

Empirical analysis on Italian municipalities

In what follow I am going to replicate the analysis of the main text at the municipal level. In what follow I am going to replicate the analysis of the main text at the municipal level. Table C1 provides summary statistics for the variables of interest, while the spatial distribution of high-profile murders, innocent victims, and confiscations is illustrated in panels a, b, and c of Figure C1, respectively. Then, in Table C2 I replicate the analysis of Table 2, substantially confirming the results. As for the IV-analysis, I will directly show the result on the period 1972-1992 with the full set of controls. Moreover, given the high prevalence of 0 and 1, I mainly use dummies instead of count variables. Finally, I take a Cox Box (Box and Cox, 1964) transformation to my instrumental variable (drug profit), in order to reduce its variability with respect to



(a) High-profile murders (b) Innocent victims (c) Confiscations

Figure C1: Municipal distribution of high profile murders, innocent murders and confiscations in Sicily, Calabria, Campania and Apulia.

that of the endogenous variable (confiscation). The regression outcomes (always statistically significant) are shown in Table C3. However, the challenge posed by the low dimension of Italian municipalities is evident in the analysis, highlighted by the weak instrument problem in column 1, where the explanatory variable is the dummy for confiscation. To address this, I aggregate confiscation events along temporal and spatial dimensions (see the Notes). First, in column 2 I follow Table B6's strategy and use as dependent variable a dummy equal to 1 if at least one asset was confiscated ad time t or t+1. In this case, the Kleibergen-Paap F statistics

y=	HPM					Innocent victims				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Confiscation	.386**	.224**	.171**	.082*	.356***	1.863***	1.079***	.823***	.394***	.170***
	(.159)	(.111)	(.089)	(.049)	(.058)	(.652)	(.320)	(.230)	(.112)	(.034)
Full set of controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Period	1972-92	1972-92	1972-92	1972-92	1950-92	1972-92	1972-92	1972-92	1972-92	1950-92
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Municipality FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	32739	32739	32739	32739	45211	32739	32739	32739	32739	62360
R-squared	-.37	-.23	-.18	-.17	.36	-2.50	-1.52	-1.22	-1.15	.36
Municipalities	1559	1559	1559	1559	1559	1559	1559	1559	1559	1559
Kleibergen-Paap F statistics	8.02	12.93	14.76	27.63		8.02	12.93	14.76	27.63	

Table C3: The impact of confiscation on high-profile murders-IV and IVPPML results.

Notes: Robust standard errors (columns 5 and 10) clustered at the municipal level (columns 1-4 and 6-9) in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. In columns 1-4 and 6-9 I report the OLS coefficients, whereas in columns 5 and 10 I perform a Poisson Pseudo Maximum Likelihood estimation. The variable confiscation denotes: (i) a dummy equal to 1 if at least one asset was confiscated at time t in columns 1, 5, 6 and 10, (ii) a dummy equal to 1 if at least one asset was confiscated ad time t or t+1 in columns 2 and 7, (iii) a dummy equal to 1 if at least one asset was confiscated ad time t or t+1 or t+1 in columns 3 and 8, (iv) a dummy that takes value 1 if at least one asset was confiscated within 20 km of distance from the considered municipality (columns 4 and 9). First stage results are reported in Appendix D.

is higher than 10, suggesting a strengthening of the instrument. In column 3 I further enlarge the dummy for confiscation, assigning value 1 if at least one asset was confiscated from time t to time t+2, obtaining a further increase in the strength of the instrument. Then, in column 4 I create a dummy that takes value 1 if at least one asset was confiscated within 20 km of distance from the considered municipality, obtaining a considerable improvement in the Kleibergen-Paap F statistics. Moreover, I turn to count variables and estimate the Poisson Pseudo-Maximum Likelihood model from column 6 of Table B8, still confirming the results. Finally, I rerun all regressions using innocent victims as dependent variable, finding a remarkable increase in both the magnitude and significance of the coefficients.

Remarkably, whereas Table C3 suggests the existence of spillovers among municipalities, Table C4 draws the opposite conclusion regarding spillovers among provinces. Specifically, the first three columns replicate the analysis using the most demanding specifications from Tables 2, 5, and 6. These columns include an OLS and two IV regressions (with the second regression restricted to the years between 1972 and 1992), employing dummies as both dependent and explanatory variables, along with the full set of controls and fixed effects. Unlike the regressions in the main text, the explanatory variable is a dummy taking value 1 if at least one asset has been confiscated at time t in a contiguous province, and 0 otherwise. None of the coefficients is statistically significant. A similar conclusion is reached in column 4, where the explanatory variable is a dummy taking value 1 if at least a high-profile murders occurred in a contiguous province at time t and 0 otherwise. This result sharply contrasts with the findings from the municipality-year panel, thereby aligning closely with the discussed anecdotal evidence on the decision-making process of the Provincial Commission for high-profile murders (Catanzaro, 1992). This suggests ruling out the role of geographical spillovers across provinces in terms of both state responses and violence. As a final check on the impact of confiscations on high-profile murders at the municipal level, Table C5 replicates the staggered DID analysis of Table 3. All coefficients are positive and statistically significant, albeit with a lower magnitude compared to the estimations of the provincial model. This discrepancy is reasonable, considering the low average dimension of municipalities, which may lead to some murders occurring outside the boundaries of the municipality where the confiscation took place. Indeed, the difference between the coefficients of the provincial and municipal model decreases when using dummies instead of the count variables (columns 4 and 8).

External validity: the Colombian and Mexican cases

In this subsection I briefly summarize the recent history of the drug cartels-state interaction in Colombia and Mexico, finding many similarities with the pattern highlighted by Figure 1 for Italy. Then, I will also replicate a slightly modified version of the empirical exercises presented in the main text on the Mexican case.

y=High-profile murders (Dummy)				
X= Neighbouring (Dummy) for:	Confiscations			High-profile murders
	(1)	(2)	(3)	(4)
	OLS	IV	IV	OLS
X	-.015	1.460	1.079	-.016
	(.044)	(1.561)	(1.584)	(.028)
Full set of controls	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Period	1950-92	1950-92	1972-92	1950-92
Observations	1075	1075	525	1075
R-squared	.16	-1.99	-1.25	.16
Provinces	25	25	25	25
Kleibergen-Paap F statistics		2.28	.86	

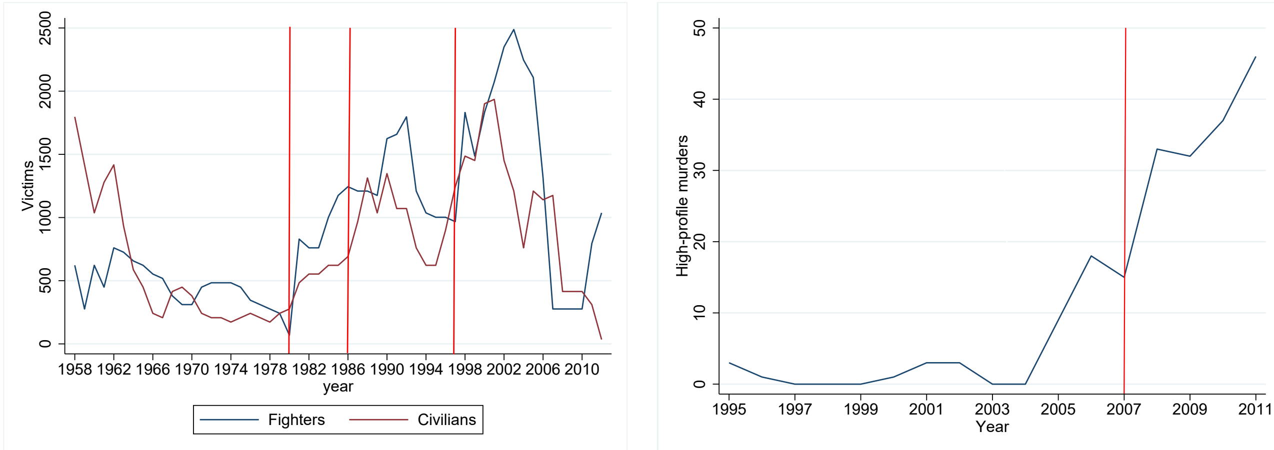
Table C4: The impact of confiscation in neighbouring provinces on high-profile murders-OLS and IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

y=	High-profile murders				Innocent victims			
	Absolute Value			Dummy	Absolute Value			Dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First treatment	.047*	.046*	.045*	.021**	.162**	.158**	.155**	.055***
	(.027)	(.027)	(.026)	(.009)	(.069)	(.067)	(.067)	(.015)
GDP and Pop controls		✓	✓	✓		✓	✓	✓
Other controls			✓	✓			✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	67037	67037	67037	67037	67037	67037	67037	67037
R-squared	.01	.01	.01	.01	.02	.02	.02	.02
Provinces	1559	1559	1559	1559	1559	1559	1559	1559

Table C5: The impact of the staggered introduction of confiscations-OLS (DID) results.

Notes: Robust standard errors clustered at the municipal level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.



(a) Victims of Colombian armed conflict. (b) High-profile murders in Mexico.

Figure C2: Drug cartels external violence in Latin America.

Notes (panel a): The three solid lines represent the introduction and subsequent strengthenings of the law on confiscation. Fighters is the sum of all armed actors (drug traffickers, paramilitaries, soldiers and policemen) *Notes (panel b):*The solid line in the right panel (own elaboration of Trejo and Ley (2021)) denotes the introduction of asset confiscation.

As depicted in Figure C2, homicides in Colombia remained relatively stable for twenty years in the mid-20th century, similar to the situation observed in Italy.

Previous studies (Acemoglu et al., 2013) claim that the sudden upsurge in violence that began in the Eighties despite the massive military effort exerted by the state followed the significant increase in drug profits obtained by the Colombian drug traffickers (who gained control of the growing cocaine market). Around the same time, the Colombian government implemented its first asset confiscation law in 1980, which became even stricter after the reforms of 1986 and 1997. The latter reform was soon (1999) followed by the aerial spraying of illegal-crop fields during the first phase of the "Plan Colombia"(Abadie et al., 2014), which lasted until 2005. Notably, Figure C2 (panel a) shows that these events coincide with a rapid upsurge in violence. Although distinguishing between victims among public officers, drug traffickers, and paramilitaries was not possible, the increase in the conflict intensity is evident, as also demonstrated by the boost in murders of civilians.

It is noteworthy that the steady decline in homicides began in the mid 2000s coincides with the onset of violence in Mexico (Figure C2, panel b). During the 1990s, Colombian drug traffickers faced a relative weakening compared to their Mexican counterparts, who gradually assumed control of the drug trade to the United States.

The literature on the Mexican drug war extensively discusses the impact of the victory of the PAN party and President Calderón's aggressive war on drugs, which led to the breakdown of the long-standing peaceful coexistence that had prevailed for over fifty years (Dell, 2015; Atuesta and Ponce, 2017). While this explanation accounts for the emergence of mafia wars in Mexico, Trejo and Ley (2021) argue and provide empirical evidence that violent state repression alone cannot fully explain the wave of high-profile assassinations in recent Mexican history.

Notably, despite the increased profits from the drug trade and the initial military crackdown initiated by President Vicente Fox (2000-2006), Mexican drug cartels were able to "peacefully coexist"for over a decade, avoiding direct a confrontation with the state.

Moreover, Figure C2 (panel b) shows that President Calderón's war on drugs, declared in 2006, did not immediately trigger a retaliatory response, as suggested by the slight reduction in high-profile murders which boosted only two years later.

Interestingly, during President Calderón's visit to Italy in 2007 (marked by the vertical red line), he expressed his intention to introduce asset confiscation measures inspired by the Rognoni-La Torre law.

In the remaining part of this section, I demonstrate that a strong positive relation between economic response and high-profile murders also emerges when analyzing the Mexican case (1995-2011). Note that the greater average dimension of Mexican municipalities with respect to the Italian ones allows me to aggregate data at the municipal level (descriptive statistic are reported in Table C6).

First, I merged municipal data on seizures (lagged by one year) from the CIDE-PPD database on events related to the Mexican Drug war (Atuesta and Ponce, 2017) with data coming from the work by Trejo and Ley (2021) on high-profile murders.

Then, I collected some socio-demographic and economic control variables from the Mexican censuses of 2000 and 2012 (INEGI). Formally, I estimate the following equation:

$$HPM_{i,t} = \beta_0 + \beta_1 seizure_{i,t-1} + \gamma X_{i,t} + \eta_i + \alpha_t + u_{i,t} \tag{C.1}$$

Finally, I adapt the instrument used in the main text to the features of Mexican drug trafficking by interacting deaths from overdose in the US with the distance of each Mexican municipality from the US frontier (Dell, 2015).

Although the available information provides less convincing support for the exclusion restriction hypothesis compared to the Italian case, the OLS and IV estimations (Table C7, columns 1-4) offer suggestive evidence in favor of the external validity of the results presented in the main text. As a further check, the last two columns corroborates these estimations employing the Staggered DID approach[35] used in Table 3.

Notably, the IV coefficients are more than three times the OLS ones. The OLS downward bias, likely attributable to reverse causality and measurement error, aligns with theoretical

[35] As for the Italian case, the parallel trends assumption is necessarily met, as there were almost no high-profile murders before 2006 (Figure Figure C2, panel b).

VARIABLES	N	mean	sd	min	max
Confiscation	41259	.129	3.001	0	407
High-profile murders	41259	.03	.481	0	46
Overdose	41259	22.707	8.628	11.133	37.443
Distance US	41259	15.788	13.628	0	105
Profit (thousands)	41259	3.394	5.935	.105	37.443
Log(population)	41243	9.339	1.49	4.517	14.362
Share of population under 25	41243	.26	.144	.026	.815
Share of illiterate population	41243	.134	.083	.008	.655
Unemployment rate	41243	.02	.024	0	.543

Table C6: Descriptive statistics for Mexican municipalities.

y=HPM	Absolute Number			Dummy		
	OLS	IV	DID	LPM	IV	DID
	(1)	(2)	(3)	(4)	(5)	(6)
Seizure(t-1)	.096***	.308***		.194***	.718***	
	(.021)	(.108)		(.022)	(.191)	
First treatment			.692***			.213***
			(.098)			(.014)
Controls	✓	✓	✓	✓	✓	✓
Observations	41243	41243	41243	41243	41243	41243
R-squared	.09	-.25	.07	.09	-.26	.14
Municipalities	2427	2427	2427	2427	2427	2427
Kleibergen-Paap F statistics		17.61			18.71	

Table C7: The impact of seizure on high-profile murders in Mexico.

Notes: Robust standard errors clustered at the municipal level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. First stage results are reported in Appendix D.

predictions and the results obtained in the main text.

Moreover, the magnitude of both OLS and IV coefficients is considerably higher than that found for the Italian mafias, and this difference is only marginally explainable by the (slightly) different set of control variables. Comparing Tables 5 and C7, one can see that, despite a lower number of confiscated assets, Mexico experienced a far more violent wave of lethal attacks towards the institutions. Last, note that (see Appendix D) in the first stage the instrument is negatively correlated with the endogenous variable, i.e. increase in profit are associated with a reduction in seizures.

I interpret these differences with the Italian case as a suggestive evidence of the effect of effective law enforcement.

Notably, Figure 3 depicts a discontinuous downward jump in confiscations after the onset of mafia violence but before that of law enforcement. In those intervals, confiscations are actually negatively correlated with profits. I speculate that, despite the massive military investment *strictu sensu*, the Mexican state was not effectively achieving the elimination of the mightiest mobsters.

For instance, the New York Times (2009) documented that imprisoned Mexican drug lords enjoyed approximately the same freedom they had before being convicted to jail, similar to the

y=Confiscation	Number of asset			Dummy
	(1)	(2)	(3)	(4)
Profit	.306***	312***	.300***	.009***
	(.045)	(.047)	(.041)	(.002)
GDP and Pop controls		✓	✓	✓
Other controls			✓	✓
Period	1950-92	1950-92	1950-92	1950-92
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1075	1075	1075	1075
R-squared	.19	.19	.21	.43
Provinces	25	25	25	25

Table D1: The impact of confiscation on high-profile murders and innocent victims-IV first stage results

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^6.

Italian situation before the introduction of harsh imprisonment regime in late 1992. Remarkably, Figures 1 (panel b) and 6 show that for the whole Eighties up to the early Nineties (i.e., between the onset of confiscation and the introduction of the harsh imprisonment regime) confiscation were negatively related to drug profit also in Italy.

Appendix D

In what follows, I present the first stage of all IV regressions. In Table D1, I show the first stage results of the regressions presented in Table 5.

The first stage results of columns of Table 6 are reported in Table D2.

Next, Table D3 reports the first stage of columns 5-8 of Table B2, whereas Table D4 reports the first stage of columns 3 and 6 of Table B3. Table D5 reports the first stage of columns 2, 4 and 6 of Table B6.

Then, Table D6 presents the first stage results of columns 5-7 of Table B8, whereas Table D7 reports the first stage of columns 2-4 of Table B10. Next, Table D8 displays the first stage of columns 2,4 and 6 of Table B11. Next, Tables D9 reports the first stage regressions of Table B12. Then, in Table D10 I report the first stage of columns 1-5 of Table C3. Finally, Table D11 shows the first stage for columns 2 and 3 of Table C4, whereas Table D12 shows the first stage for columns 2 and 4 of Table C7.

y=Confiscation				
	(1)	(2)	(3)	(4)
Profit	617***	.658***	243***	.235***
	(.067)	(.083)	(.039)	(.034)
GDP and Pop controls	✓	✓	✓	✓
Other controls		✓		✓
Period	1972-92	1972-92	1950-92	1950-92
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	525	525	1075	1075
R-squared	.19	.21	.19	.21
Provinces	25	25	25	25

Table D2: The impact of confiscation on high-profile murders and innocent victims, 1972-1992-IV first stage results

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^6.

y=Confiscation	Absolute number			Dummy
	(1)	(2)	(3)	(4)
Profit	.306***	.312***	300***	.009***
	(.086)	(.087)	(.085)	(.002)
GDP and Pop controls		✓	✓	
Other controls			✓	✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1075	1075	1075	1075
R-squared	.19	.19	.21	.43
Provinces	25	25	25	25

Table D3: The impact of confiscations on high-profile-murders-IV first stage results.

Notes: Bootstrap standard error in parentheses. In all columns the number of bootstrap samples is 1000. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

y=Confiscation	Absolute number	Dummy
	(3)	(6)
Profit × Mafia regions	.390***	.014***
	(.098)	(.004)
Full set of controls	✓	✓
Time FE	✓	✓
Province FE	✓	✓
Observations	4730	4730
R-squared	.12	.23
Provinces	110	110

Table D4: The impact of confiscation on high-profile murders in Italy-First stage IV results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

y=Confiscation^T	Absolute number		Dummy
	(2)	(4)	(6)
Profit	.680***	655***	.008***
	(.156)	(.139)	(.002)
GDP and Pop controls	✓	✓	✓
Other controls		✓	✓
Period	1950-92	1950-92	1950-92
Time FE	✓	✓	✓
Province FE	✓	✓	✓
Observations	1075	1075	1075
R-squared	.24	.27	.52
Provinces	25	25	25

Table D5: The impact of two years confiscations on high-profile murders-IV first stage results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^3.

y=confiscation			
	(5)	(6)	(7)
Profit	.306***	.312***	.300***
	(.043)	(.046)	(.046)
Full set of controls	✓	✓	✓
Period	1950-92	1950-92	1950-92
Time FE	✓	✓	✓
Province FE	✓	✓	✓
Observations	1075	1075	1075
R-squared	.19	.19	.21
Provinces	25	25	25

Table D6: The impact of confiscation on high-profile murders-PPML and IV PPML results.

Notes: Robust standard error in parentheses. The variable profit is divided by 10^6.

y=Confiscation		
	(2)	(4)
Profit	223***	.543***
	(.036)	(.068)
Full set of controls	✓	✓
Period	1950-92	1972-92
Time FE	✓	✓
Province FE	✓	✓
Observations	731	357
R-squared	.27	.28
Provinces	17	17

Table D7: Accounting for different levels of mafia penetration-IV first stage results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^6.

y=Total Confiscation	Number of asset		Dummy
	(1)	(2)	(3)
Profit	321***	.309***	.009***
	(.050)	(.043)	(.002)
GDP and Pop controls	✓	✓	✓
Other controls		✓	✓
Period	1950-92	1950-92	1950-92
Time FE	✓	✓	✓
Province FE	✓	✓	✓
Observations	1075	1075	1075
R-squared	.19	.21	.43
Provinces	25	25	25

Table D8: The impact of total confiscation on high-profile murders-IV first stage results

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^6. Total confiscation denotes the number of real estates and firms confiscated at time t.

y=Confiscation	Absolute Value		Dummy	
	(1)	(2)	(3)	(4)
Profit (East coast)	2.051***	2.303***	.060***	.074***
	(.282)	(.339)	(.008)	(.008)
East coast territories	States	Counties	States	Counties
Full set of controls	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	1075	1075	1075	1075
R-squared	.20	.20	.41	.41
Provinces	25	25	25	25

Table D9: The impact of confiscations on high-profile-murders and innocent victims-alternative IV first stage results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit (East coast) is divided by 10^6.

y=Confiscation					
	(1)	(2)	(3)	(4)	(5)
Profit	.069***	.119***	156***	.327***	.315***
	(.024)	(.033)	(.041)	(.062)	(.033)
Full set of controls	✓	✓	✓	✓	✓
Period	1972-92	1972-92	1972-92	1972-92	1950-92
Time FE	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓
Observations	67037	67037	67037	67037	67037
R-squared	.02	.04	.05	.26	.01
Municipalities	1559	1559	1559	1559	1559

Table D10: The impact of confiscation on high-profile murders and innocent victims-IV and IVPPML first stage results.

Notes: Robust standard errors (column 5) clustered at the municipal level (columns 1-4) in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit(square root) is divided by 10^3.

y=Neighbouring (Dummy) for:	Confiscations	
	(2)	(3)
Profit	.004	.004
	(.003)	(.004)
Full set of controls	✓	✓
Time FE	✓	✓
Province FE	✓	✓
Period	1950-92	1972-92
Observations	1075	525
R-squared	.65	.58
Provinces	25	25

Table D11: The impact of confiscation in neighbouring provinces on high-profile murders-IV first stage results.

Notes: Robust standard errors clustered at the provincial level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^6.

y=Seizure(t-1)	Absolute number	Dummy
	(2)	(4)
Profit	-.013***	-.001***
	(.003)	(0)
Controls	✓	✓
Observations	41243	412433
R-squared	.03	.08
Municipalities	2426	2426

Table D12: The impact of seizure on high-profile murders in Mexico- IV first stage.

Notes: Robust standard errors clustered at the municipal level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable profit is divided by 10^3.

Organized Crime, Violence, and Targeted Repression*

Alessio Carrozzo Magli[1], Piero Manfredi[2], Paolo Vanin[1]

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[1] Dipartimento di Scienze Economiche, Università di Bologna, Piazza Scaravilli 2, 40126 Bologna, (Italy).

[2] Dipartimento di Economia & Management, Università di Pisa, Via Ridolfi 10, 56124 Pisa, (Italy).

Abstract

We study the effects of targeted repression of organized crime on inter-clan violence and illegal activity. We investigate the possible trade-off between curbing violence and illegal activity. If clans fight for territorial control, targeting the strongest ones reduces violence, but if surviving clans are the most productive, it also boosts illegal activity and profits. Targeting the weakest clans has opposite effects. If instead clans are able to sustain a peaceful territory-splitting agreement, targeting the strongest clans may raise violence by triggering a succession war. Conversely, targeting the weakest clans may allow the strongest ones to peacefully thrive. Our theoretical analysis helps interpret the evolution of violence and illegal activity after different kinds of repressive policy adopted in Italy, Mexico and Colombia.

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1 Introduction

Curbing criminal organisations such as drug cartels or mafia clans is one of the most formidable challenges faced by many governments. One source of difficulty, which has attracted substantial attention by economists, is the possibility that criminal organizations use corruption and violence to condition electoral outcomes (Acemoglu et al., 2013, De Feo and De Luca, 2017) or elected politicians and public officials' behavior (Alesina et al., 2019, Dal Bó and Di Tella, 2003, Dal Bó et al., 2006, Kugler et al., 2005). Another challenge comes from the fact, when cartels or clans fight one another to control illegal markets, governments may face a trade-off between curbing violence and reducing illegal activities. This may happen if, by eliminating some players, repression makes it easier for the surviving ones to reach a peaceful collusive agreement (Castillo and Kronick, 2020, Kleiman, 2011, Lessing, 2015). Alternatively, by removing an important part of illegal production, repression may trigger a succession war (Calderón et al., 2015, Durán-Martínez, 2017, Snyder and Duran-Martinez, 2009).

In this paper, we abstract from corruption and violence against the state, and instead focus on state's trade-off between inter-clan violence and illegal activity. We develop a model in which heterogeneous profit-seeking clans may split the territory either through violent fight or through peaceful bargaining under the threat of violence, and then produce and sell as local monopolists in the controlled territory. The question we ask is whether targeting repression activities towards clans with specific characteristics, such as the stronger or the weaker ones, is more or less conducive to inter-clan violence and illegal activity.

When war is unavoidable, if clans specialize in productive or predatory activities, so that strong clans are less productive than weak ones, eliminating the former (what we call targeted repression) may reduce violence and increase illegal profits, because it allows the most productive clans to expand and gain additional market shares, while spending less on fighting one another. Targeting the weakest ones (anti-targeted repression) would have the opposite effect. This type of repression is possibly quite common in reality, for example in a weak-state setting (Acemoglu et al., 2020, La Ferrara and Bates, 2001) or -as we will argue later on - due to information issues: it is the weakest clans i.e., the "losing" ones, that are more likely to provide information to state bodies (Gambetta, 1996).

When peaceful agreements may be sustained under the threat of violence, the effects are different. Since targeted repression reduces clans' violence in case of war, it weakens the threat that allows sustaining peace in equilibrium, possibly triggering a succession war. Conversely, anti-targeted repression raises the cost of war and may allow strong clans to peacefully thrive: in this case, the state would "do the dirty job" for strong clans by eliminating their weaker competitors. Clearly, the effects and desirability of targeted repression activities change if the strongest clans are also the most productive, as we study in the next sections.

We present original evidence that anti-targeted repression in southern Italy reduced inter-clan violence. In particular, we leverage a whistle-blower protection program that led to a surge in the number of justice collaborators, especially belonging to weaker clans, and which disproportionately led to the capture and conviction of members of weak clans.

Our results on targeted repression help understand the striking surge in violence documented in Mexico after the War on Drugs declared in December 2006 by the elected president Calderón (Atuesta and Ponce, 2017, Osorio, 2015). Dell (2015) demonstrates that the crackdown of incumbent clans following state repression resulted in an increase in violence justified by the attempt of new strains of criminals to usurp the former' influence area, whereas Osorio (2015) and Atuesta and Ponce (2017) argue that such crackdowns altered the pre-existing balance of power between the surviving clans.

Similarly, our theory aligns with the violent escalation observed after the elimination of Pablo Escobar in 1993 as well as that following the subsequent repressive military measures implemented to enforce the "Colombia Plan" between 1999 and 2005 (Abadie et al., 2014).

Our work contributes to two main strands of literature. First, it adds to the research on the strategic interactions between states and large-scale criminal organizations. Besides the studies on the lobbying power of organized crime cited above, several authors have studied how crackdowns affect mafia attacks against the state and its representatives (Lessing, 2017, Ríos, 2013, Trejo and Ley, 2021). We contribute to this strand by analysing instead the impact of state repression on internal struggles. Second, this work complements the recent literature on mafia wars. Whereas the aforementioned empirical evidence suggests that internal struggles tend to increase after state crackdowns against incumbent criminal clans, especially if the market still demands for the contested "criminal" services (Phillips, 2015), theoretical investigations in this area are scarce and often yield ambiguous results.

Among these, Castillo and Kronick (2020) have developed a repeated game framework involving symmetric drug cartels, arguing that a credible threat of beheading against (the most) violent clans decreases the incentive to engage a mafia war (Kleiman, 2011). Instead, introducing military and economic asymmetries, we study the impact of the actual implementation of different repression strategies on inter-clan violence and on the volume of illegal activity. Last, our work has the ultimate goal to identify the best intervention strategies against large scale criminal organizations i.e., whether to attack all clans rather than a only a few, and, in the latter case, whether to attack strong or weak clans.

The rest of the article is organized as follows. Section 2 presents a game-theoretic model of inter-clan violence and illegal activity. Section 3 introduces different types of targeted repression strategies by the state, and studies their impact in a one-shot game. Section 4 extends the analysis to a repeated game. Section 5 presents empirical evidence for Italy supporting the prediction that anti-targeted repression may reduce violence, and Section 6 discusses evidence that targeted repression in Mexico and Colombia increased violence. Concluding remarks follow.

2 A model of inter-clan violence and illegal activity

This section is organized as follows. Section 2.1 introduces a baseline model in which heterogeneous clans fight for territory and then produce and sell on the territory share they control. Section 2.2 derives the equilibrium in the one-shot game, which can be completely characterized in closed form under a specific distribution of clans' strength, as shown in Section 2.3.

2.1 The model setup

Consider a two-stage game among N criminal clans, who can produce and sell a good (e.g., protection or drug) to some buyers, but who use violence to gain access to buyers and exclude competitors. We assume that buyers have a linear demand $q^D(p) = a - p$ for the good, which is homogeneously distributed within a territory of length one.

At stage one, all clans $i \in 1, ..., N$ choose a level of violence $g_i \geq 0$, and obtain control over a territory share $\theta_i = \frac{g_i}{G}$, where $G = \sum_{i=1}^{n} g_i$ and n are active clans (those with $g_>0$), according to the standard ratio contest function à la Tullock (1980) often used in the conflicts literature (Corchón, 2007, Garfinkel and Skaperdas, 2007, Hirshleifer, 1991).

At stage two, clans choose the their level of output q_i, which they sell as local monopolists in the share of territory they control. Consequently, the demand enjoyed by clan i is $q^D(p_i) = \frac{g_i}{G}(a - p_i)$, which generates an inverse demand $p(q_i) = a - \frac{G}{g_i} q_i$.

We assume that clans are heterogeneous in both productive and military strength, as reflected in different marginal costs of output, b_i, and violence, c_i. Their goal is to maximize profits

$$W_i = [p(q_i) - b_i]q_i - c_i g_i \tag{1}$$

2.2 The one shot game

The game is solved by backward induction, starting from the second stage. As local monopolists, clans produce quantity

$$q_i^* = \frac{a - b_i}{2}\frac{g_i}{G}, \tag{2}$$

sell it at price $p(q_i^*) = \frac{a+b_i}{2}$, and make profits $W_i = \frac{g_i}{G}\pi_i - c_i g_i$, where

$$\pi_i = \left(\frac{a - b_i}{2}\right)^2 \tag{3}$$

are operating profits per unit of territory.[1] Maximizing this with respect to g_i yields an equilibrium in the first stage, in which the $n \leq N$ strongest clans are active. It is convenient to summarize clan i's (inverse) "overall strength" by

$$x_i = \frac{c_i}{\pi_i}. \tag{4}$$

A clan is stronger, the lower its x_i, i.e., the lower its marginal costs of violence and production, c_i and b_i. Letting $\bar{x}_n = \frac{1}{n}\sum_{i=1}^{n} x_i$ denote the average strength of active clans, the equilibrium

[1] Differentiating equations (1) with respect to q_i we obtain the system of first order conditions (FOCs), $a - 2\frac{G}{g_i}q_i - b_i = 0$. Observe that clans with different productivity sell at different prices, but buyers cannot move and change providers because of the violent control over the territory.

is characterized by[2]

$$
\begin{cases}
G^* = \frac{n-1}{n\bar{x}_n} \\
g_i^* = G^* \left(1 - G^* x_i\right) \\
W_i^* = \left(\frac{g_i^*}{G^*}\right)^2 \pi_i.
\end{cases}
\tag{5}
$$

Three observations are in order. First, the stronger a clan, the larger the amount of violence it exerts and the larger the territory share it controls: $\theta_i^* = \frac{g_i^*}{G^*} = 1 - \frac{(n-1)x_i}{n\bar{x}_n}$. Second, the overall level of violence G^* is increasing in the (endogenous) number n of active clans and in their average strength. Third, active clans' equilibrium profits are equal to the square of their territory share times their operating profits per unit of territory.[3] To gain additional insights, it is useful to focus on a specific strength distribution.

2.3 Closed-form solution under uniform strength distribution

To obtain closed-form solutions for all variables, including total criminal output and profits, we approximate the distribution of overall strength across the N clans by a continuous uniform distribution over the interval $[\alpha, \beta]$. We rank clans in order of strength, so that lower indices correspond to stronger clans: $x_i > x_j \iff i > j$. Hence, x_n denotes the strength of the marginal clan, the one that in equilibrium makes zero profits and determines the set of active clans $\{1, ..., n\}$. The model is solved analytically for $\beta > \alpha > 0$ in Appendix A. Here, for the sake of illustration, let $\alpha = 1$, $\beta = 2$. When $x_i \sim U[1, 2]$, the number of active clans, their average strength and the strength of the marginal clan become[4]

$$
\begin{cases}
n^* = 1 + \sqrt{1 + 2N} \\
\bar{x}_n^* = 1 + \frac{1+\sqrt{1+2N}}{2N} \\
x_n^* = 1 + \frac{1+\sqrt{1+2N}}{N}
\end{cases}
\tag{6}
$$

[2] Maximizing first stage profits (i.e., W_i when producing q_i^*) with respect to g_i yields the system of FOCs $\frac{G_{-i}}{G^2}\pi_i - c_i = 0$, where $G_{-i} = \sum_{k \neq i} g_k$ is the total violence exerted by all clans but i. The previous equations have a unique solution for g_i. Differentiating again the LHS with respect to g_i (which enters only at the denominator of the first order condition) yields a negative expression. In other words, the second order conditions are verified and the optimization problem admits a unique maximum, which is economically meaningful. Summing the FOCs and solving for G yields G^* in 5, which plugged in the FOCs gives G_{-i}, and subtracting this from G^* one gets g_i^* and hence W^* in 5.

[3] Active clans are those with $g_i^* > 0$, that is $\frac{x_i}{\bar{x}_n} < \frac{n}{n-1}$. Heterogeneous clans may be active as long as competition is not too fierce; if the (endogenous) number n of active clans were very large, the condition for being active would essentially become $x_i = \bar{x}_n$, meaning that only the clans with the highest possible strength level would be active.

[4] With $x_n \in [1, 2]$ and a uniform distribution, the number of active clans is $n = N(x_n - 1)$ and their average strength is determined by integrating over the truncated distribution: $\bar{x}_n = \frac{\int_1^{x_n} x_i dx_i}{x_n - 1} = \frac{1+x_n}{2}$. Substituting this value in the condition for the marginal clan, $g_n^* = 0$, i.e., $\frac{x_n}{\bar{x}_n} = \frac{n}{n-1}$, and solving for x_n yields the strength of the marginal active clan. From this, one immediately derives $\bar{x}_n$ and n. The latter is generally non-integer due to the continuous approximation of the strength distribution.

Plugging 6 into 5, we can write:

$$\begin{cases} G^* = \frac{1}{x_n^*} \\ g_i^* = \frac{x_n^* - x_i}{(x_n^*)^2} \\ W_i = \left(1 - \frac{x_i}{x_n^*}\right)^2 \pi_i \end{cases} \tag{7}$$

where clan i controls territory share $\theta_i^* = \left(1 - \frac{x_i}{x_n^*}\right)$.[5]

These equilibrium conditions have simple and important comparative static properties in N. The higher N, the higher the levels of competition among active clans (n^*), marginal and average strength (lower x_n^* and $\bar{x}_n^*$), and total violence (G^*), and the lower the levels of each active clan's individual violence (g_i^*), territory share (θ_i^*) and profit (W_i^*).[6]

The assumption on the distribution of x_i allows summarizing in a compact way two dimensions of heterogeneity –economic productivity and military strength– and providing a simple equilibrium characterization. At the same time, while necessarily establishing a link between these two dimensions, due to the way in which overall, economic and military strength are related (equations 3 and 4), this formulation is also very flexible. In particular, it is compatible with different relations between productive and military strength, $b_i = b(x_i)$ (with $c_i = x_i(a - b(x_i))^2/4$).

Given a particular relation $b_i = b(x_i)$, one can simply compute the total levels of criminal output and profit:

$$\begin{cases} Q^* = N \times \int_1^{x_n} \frac{a - b(x_i)}{2} \left(1 - \frac{x_i}{x_n}\right) dx_i \\ W^* = N \times \int_1^{x_n} \left(\frac{a - b(x_i)}{2}\right)^2 \left(1 - \frac{x_i}{x_n}\right)^2 dx_i \end{cases} \tag{8}$$

We will focus on the following possibilities:

- **Independence (I)**: all clans are equally productive, $\forall i : b_i = b$
- **Specialization (S)**: stronger clans are less productive, $\forall i, j : b_i \leq b_j \iff x_i \geq x_j$
- **Complementarity (C)**: stronger clans are more productive, $\forall i, j : b_i \leq b_j \iff x_i \leq x_j$

Notice that in equilibrium stronger clans control larger territory shares, so the above conditions may be rephrased as establishing whether clans with larger territory shares are more or less productive than their competitors.

The case of Independence is particularly simple, as there is only one dimension of heterogeneity, namely military strength.[7] This implies that, despite the fact that stronger clans are more violent and control larger territory shares, all active clans sell at the same price and produce the same quantity per unit of territory, so that operating profits (per unit of territory and aggregate) as well as total criminal output are independent of N, whereas total criminal profits

[5] More explicitly, the expressions in 7 can be written as $G^* = \frac{N}{1+N+\sqrt{1+2N}}$, $g_i^* = \frac{N(1+N+\sqrt{1+2N}-Nx_i)}{(1+N+\sqrt{1+2N})^2}$ and $W_i^* = \left[1 - \frac{Nx_i}{(1+N+\sqrt{1+2N})}\right]^2 \pi_i$.

[6] Observe that our continuous approximation makes sense for large values of N. For instance, if there are 100 clans, then approximately 15 will be active.

[7] Letting $\pi = (a-b)^2/4$, $x_i \sim U[1, 2]$ implies $c_i \sim U[\pi, 2\pi]$.

decrease in N because higher competition generates more violence, whose costs reduce profits. Under Independence, as $b(x) = b$, one has

$$\begin{cases} Q_I^* = \frac{a-b}{2} \\ W_I^* = \frac{(a-b)^2}{3(1+\sqrt{1+2N})} \end{cases} \tag{9}$$

The case of Specialization considers the possibility that clans are specialized either productive or predatory skills (Dal Bó and Dal Bó, 2011, Garfinkel and Skaperdas, 2007, Konrad and Skaperdas, 2012). For instance, for drug-refining clans, it might be the case that some clans have good soldiers and bad chemists, and therefore control large territory shares but have low productivity, whereas for other clans it is the other way around. The case of Complementarity may be intuitively more appealing if one thinks of mafia clans offering protection, and if the capacity to exert or threaten violence is a key input in the production process of protection (Gambetta, 1996). In that case, stronger clans would be more productive. Criminal organizations in reality may offer both protection and drugs, and may be involved in a variety of other legal and illegal businesses. Scholars and governments may often more easily have information on their strength and controlled territory than on their productivity, making the mapping between the different theoretical cases and actual criminal organizations somewhat difficult. Even more, the conditions generating Specialization or Complementarity might change over time, a possibility we do not investigate. Still, focusing on the above mentioned cases is insightful on the possible trade-off between violence and illegal activity.[8]

3 Targeted state repression

3.1 Repression strategies

The above equilibrium has been characterized in the absence of any state intervention. We therefore refer to it as *Laisser faire*. Yet, the state may try to fight criminal organizations in different ways, for instance because it aims at reducing violence (G), or the negative externalities associated to the volume of illegal activities (Q), or the overall amount of illegal profits (W) that allow criminal organizations to thrive. We remain agnostic on the weight of G, Q and W in the state objective function, and we study the impact of different repression strategies on all these elements.

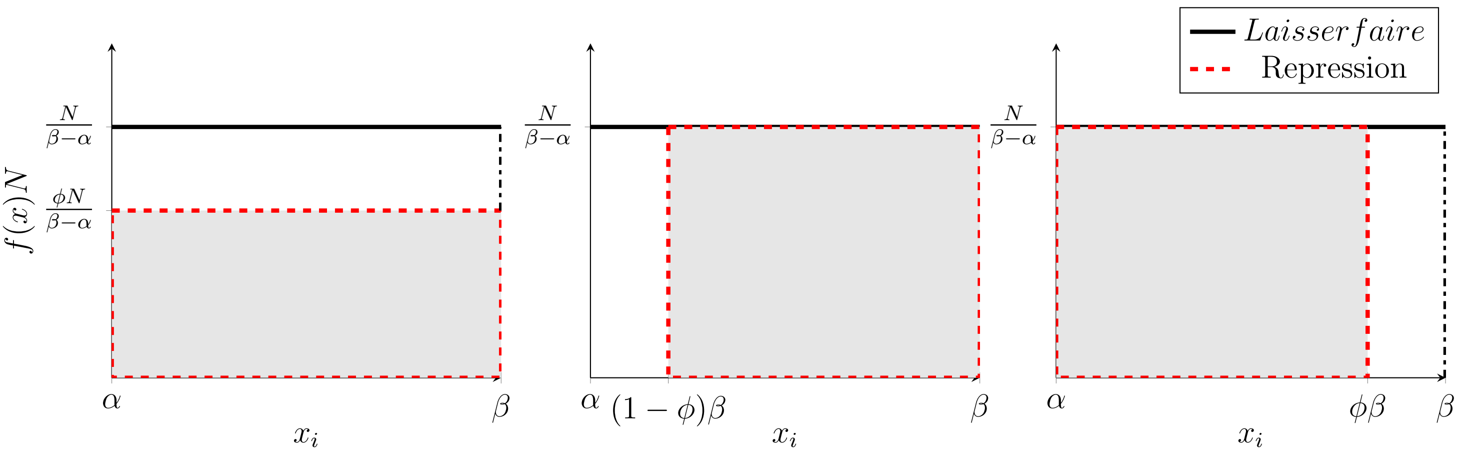
We compare the impact of targeted and non-targeted repression strategies, under the assumption that before stage one the state observes the strength distribution, and has the possibility to intervene and the capacity to eliminate a fraction $1 - \phi$ of the N clans. The illegal market then adjusts accordingly. We represent state repression by appropriate "cuts" to the absolute

[8] As in 9, under specific assumptions on $b(x)$ one can obtain analytic expressions for total illegal output and profits also in the other cases. Two simple examples are $b(x) = a - x$ for Specialization and $b(x) = x$ for Complementarity. In the former case one has $Q_T^* = \frac{1+3N+\sqrt{1+2N}}{6N}$ and $W_T^* = \frac{1+\sqrt{1+2N}+5N\sqrt{1+2N}}{30N^2}$, in the latter $Q_C^* = \frac{3N(a-1)-(1+\sqrt{1+2N})}{6N}$ and $W_C^* = \frac{1+\sqrt{1+2N}+5N(a-1)(\sqrt{1+2N}(a-1)-a)}{30N^2}$. The results we derive in the following sections are more general than these specific examples.

(i.e., non-normalised) distribution of overall strength among clans, given by $Nf(x)$ (Figure 1), where $f(x) = \frac{1}{\beta-\alpha}$ is the density of the uniform distribution. We consider the following repression strategies:

- **Un-targeted (U)**: elimination of clans irrespective of their strenght
- **Targeted (T)**: elimination of the strongest clans
- **Anti-targeted (A)**: elimination of the weakest clans
- **Laisser faire (*)**: no intervention

Formally, Targeted repression generates a left tale truncation of the distribution of x_i. Anti-targeted repression corresponds to a right tale truncation, eliminating some clans that in the absence of intervention would have been inactive and some that would have been active. Un-targeted repression is the elimination of a uniform subset of clans for each strength level, which uniformly lowers the absolute strength distribution. Under Laisser faire, the equilibrium is as characterized in the previous section.



(a) Un-targeted repression (b) Targeted repression (c) Anti-targeted repression

Figure 1: Repression: elimination of a fraction $1-\phi$ of the clans under uniform strength distribution

Notes: The grey area represents the number (and overall strength level) of surviving clans after repression, whereas the white area below the dark bold line represents the number (and overall strength level) of eliminated clans.

3.2 Impact of repression strategies in the one-shot game

What is the aggregate effect of the different repression strategies on violence, and on illegal output and profits? It turns out that they can be ordered. Let us denote by U, T, A and $*$ the strategies outlined above (un-targeted, targeted, anti-targeted repression, and laisser faire, respectively) and by subscript I, S and C the cases of independence, specialization and complementarity.

Proposition 1: In the one-shot game, targeted repression minimizes violence, followed by un-targeted and anti-targeted repression, and laissez faire maximizes violence:

$$G^T < G^U < G^A < G^*$$

Proof.
See Appendix A.

The intuition is straightforward. Let us start from un-targeted repression: relative to laisser faire, it acts in the same way as a reduction of N. As noticed above, this reduces competition (the number of active clans), expands their territory shares, and reduces individual and total violence ($G^U < G^*$). Anti-targeted repression has all these effects, but the marginal and average active clan is stronger under A than under U ($G^U < G^A < G^*$). Targeted repression instead makes weaker clans enter in place of stronger ones, increases competition, reduces territory shares, and reduces average strength and violence ($G^T < G^U$).
Let us now turn to the impact on the volume of illegal activities.

Proposition 2: In the one-shot game, the volume of illegal output is as follows:

1. Under Independence, illegal output is constant across policies.

2. Under Specialization, anti-targeted repression minimizes illegal output, followed by laisser faire, un-targeted and targeted repression:

$$Q_S^T > Q_S^U > Q_S^* > Q_S^A$$

3. Under Complementarity, targeted repression minimizes output, followed by un-targeted repression, laisser faire and anti-targeted repression:

$$Q_C^T < Q_C^U < Q_C^* < Q_C^A$$

Proof.
See Appendix A.

As argued above, under Independence all active clans sell at the same price and produce the same quantity per unit of territory, so that total output is independent of the number of active clans and their territory shares, and hence of repression policies. Under Specialization, anti-targeted repression eliminates the weakest clans and leaves the market to stronger but less productive ones. Under Complementarity, the opposite holds.
Finally, we turn to the effect on total illegal profits.

Proposition 3: In the one-shot game, total illegal profits are as follows:

1. Under Independence, targeted repression minimizes illegal profits, followed by laisser faire, anti-targeted repression and un-targeted repression:

$$W_I^U > W_I^A > W_I^* > W_I^T$$

2. Under Specialization AND if b_i is a sufficiently steep function of x_i, then anti-targeted repression minimizes the total profits:

$$W_S^T > W_S^U > W_S^* > W_S^A$$

3. Under Complementarity, targeted repression minimizes illegal profits. If b_i is a sufficiently steep function of x_i, it is followed by laisser faire, un-targeted repression and anti-targeted repression:

$$W_C^A > W_C^* > W_C^U > W_C^T$$

Proof.
See Appendix A.

Under Independence and Complementarity, stronger clans are more profitable. Hence, eliminating them minimizes illegal profits. Under Specialization, the relation between a clan's strength and its profitability is less trivial: weaker clans have lower territory shares but are more productive, so they make larger profits only if they are sufficiently more productive. In this case, it is the elimination of weaker clans that minimizes illegal profits.
The main insights from the one-shot game can be summarized as follows. Targeted repression minimizes violence. Under Independence or Complementarity, it also minimizes illegal output and profits. Yet, under Specialization, it poses a trade-off, because it maximizes output and, if weaker clans are sufficiently more productive, also profits. Anti-targeted repression does the opposite, whereas un-targeted repression generates intermediate outcomes.

4 The repeated game

In the one-shot game outlined so far the actual display of violence is unavoidable, as there is no other mean of defining territory shares and, if other clans do not exert any violence, then any positive amount of it would allow a single clan to control the entire territory and become a global monopolist. This generates a prisoner's dilemma and an inefficient outcome for clans, who would be better off it they could split the territory peacefully, avoiding the cost of violence.[9]

[9] To see this in the simplest way, consider the one-shot game played by N symmetric clans ($\pi_i = \pi$ and $c_i = c\ \forall i$). Each of them obtains a territory share of $\theta_i = \frac{1}{N}$ and a profit equal to $W_i = \frac{\pi}{N^2}$, whereas if they could peacefully reach an equal splitting of the territory, each would receive $\frac{\pi}{N}$.

While inter-clan violence is clearly relevant in the real world, it is also often the case that the threat of violence is sufficient to sustain peaceful agreements. Such collusive peace can be sustained in equilibrium if the game is indefinitely repeated and clans attribute enough weight to the future (Castillo and Kronick, 2020, Friedman, 1971).

4.1 The Nash bargaining stage

We assume that, under peaceful collusion, territory shares are assigned through Nash bargaining among active clans, after an initial entry stage, so as to maximize the product of their surplus from peace.[10] Clan i's surplus from peace is equal to the the difference in profits between peace and war, $S_i - W_i$. The former is simply equal to the territory share under peace times the operating profit per unit of territory: $S_i = s_i \pi_i$; the latter, W_i, is as calculated in the one-shot game. Denote by $w_i = \frac{W_i}{\pi_i}$, which is the square of the territory share under war (equation 7). Territory shares under Nash bargaining are obtained from:

$$\max_{s_1,\ldots,s_n} \left[\prod_{i=1}^{n} (s_i - w_i)\pi_i \right] \tag{10}$$

In Appendix A we show that this yields the following division rule:

$$s_i = \frac{1}{n} + w_i - \bar{w} \tag{11}$$

where $\bar{w} = \sum_{j=1}^{n} w_j$. Just as war, peaceful bargaining assigns larger territory shares to stronger clans. Yet, relative to war, peace redistributes territory in favor of weaker clans.[11] Due to this redistribution, relative to war, output in peace is higher under Specialization, lower under Complementarity, and equal under Independence.

4.2 The repeated game equilibrium

Let $\delta \in (0,1)$ be clans' common discount factor.[12] We study the possibility of a peaceful collusive agreement under grim trigger strategies, i.e., clans start from peace and keep colluding until one deviates, and revert to war afterwards. A unilateral deviation allows conquering the entire market for one period, but then yields the one-shot payoff ever after. Peace is sustainable in equilibrium if all clans prefer not to attack, i.e., if the discounted payoff from (peaceful)

[10] We restrict Nash bargaining to those clans that would be active under war, assuming that those clans who would not exert any violence in case of war, and hence would not have access to the market, are immediately excluded from negotiations.

[11] To see this, notice that the marginal active clan receives has $w_i = 0$ under war, whereas it controls a territory share equal to $s_n = \frac{1}{n} - \bar{w} > 0$ under peace.

[12] Our main results are reinforced if stronger clans are more patient.

collusion is greater than the discounted payoff from war:

$$\forall i, \ \frac{\frac{1}{n} + w_i - \bar{w}}{1 - \delta} > 1 + \frac{\delta}{1 - \delta} w_i \tag{12}$$

The latter expression yields the condition:

$$\delta > \tau \tag{13}$$

where $\tau = max\{\tau_i\}$ and $\tau_i = \left[1 - \frac{\frac{1}{n} - \bar{w}}{1 - w_i}\right]$ is the discount factor that makes clan i indifferent between deviating or not. The threshold τ is the minimum discount factor sustaining peace. The higher τ, the smaller is the set of values of δ for which peace is an equilibrium, and hence the more fragile is peaceful collusion. We refer to higher values of τ in terms of higher likelihood of war. We can prove the following:

Proposition 4: Given a set of active clans, the overall weakest of them is the most likely to deviate from the collusive agreement:

$$\tau^i > \tau^j \iff x_i > x_j$$

Proof.
Given n and $\bar{w}$, τ_i is increasing in w_i, which is increasing in x_i.

Deviating from peaceful collusion allows gaining the whole market for one period, followed by war afterwards. Among a given set of active clans, the weakest makes the lowest profits both under peace and under war, and it is the one for whom the one-period gain of the entire market is more attractive.

4.3 Targeted repression in the repeated game

State repression strategies modify the set of active clans and hence the threshold τ sustaining peace. The first question we address is how different repression strategies compare in terms of the likelihood of war.

Proposition 5: The likelihood of war is lowest under un-targeted repression (or anti-targeted repression if repression intensity is very high), intermediate under laisser faire and highest under targeted repression:

$$min\{\tau^U, \tau^A\} < max\{\tau^U, \tau^A\} < \tau^* < \tau^T$$

Proof.
See Appendix A.

Relative to laisser-faire, both un-targeted and anti-targeted repression reduce the number of active clans n, making collusion easier to sustain. One has $n^U < n^A$, because the two policies eliminate the same fraction of clans, but under anti-targeted repression all of the remaining ones are strong enough as to profitably enter the market, whereas under un-targeted repression this is true only for a fraction of them. This would suggest that $\tau^U < \tau^A$. At the same time, relative to un-targeted, anti-targeted repression specifically eliminates the wekest clans, which are easy deviators, suggesting $\tau^A < \tau^U$. Numerical simulations show that the first effect tends to dominate, and so $\tau^U < \tau^A$, for plausibly mild values of repression intensity, whereas the inequality is reversed only for particularly high values. Targeted repression instead increases n relative to relative to laisser faire and makes easy deviators enter.

The next question is how the different repression strategies compare in terms of the volume of illegal activities. Total output in case of peace, denoted by Q_P, differs its value in case of war, dentoted by Q, due to the different allocation of territory shares. For the sake of simplicity, we will focus the analysis on the case of non-extreme repression intensity, so that $\tau^U < \tau^A < \tau^* < \tau^T$. We then have five possible ranges of δ.

- If $\delta > \tau^T$, grim-trigger strategies sustain peace in equilibrium under any policy, so that $G^U = G^T = G^A = G^* = 0$. The ordering of the policies in terms of total illegal output under peace is the same as that outlined in Proposition 2 under war: (i) under Independence, illegal output is constant across policies; (ii) under Specialization, anti-targeted repression minimizes illegal output, followed by laisser faire, un-targeted and targeted repression: $Q^T_{P,S} > Q^U_{P,S} > Q^*_{P,S} > Q^A_{P,S}$; (iii) under Complementarity, targeted repression minimizes output, followed by un-targeted repression, laisser faire and anti-targeted repression: $Q^T_{P,C} < Q^U_{P,C} < Q^*_{P,C} < Q^A_{P,C}$.[13]

- If $\tau^* < \delta < \tau^T$, peaceful collusion is an equilibrium under the other policies, but not under targeted repression. Unlike the one-shot game, targeted repression therefore maximizes violence: $G^T > 0 = G^A = G^U = G^*$. In terms of total illegal output, one has the following: under Specialization, $Q^T_T > Q^U_{P,S} > Q^*_{P,S} > Q^A_{P,S}$; and under Complementarity $Q^T_C < Q^U_{P,C} < Q^*_{P,C} < Q^A_{P,C}$. In this case, under Specialization anti-targeted repression minimizes both violence and illegal output, whereas under Complementarity a trade-off emerges: targeted repression minimizes illegal output, but at the cost of maximizing violence. Here un-targeted repression emerges as an interesting alternative, as it minimizes output conditional on preserving peace.

- If $\tau^A < \delta < \tau^*$, peaceful collusion emerge in equilibrium under un-targeted and anti-targeted repression, but neither under laisser faire and nor under targeted repression: $G^* > G^T > 0 = G^A = G^U$. Total output is lowest under anti-targeted repression in case of Specialization and under targeted repression in case of Complementarity. More specifically, one has $Q^T_T > Q^U_{P,S} (> Q^U_T) > Q^*_T > Q^A_{P,S}$ and $Q^T_C < Q^U_{P,C} < Q^*_C < Q^A_{P,C}$, respectively. In other words, as in the previous cases, under Specialization anti-targeted

[13] As there is no spending in violence, the ordering in terms of profits matches that in terms of production.

repression minimizes both violence and illegal output, whereas under Complementarity targeted repression minimizes illegal output, but at the cost of triggering violence, and again un-targeted repression minimizes output conditional on preserving peace.

- If $\tau^U < \delta < \tau^A$, peace is an equilibrium only under un-targeted repression: $G^* > G^T > G^A > G^U = 0$. Results for total output are again similar, with $Q_T^T > Q_{P,S}^U (> Q_T^U) > Q_T^* > Q_T^A$ and $Q_C^T < Q_{P,C}^U < Q_C^* < Q_C^A$. Under Specialization anti-targeted repression minimizes illegal output, but at the cost of some violence, and un-targeted repression minimizes violence, but at the cost of higher levels of output; under Complementarity targeted repression minimizes illegal output, but at the cost of some violence, and un-targeted repression avoids violence, but at the cost of higher output.

- If $\delta < \tau^U$, peace is not an equilibrium under any policy and inter-clan war is unavoidable. This essentially brings us back to the situation analyzed in the one-shot game.

We can summarize the above analysis in the following:

Proposition 6: In the repeated game

- Targeted repression most easily breaks peaceful collusion and triggers succession wars; it maximizes illegal output under Specialization and minimizes it under Complementarity.

- Un-targeted repression most easily sustains peaceful collusion; it has an intermediate impact on output.

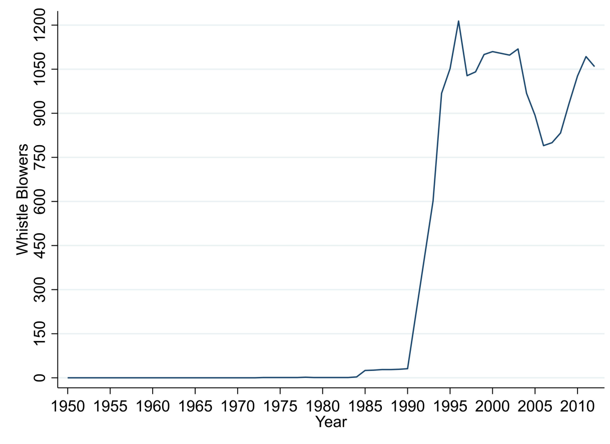
- Anti-targeted repression easily sustains peaceful collusion; it minimizes illegal output under Specialization and maximizes it under Complementarity.

Proof.
See Appendix A.

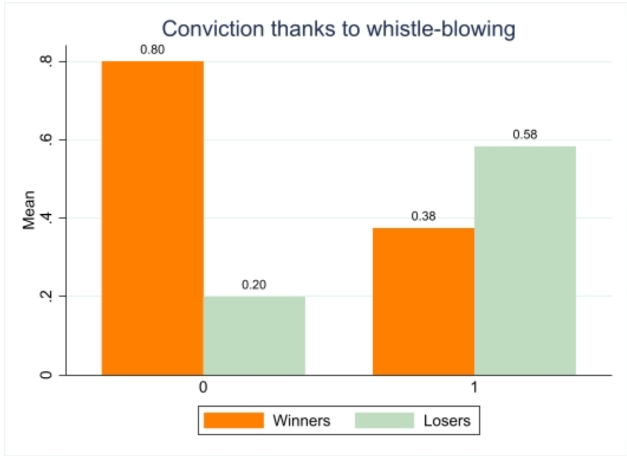
Notice that targeted repression most easily triggers violence in the repeated game, whereas it minimizes the amount of violence in the one-shot game. This contradiction is only apparent: it is precisely by reducing the cost of war that targeted repression makes its threat less powerful in sustaining peace. Finally, observe that the ordering in terms of total illegal profits need not mechanically follow that in terms of output. We provide some additional details on this in Appendix A.

5 Anti-targeted repression of Italian mafia

One key prediction of our model is that anti-targeted repression favors peaceful collusion among clans. We provide some evidence suggesting that the introduction of whistle-blowers protection programs in 1991 in Italy was an anti-targeted repression strategy, and that it had the effect of reducing inter-clan violence.



(a) Whistle blowers in Southern Italy



(b) 1st wave of harsh imprisonment regime (1992)

Figure 2: Whistle-blowing in Southern Italy and its impact on targeted repression.

Notes: Panel a plots the number of whistle-blowers belonging to the four main criminal organizations in Italy, namely Cosa Nostra, 'Ndrangheta, Camorra and Sacra Corona Unita. Panel b plots the conditional distributions for the first 37 mobsters sentenced under the harsh imprisonment regime (Art 41bis), differentiating between those who were in the winning and losing factions of the last mafia feud they participated in, categorized by a dummy taking value 1 if their conviction was assisted by the information provided by whistle-blowers and zero otherwise.

Since the 1980s, tough investigative work by a small group of courageous prosecutors in Palermo led to a surge in repression activity against Cosa Nostra (the Sicilian mafia, at the time the most important mafia organization in southern Italy), culminating into the so-called "Maxi trial" in 1986, where hundreds of members of several clans were brought into a trial (Lodato, 2012). One of the clues of this success was represented by the information on the structure and organization of Cosa Nostra supplied by whistle-blowers (Lodato, 2012). This started with Tommaso Buscetta's collaboration with judge Giovanni Falcone in 1984, and the number of justice collaborators exploded in 1991 with the introduction of a protection program for whistle-blowers (Acconcia et al., 2014), as shown in Figure 2a.

An interesting and less known aspect about whistle-blowers is that most of them belonged to the clans that lost the second mafia war and sought for state protection, so they belonged to the weakest clans. Indeed, the Corleonesi (the winning clan), were sentenced *in absentia* and convicted years (or decades) later. While whistleblowers were typically willing to provide information on rival clans, they were at the same time best informed on their own clan. Preliminary evidence, shown in Figure 2b suggests that they mostly contributed to the conviction of members of losing clans in past mafia wars: among the first 37 mobsters sentenced to harsh imprisonment (Art 41bis), most belonged to the winning clans in the last mafia feud, but among those who were convicted thanks to information provided by whistle-blowers, most belonged to the losing clans. Figure 3 shows that, after years of high inter-clan violence, the spread of whistle-blowers in 1991 was followed by a sharp reduction in the number of homicides of mobsters.

The number of victims of mafia wars is obtained subtracting the numbers of innocent victims of organized crime (Libera, Wikimafia) from the total number of mafia-related homicides (Ministero dell'Interno). It is available at the province-year level. By contrast, the number of

Figure 3: Homicides of mobsters in Southern Italy

Notes: The number of mobsters victims of mafia wars in Sicily, Calabria, Campania and Apulia.

whistle-blowers for each year is only available at the national level. We know they were mostly concentrated in southern Italy, but we lack information on their names and place of origin.
This allows constructing a panel dataset for the provinces belonging to the four Italian regions most afflicted by the presence of criminal organizations, namely Sicily (*Cosa Nostra*), Calabria (*'Ndrangheta*), Campania (*Camorra*) and Apulia (*Sacra Corona Unita*), covering the years between 1983 and 2012.[14] We estimate the following regression model:

$$Mafia\ wars_{it} = \beta mafia_i * anti\text{-}targeted_t + \gamma X_{it} + \alpha_i + \varepsilon_t + \eta_{jt} + u_{it} \tag{14}$$

The dependent variable in equation (14) (*Mafia wars*) is the number (both in absolute terms and in rates out of 100,000 inhabitants) of mobsters victims of mafia wars in province i at time t. The explanatory variable is an interaction term between a measure of mafia penetration in a province and a measure of anti-targeted repression: *mafia* is a dummy taking value one for provinces with a mafia penetration index ranking within the first quartile according to the index elaborated by Transcrime (2015), and *anti-targeted* is either a dummy for years after 1990 (*Post 1990*) or the number of whistle-blowers belonging to the four aforementioned criminal organizations (Document XCI-1) in a given year (*wistle-blowers*).
The coefficient of interest, β, captures the differential impact of anti-targeted repression on inter-clan violence in provinces with high mafia penetration, relative to those with low mafia penetration.
Following Alesina et al (Alesina et al., 2019), the set of controls X_{it} includes the log of population and a measure related to provincial GDP, namely young male unemployment. a_i, ε_t and η_{jt} respectively denote province, time, and region-time fixed effects (where j is the region of province i). Due to the limited number of provinces (22), we bootstrap standard errors. Summary statistics in Table 1.

[14] A province corresponds to the NUTS 3 Eurostat level of territorial delimitation. Provinces align with the old administrative boundaries as of the starting year (1983).

VARIABLES	N	mean	sd	min	max
Mafia wars	660	8.418	19.380	0	169
Whistle-blowers	594	739.704	443.562	1	1214
Mafia	660	.636	.481	0	1
Log(population)	660	13.298	.630	12.062	14.935
Share of male labour force searching first occupation	660	.058	.079	.000	.212
Murders pre-1981	660	.272	.446	0	1

Table 1: Summary statistics for Sicilian, Calabrian, Campanian and Apulian provinces, 1983-2012.

y=Mafia wars	Absolute number				Rate per 100,000 inhabitants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mafia ×Whistle-blowers	-.008**	-.008*			-.001*	-.001*		
	(.004)	(.004)			(.001)	(.001)		
Mafia ×Post 1990			-7.0451*	-8.073*			-.872*	-.978*
			(3.898)	(4.503)			(.455)	(.587)
GDP and Pop controls		✓		✓		✓		✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Time ×Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	594	594	660	660	594	594	660	660
R-squared	.39	.42	.40	.42	.44	.48	.46	.50
Provinces	22	22	22	22	22	22	22	22

Table 2: The impact of whistle-blowing on mafia wars-OLS results.

Notes: Bootstrap standard errors in parentheses. In all columns the number of bootstrap samples is 1000. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

Table 2 presents the OLS estimations of Equation (14). In the first column, the number of mobsters who are victims of mafia wars is regressed on the interaction between the dummy variable Mafia and the number of whistle-blowers providing information to judicial authorities. The second column includes controls for young male unemployment and the logarithm of population. As the number of whistle-blowers may be endogenous, in columns 3-4, we replicate the analysis using as explanatory variable the interaction between the dummy variable Mafia and the dummy variable taking value one after the introduction of the protection program for whistle-blowers (1991 onward). As predicted by the theory, all coefficients are negative and statistically significant, indicating that the proliferation of whistle-blowing has reduced the intensity of mafia wars. These results are further supported in the last four columns, where the dependent variable is the rate of mafia war-related murders per 100,000 inhabitants.

The dummy variable Mafia is potentially endogenous too, suggesting caution with causal interpretation of the results.[15] We partly mitigate this concern in Table 3, where our explanatory variable is the interaction between the *Post 1990* dummy and another dummy taking value 1 if province i ranked in the top quartile for mafia-related murders of innocent people between 1950 and 1980 (*Murders pre-1981*) according to the Libera and Wiki-Mafia's database (Libera, Wikimafia).[16] This specification addresses both reverse causality, as murders are measured well before the last wave of violence, and measurement error, as data on murders are more precise

[15]The establishment of a causal relation is in progress.

[16]The intuition behind this empirical strategy is that only very powerful criminal groups get involved in murders outside the organization since, in general, this strategy attracts unwanted attention and is outperformed by the "secrecy of bribery" (Trejo and Ley, 2021).

y=Mafia wars	Absolute number		Rate per 100,000 inhabitants	
	(1)	(2)	(3)	(4)
Murders pre-1981 ×Post 1990	-14.065***	-17.938**	-1.161*	-1.549
	(5.478)	(7.036)	(.653)	(1.010)
GDP and Pop controls		✓		✓
Time FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Time ×Region FE	✓	✓	✓	✓
Observations	660	660	660	660
R-squared	.42	.45	.10	.50
Provinces	22	22	22	22

Table 3: The impact of whistle-blowing in the most violent mafia provinces-OLS results.
Notes: Bootstrap standard errors in parentheses. In all columns the number of bootstrap samples is 1000. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$.

than abstract measures of mafia presence.
Column 1 considers a model with time, province and region-time fixed effects, whereas the second columns adds the controls for population and young male unemployment. The last two columns replicate the analysis using the rate of mafia murders per 100,000 inhabitants as the dependent variable. The coefficient of interest has roughly double the magnitude compared to Table 2. In the specification with the full set of controls, it suggests that the introduction of the protection program for whistle-blowers has reduced mafia-related homicides by 18 units in the provinces most plagued by organized crime. The statistical significance is higher in the preferred specifications with the absolute number of homicides as the dependent variable, and it becomes marginally insignificant (with a p-value of .125) in the specification with rates per 100,000 inhabitants.

Overall, the previous regressions support the theoretical prediction that the spread of whistle-blowing, taken as a form of anti-targeted repression, was associated with a significant reduction in inter-clans violence (as measured through the number of mobsters victims of mafia wars).

6 Mexican and Colombian drug cartels: from state-sponsored protection to targeted repression?

In this section, we argue that Mexico and Colombia shared a similar interlinked pathway where an initial prolonged epoch of non belligerent clans' collusion was halted by a violence explosion triggered by the boom of drug profits. This in turn called, at some stage, for a violent repressive response by the state which eventually yielded a further violence blow-up.
In the case of Mexico, several studies documented the striking increase in violence (Sobrino, 2019) that followed the Mexican "War on Drugs" (Atuesta and Ponce, 2017, Calderón et al., 2015) carried out after 2007 by the Mexican government to eradicate the leading drug cartels. In particular, Dell (2015) has brought convincing empirical evidence that the crackdown induced by state repression weakened incumbent clans, incentivizing new criminal strains to enter the market and engage in the drug war.

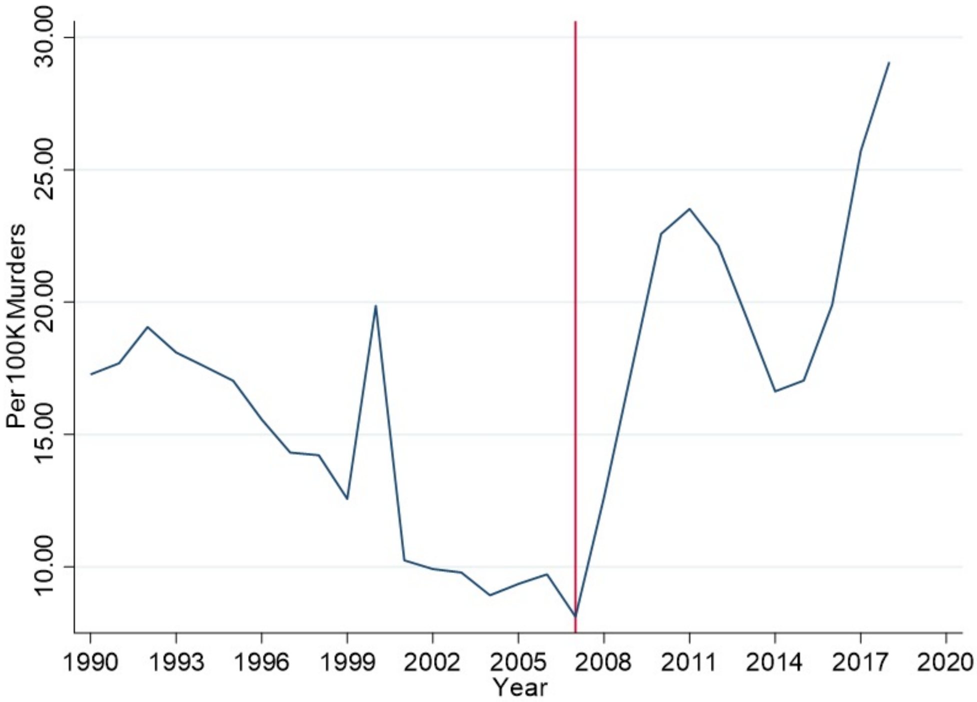


Figure 4: Murders per 100000 inhabitants in Mexico, 1990-2020.

Notes: The figure plots the murder rate per 100,000 inhabitants in Mexico from 1990 to 2020. The vertical line in 2007 corresponds to the onset of the War on Drugs.

Our framework offers a mechanism explaining the previously cited evidences as a consequence of the targeted repressive action enacted by the state, which enabled weaker clans, initially kept outside the market by the mightier incumbent groups, to enter the criminal arena and challenge the pre-existing drug lords for control of the drug market.

Our model also encompasses the alternative explanation provided by Osorio (2015) and Atuesta and Ponce (2017), namely that state repression alters the pre-existing balance of power between the surviving clans, thereby potentially increasing the incentive for a new war.

Notably, both channels may have influenced the dynamics of violence in Mexico after President Calderón declared war to drug traffickers in December 2006 (Figure 4).

In the case of Colombia, several studies documented that the declining trend of murders observed during the Sixties and Seventies reversed (Figure 5) after the boom in the international cocaine traffic (Brauer and Gómez-Sorzano, 2004) and the ensuing attempts to behead the Medellín cartel (The New York Times, 1984).

Note that a temporary decline in homicides is observed after his "self-imprisonmen" in 1991, as part of the agreement he made with the Colombian government (Márquez, 2011), although this inter-reign ended with his elimination in 1993. The latter event shares the characteristics of a targeted repression.

Moreover, Abadie et al (2014) have documented the conflict-fuelling role of the aid packages known as "Plan Colombia" (1999-2005). Specifically, this attempt to eradicate illegal crops intensified guerrilla violence, triggering in turn a massive military intervention from the state

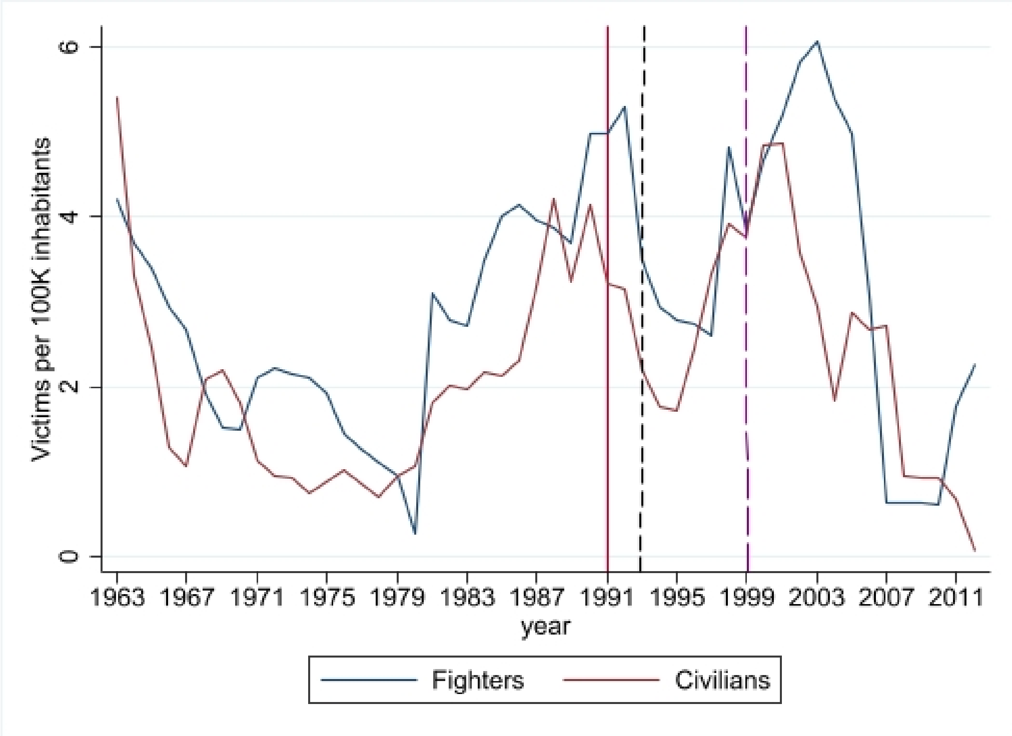


Figure 5: Victims of the Colombian armed conflict, 1963-2012.

Notes: The figure plots the rate of victims per 100,000 inhabitants of the Colombian armed conflicts between 1963 and 2012, distinguishing between fighters(drug traffickers, paramilitaries, soldiers and policemen) and civilians. The solid and dot-dashed lines respectively denote the conviction and killing of Pablo Escobar, whereas the long-dashed line denotes the onset of the Plan Colombia.

which eventually brought to a new wave of violence and homicides among both fighters and civilians.

Finally, the normalization in the mid 2000s might reflect, among other factors, a decline in the profitability of cocaine traffic, due in part to the Mexican drug cartels' ability to take the lead over the Colombian ones (Trejo and Ley, 2021).

Conclusions

Organized crime often imposes high costs on the society, yet its repression is also costly, both because it absorbs human and material resources and because it alters the equilibrium among clans and may trigger responses that are themselves socially costly. An important question is whether it is desirable to concentrate repression activities against clans with specific characteristics, for instance against the strongest or the weakest ones, or it is better not to discriminate. We have labelled these strategies targeted, anti-targeted and un-targeted repression, respectively. We have developed a model with heterogeneous clans that allows addressing such question, and in particular studying the consequences of different repression strategies on inter-clan violence and on the level of illegal activity. In the model, clans may fight to become local monopolists over some territory, but they may also bargain and reach peaceful agreements under the threat of violence. The number of active clans, the level of violence and that of illegal output (and profits) are endogenously determined and depend on state repression policy. This setup highlights a possible trade-off between curbing violence and illegal activity.

When war is unavoidable, as it is the case from a one-shot game perspective, any repression strategy reduces violence relative to laisser faire, but targeted repression is the most effective in reducing violence, followed by un-targeted and then anti-targeged repression. Targeted repression also minimizes illegal activity if stronger clans are more productive. Yet, if clans specialize either in productive or predatory skills, so that stronger clans are less productive, a trade-off emerges: targeted repression minimizes violence but maximizes illegal activity. Anti-targeted repression does the opposite: by eliminating the weakest clans, it maximizes violence but, if clans specialize, it minimizes illegal activity. Un-targeted repression reduces illegal activity relative to laisser faire, with an intermediate impact between that of targeted and anti-targeted repression.

From a repeated interaction perspective, inter-clan war is not unavoidable, as the threat of violence may allow sustaining peaceful splitting agreements. A trade-off between violence and illegal activity may still emerge, but it is different from the one outlined above. Targeted repression weakens the threat of violence and thus makes a peaceful equilibrium less likely. The elimination of stronger clans may precipitate a succession war, with new clans entering and fighting to gain control of some territory share, thus raising rather than reducing the level of violence. Anti-targeted and un-targeted repression instead strengthen the threat of violence and may let clans move from war to peace. In this case, by eliminating some competitors, the state makes peaceful collusion easier.

The effects on the level of illegal activity depends on the joint distribution of military strength and economic productivity. If stronger clans are also more productive, targeted repression minimizes illegal activity, but it most easily triggers a succession war, whereas anti-targeted repression easily sustains peace, but it maximizes the level of illegal activity. If stronger clans are instead less productive, targeted repression is likely to be a very costly strategy in terms of both violence and illegal activity, whereas anti-targeted repression is likely to be very effective on the two sides. Un-targeted repression has an intermediate impact on the level of illegal activity compared to the other two repression strategies.

As the above discussion makes clear, the impact of different policies on violence and illegal activity depends on a number of conditions, which are not necessarily the same across contexts. Yet, an important conclusion is that anti-targeted and un-targeted repression may break down inter-clan war and trigger peace. We provide preliminary evidence that the introduction of whistle-blowers' protection in Italy, which allowed the capture and conviction of many mafia affiliates, especially belonging to weaker clans, led to a reduction in inter-clan violence. We also present some additional evidence from Mexico and Colombia, which also corroborates the model.

Our analysis advances our understanding of state repression of organized crime in two main ways. Relative to (Castillo and Kronick, 2020), we consider heterogeneous clans. This allows investigating the consequences of different ways of targeting repression. Moreover, we allow both illegal production and violence to happen in equilibrium, which allows studying the trade-off between these two dimensions along the equilibrium path.

Our model endogenizes the number and type of clans that enter the market, whether and how much they fight, and how much they produce. What we take as exogenously given is the distribution of clans' military strength and economic productivity. In different contexts one might expect these two dimensions to be complementary or substitute, and we study both cases. Our analysis focuses on the impact of different repression strategies.

A future extension of our work might endogenize clans' specialization choice or the investment in specific skills. We also neglect other channels of interaction between states and organized crime, such as corruption and violence against the state, but this allows to study the trade-off between inter-clan violence and illegal activity in the clearest way.

To draw conclusions on optimal policy one should combine it with information on social preferences over violence and illegal activity and on the cost of implementing the different policies. For instance, if it is more costly to eliminate a given number of strong rather than weak clans, or if the society has a stronger aversion to violence, then the desirability of un-targeted or anti-targeted repression increases, provided it can reduce violence.

We have provided preliminary original evidence that, as predicted by the model, an anti-targeted repression strategy reduced inter-clan violence in southern Italy, and we have discussed evidence that targeted repression in Mexico and Colombia fuelled inter-clan conflict. We are currently in the process of refining such evidence.

References

A. Abadie, M. C. Acevedo, M. Kugler, and J. Vargas. Inside the war on drugs: Effectiveness and unintended consequences of, 2014.

A. Acconcia, G. Immordino, S. Piccolo, and P. Rey. Accomplice witnesses and organized crime: Theory and evidence from italy. *The Scandinavian Journal of Economics*, 116(4):1116–1159, 2014.

D. Acemoglu, J. A. Robinson, and R. J. Santos. The monopoly of violence: Evidence from colombia. *Journal of the European Economic Association*, 11(suppl_1):5–44, 2013.

D. Acemoglu, G. De Feo, and G. D. De Luca. Weak states: Causes and consequences of the sicilian mafia. *The Review of Economic Studies*, 87(2):537–581, 2020.

A. Alesina, S. Piccolo, and P. Pinotti. Organized crime, violence, and politics. *The Review of Economic Studies*, 86(2):457–499, 2019.

L. H. Atuesta and A. F. Ponce. Meet the narco: increased competition among criminal organisations and the explosion of violence in mexico. *Global Crime*, 18(4):375–402, 2017.

J. Brauer and A. G. Gómez-Sorzano. Homicide cycles in colombia, 1950-1999. *International Journal of Applied Econometrics and Quantitative Studies*, 1(1):1–22, 2004.

G. Calderón, G. Robles, A. Díaz-Cayeros, and B. Magaloni. The beheading of criminal organizations and the dynamics of violence in mexico. *Journal of Conflict Resolution*, 59(8): 1455–1485, 2015.

J. C. Castillo and D. Kronick. The logic of violence in drug war. *American Political Science Review*, 114(3):874–887, 2020.

L. C. Corchón. The theory of contests: a survey. *Review of economic design*, 11:69–100, 2007.

E. Dal Bó and P. Dal Bó. Workers, warriors, and criminals: social conflict in general equilibrium. *Journal of the European Economic Association*, 9(4):646–677, 2011.

E. Dal Bó and R. Di Tella. Capture by threat. *Journal of Political Economy*, 111(5):1123–1154, 2003.

E. Dal Bó, P. Dal Bó, and R. Di Tella. "plata o plomo?": bribe and punishment in a theory of political influence. *American Political science review*, 100(1):41–53, 2006.

G. De Feo and G. D. De Luca. Mafia in the ballot box. *American Economic Journal: Economic Policy*, 9(3):134–167, 2017.

M. Dell. Trafficking networks and the mexican drug war. *American Economic Review*, 105(6): 1738–1779, 2015.

M. dell'Interno – Dipartimento della Pubblica Sicurezza. Banca dati interforze - ssd - mod. statdel2, Various issues.

A. Durán-Martínez. *The politics of drug violence: Criminals, cops and politicians in Colombia and Mexico*. Oxford University Press, 2017.

J. W. Friedman. A non-cooperative equilibrium for supergames. *The Review of Economic Studies*, 38(1):1–12, 1971.

D. Gambetta. *The Sicilian Mafia: the business of private protection*. Harvard University Press, 1996.

M. R. Garfinkel and S. Skaperdas. Economics of conflict: An overview. *Handbook of defense economics*, 2:649–709, 2007.

J. Hirshleifer. The paradox of power. *Economics & Politics*, 3(3):177–200, 1991.

M. Kleiman. Surgical strikes in the drug wars: smarter policies for both sides of the border. *Foreign Aff.*, 90:89, 2011.

K. A. Konrad and S. Skaperdas. The market for protection and the origin of the state. *Economic Theory*, 50:417–443, 2012.

M. Kugler, T. Verdier, and Y. Zenou. Organized crime, corruption and punishment. *Journal of Public Economics*, 89(9-10):1639–1663, 2005.

E. La Ferrara and R. H. Bates. Political competition in weak states. *Economics & Politics*, 13 (2):159–184, 2001.

B. Lessing. Logics of violence in criminal war. *Journal of Conflict Resolution*, 59(8):1486–1516, 2015.

B. Lessing. *Making peace in drug wars: Crackdowns and cartels in Latin America*. Cambridge University Press, 2017.

Libera. Associazioni, nomi e numeri contro le mafie. URL https://vivi.libera.it/it-ricercanomi.

S. Lodato. *Quarant'anni di mafia*. Bur, 2012.

G. G. Márquez. *Noticia de un secuestro*. Vintage Espanol, 2011.

J. Osorio. The contagion of drug violence: spatiotemporal dynamics of the mexican war on drugs. *Journal of Conflict Resolution*, 59(8):1403–1432, 2015.

I. Parliament. Relazione sui programmi di protezione, sulla loro efficcacia, e sulle modalità generali di applicazione per coloro che collaborano con la giustizia (documento xci n.1), Various issues.

B. J. Phillips. How does leadership decapitation affect violence? the case of drug trafficking organizations in mexico. *The Journal of Politics*, 77(2):324–336, 2015.

V. Ríos. Why did mexico become so violent? a self-reinforcing violent equilibrium caused by competition and enforcement. *Trends in organized crime*, 16:138–155, 2013.

E. U. Savona, M. Riccardi, et al. From illegal markets to legitimate businesses: the portfolio of organised crime in europe-final report of project ocp organized crime portfolio. 2015.

R. Snyder and A. Duran-Martinez. Does illegality breed violence? drug trafficking and state-sponsored protection rackets. *Crime, law and social change*, 52:253–273, 2009.

F. Sobrino. Mexican cartel wars: Fighting for the us opioid market. 2019. URL https://www.fersobrino.com/files/DraftPaper.pdf.

The New York Times, 1984. URL https://www.nytimes.com/1984/05/01/world/justice-minister-slain-in-bogota.html.

G. Trejo and S. Ley. High-profile criminal violence: Why drug cartels murder government officials and party candidates in mexico. *British Journal of Political Science*, 51(1):203–229, 2021.

G. Tullock. Efficient rent seeking. *In Buchanan, James M and Tollison, Robert D and Tullock, Gordon: Toward a theory of the rent-seeking society*, pages 97–112, 1980.

Wikimafia. URL https://www.wikimafia.it/wiki/Categoria:Vittimeinnocentidellemafie.

Appendix A

General solution of the game with $\beta > \alpha > 0$

Replicating the analysis presented in Section 2.3, one gets the following expressions:

$$\begin{cases} x_n = \alpha + (\beta-\alpha)\frac{1+\sqrt{1+\frac{2\alpha N}{\beta-\alpha}}}{N} \\ \bar{x}_n = \alpha + (\beta-\alpha)\frac{1+\sqrt{1+\frac{2\alpha N}{\beta-\alpha}}}{2N} \\ n^* = 1+\sqrt{1+\frac{2\alpha N}{\beta-\alpha}} \\ W_i^* = \left[1-\frac{2N\sqrt{1+\frac{2\alpha N}{\beta-\alpha}}x_i}{\left(\sqrt{1+\frac{2\alpha N}{\beta-\alpha}}+1\right)\left(2\alpha N+(\beta-\alpha)\left(1+\sqrt{1+\frac{2\alpha N}{\beta-\alpha}}\right)\right)}\right]^2 \pi_i \end{cases} \tag{A.1}$$

Expressions (A.1) can be combined with the first and second equations (5) to obtain (with $Y = \sqrt{1+\frac{2\alpha N}{\beta-\alpha}}$):

$$\begin{cases} g_i^* = \frac{2Y\left(1-\frac{2Yxi}{(1+Y)\left(2\alpha+\frac{(\beta-\alpha)(1+Y)}{N}\right)}\right)}{(1+Y)\left(2\alpha+\frac{(\beta-\alpha)(1+Y)}{N}\right)} \\ G^* = \frac{2Y}{(1+Y)\left(2\alpha+\frac{(\beta-\alpha)(1+Y)}{N}\right)} \end{cases} \tag{A.2}$$

Proof of Proposition 1

- The third equation (6) shows that x_n is decreasing in N, whereas the first equation (7) shows that G^* is decreasing in x_n. These two facts imply that G is increasing in N. Since un-targeted repression is simply a reduction in N, it follows that $G^U < G^*$, where $G^U = \frac{1}{x_U} = \frac{N\phi}{1+N\phi+\sqrt{1+2N\phi}}$.

- Consider the targeted repression of all clans with an (inverse) overall strength level between 1 and x_T. The ensuing power vacuum allows the entry of clans weaker than x_n up to some x_k. This value can be endogenously determined combining the entry-condition $\frac{x_i}{\bar{x}_T} = \frac{n^T}{n^T-1}$ with the number of active clans $n^T = N(x_k - x_T)$ and yields the following:

$$\begin{cases} n^T = 1+\sqrt{1+2Nx_T} \\ \bar{x}_T = x_T + \frac{1+\sqrt{1+2Nx_T}}{2N} \\ x_k = x_T + \frac{1+\sqrt{1+2Nx_T}}{N} \end{cases} \tag{A.3}$$

Plugging (A.3) into (5):

$$\begin{cases} G^T = \frac{1}{x_k} \\ g_i^T = \frac{x_k - x_i}{x_k^2} \\ W_i^T = (1 - \frac{x_i}{x_k})^2 \pi_i \end{cases} \tag{A.4}$$

Since $x_k > x_n$, it holds $G^T < G^*$. To compare targeted and un-targeted repressive policies of equal intensity, let $\phi = (2 - x_T)$. Then:

$$x_k > x_U \iff \frac{1 + N + \sqrt{1 + 2Nx_T}}{N} > \frac{1 + N(2 - x_T) + \sqrt{1 + 2N(2 - x_T)}}{N(2 - x_T)} \tag{A.5}$$

The above inequality can be rearranged as follows:

$$(x_T - 1)\left[(2 - x_T)N - 1\right] + \left[(2 - x_T)\sqrt{1 + 2Nx_T} - \sqrt{1 + 2N(2 - x_T)}\right] > 0 \tag{A.6}$$

Since $N(2-x_T) > 1$ (otherwise there would be no survivng clan), the first term in square bracket is strictly positive. Imposing the second term in square bracket greater than zero, one finds that this is always the case. Therefore, $x_k > x_U$, which implies $G^T < G^U$.

- With anti-targeted repression, the marginal clan with x_A obtains a positive payoff, thereby preventing us to exploit the entry-condition. Substituting $n^A = N(x_A - 1)$ and $\bar{x}_A = \frac{1+x_A}{2}$ into (5):

$$\begin{cases} G^A = 2\frac{N(x_A - 1) - 1}{N(x_A^2 - 1)} \\ g_i^A = G^A(1 - G^A x_i) \\ W_i^A = (1 - G^A x_i)^2 \end{cases} \tag{A.7}$$

One can easily prove that the first equation (A.7) is increasing in x_A for all $x_A < x_n$. Since $G^A = G^*$ if $x_A = x_n$ (which corresponds to the *Laisser faire*), it must be $G^A < G^* \ \forall x_A < x_n$.

Finally, we exploit two arguments to prove that $G^A > G^U$ for repressive policies of equal intensity. First, note that $n^A > n^U$ for all $x_U \in (x_n, 2)$, because after un-targeted repression only a subset of clans enter the market, whereas under anti-targeted repression all surviving clans enter. Second, note that $\bar{x}_A = \frac{1+x_A}{2} < \frac{1+x_U}{2} = \bar{x}_U$ since $x_A < x_n < x_U$. Therefore, as the first equation (5) shows that the equilibrium level of G is increasing in N and decreasing in the (inverse) average overall strength x, it must be that $G^A < G^U$. Overall, it must be $G^* < G^A < G^U < G^T$.

Proof of Proposition 2

1. This is obvious from the first equation equation (9).

2. The proof is divided in four parts, namely: (i) $Q^U > Q^*$; (ii) $Q^A < Q^*$; (iii) $Q^T > Q^*$; (iv) $Q^T > Q^U$.

Part (i)

First, we show that all types of clan characterized by $x_i \leq x_n$ obtain a lower share of the market after un-targeted repression. Specifically, we show that part of the share previously held by clans with an overall strength of x_i is now held by clans with an overall strength of $x_j > x_n \geq x_i$. Second, we exploit Assumption S (Specialization) to prove that in the share originally held by clans of type i, production has increased because of the higher productivity of the new entrant clans. Since this holds for all $x_i \leq x_n$, total production shall necessarily increase.

Formally, we start by determining the aggregate share held by all clans with an overall strength between $q \geq 1$ and $k \leq x_n$ as follows:

$$\Theta_i = N \int_q^k \left(1 - \frac{x_i}{x_n}\right) dx_i = (k-q)N \left[1 - \frac{(k+q)}{2(1+N+\sqrt{1+2N})} N\right] \tag{A.8}$$

Differentiate the above expression with respect to N:

$$\frac{\partial \Theta_i}{\partial N} = 1 - \frac{(k+q)N}{2(1+N+\sqrt{1+2N})} - \frac{N(k+q)}{2} \left(\frac{1+N+\sqrt{1+2N} - N - \frac{N}{\sqrt{1+2N}}}{(1+N+\sqrt{1+2N})^2}\right) \tag{A.9}$$

Imposing the RHS of expression (A.9) greater than zero and simplifying, one gets:

$$4(N+1+\sqrt{1+2N}) + (2-k-q)N(N+2+2\sqrt{1+2N}) + \frac{N^2}{\sqrt{1+2N}}(k+q) > 0 \tag{A.10}$$

Notably, the LHS of expression (A.10) (let us call if $f(q,k)$) is strictly decreasing in both k and q. This is immediate if one takes the derivative with respect to either variable:

$$\frac{\partial f(q,k)}{\partial q} = \frac{\partial f(q,k)}{\partial k} = -N^2 - 2N - 2N\sqrt{1+2N} + \frac{N^2}{\sqrt{1+2N}} < 0 \ \forall N \geq 0 \tag{A.11}$$

Since $f(k,q)$ is decreasing in both q and k, it reaches its minimum when $q = k = x_n$. Plugging this into the LHS of (A.10):

$$\begin{aligned} &4 - \left(1+\sqrt{1+2N}\right) N + 2N \left(2 - \frac{1+\sqrt{1+2N}}{N}\right) + 4\sqrt{1+2N} \\ &- 2N\left(1+\sqrt{1+2N}\right)\sqrt{1+2N} + \frac{N^2}{\sqrt{1+2N}}\left(2 + \frac{1+\sqrt{1+2N}}{N}\right) \end{aligned} \tag{A.12}$$

Expanding and simplifying expression (A.12), one gets 0. Thus, it holds $\frac{\partial \Theta_i}{\partial N} > \frac{\partial \Theta_n}{\partial N} = 0 \ \forall \ i < n$. In other words, un-targeted repression (reducing N) reduces the share held by clans whose strength lies between any pair of values (q,k) between 0 and x_n. Since this holds also when $q = k$, that means that clans of all types $i < n$ hold a lower share after un-targeted repression.

Moving to the second part of the proof, rewrite the first expression (8) as follows:

$$Q^* = \int_1^{x_n} \frac{a - b(x_i)}{2} (N\theta_i)^* dx_i \tag{A.13}$$

Illegal production of clans of type i is therefore:

$$Q_i^* = \frac{a - b_i}{2} (N\theta_i)^* \tag{A.14}$$

From the first part of the proof, we have that $(N\theta_i)^* > (N\theta_i)^U \ \forall\ i < n$. In other words, the clans producing in the original share $(N\theta_i)^*$ are now relegated to producing in a lower share $(N\theta_i)^U$. Since the sum of all total shares shall be 1, there must be other clans producing in the remaining share $(N\theta_i)^* - (N\theta_i)^U$. Since this holds for all $i < n$, this $(N\theta_i)^* - (N\theta_i)^U$ (integrated over the original set of active clans) is a missing share which is necessarily penetrated by more productive clans with a (or more, if several types of clan occupy the missing share) lower $b_j < b_i \ \forall\ x_j \in [x_n, x_U]$. This is immediate since $x_U > x_n$. Therefore, illegal production after un-targeted repression in each original share prior to state intervention can be written as:

$$Q^U(N\theta_i)^* = \frac{a - b_i}{2} (N\theta_i)^U + \frac{a - b_j}{2} [(N\theta_i)^* - (N\theta_i)^U] > \frac{a - b_i}{2} (N\theta_i)^* = Q^*(N\theta_i)^* \tag{A.15}$$

The inequality above holds also at the aggregate level (note that we are integrating with respect to the shares determined before repression, and not with respect to x):

$$Q^U = \int_1^{x_n} Q^U(N\theta_i)^* d(N\theta_i)^* > \int_1^{x_n} Q^*(N\theta_i)^* d(N\theta_i)^* = Q^* \tag{A.16}$$

Part (ii)

Here, we exploit the argument used in Part (i). Specifically, the elimination of clans with overall strength between x_A and 2 generates a power vacuum in the shares controlled by clans with $x_i \in (x_A, x_n)$. This shares are necessarily occupied by clans stronger than x_A. Since these clans are less productive (Assumption S on specialization), total production shall decrease. Formally, write the aggregate share controlled by all clans with an overall strength between $q \geq 0$ and $k \leq x_A$ as follows:

$$\Theta_i^A = N \int_q^k \frac{g_i^A}{G^A} = N \int_q^k \left(1 - 2x_i \frac{N(x_A - 1) - 1}{N(x_A^2 - 1)}\right) dx_i \tag{A.17}$$

The derivative of expression (A.17) with respect to x_A is negative for all $x_A < x_n$. This means that the harsher anti-targeted repression (i.e., the lower x_A), the higher the share occupied by the surviving (non productive) clans. Since this share is subtracted to the eliminated (more productive) clans with overall strenght between x_A and x_n, total production shall necessarily decrease, that is $Q^A < Q^*$.

Part (iii)

Here, we exploit the argument used of Parts (i) and (ii). Specifically, the elimination of clans with overall strength between 1 and x_T generates a power vacuum in the shares controlled by clans with $x_i \in (x_1, x_T)$. This shares are necessarily occupied by clans weaker than x_n. Since these clans are more productive (Assumption S on specialization), total production shall increase. Formally, write the aggregate share controlled by all clans with an overall strength between $q \geq 0$ and $k \leq x_A$ as follows:

$$\Theta_i^T = N \int_q^k \frac{g_i^T}{G^T} = N \int_q^k \left(1 - \frac{Nx_i}{1 + Nx_T + \sqrt{1 + 2Nx_T}}\right) dx_i \tag{A.18}$$

Expression (A.17) is clearly increasing in x_T. This means that the harsher targeted repression, the higher the share occupied by the surviving (productive) clans. Since this share is subtracted to the eliminated (less productive) clans with overall strength between 1 and x_T, total production shall necessarily increase, that is $Q^T > Q^*$.

Part (iv)

Since $x_k > x_U$ (equation (A.5), targeted repression eliminates more non-productive clans and causes the entrance of a higher number of productive clans compared to un-targeted repression. Indeed, clans with an overall strength between 1 and x_T obtain a positive share after un-targeted repression whereas they obtain zero after targeted repression (since they are eliminated). Thus, clans weaker than x_T shall necessarily get a lower share after un-targeted repression compared to targeted repression, since they are fewer and they also compete with the strongest clans. Thus, clans belonging to all intervals (q, k) with $x_T \leq q \leq k \leq 2$ obtain a higher share after targeted repression than that after un-targeted repression, since they partly substitute stronger non productive clans with $x_j < x_T$. Formally, the intuition is the same of Parts (i), (ii) and (iii):

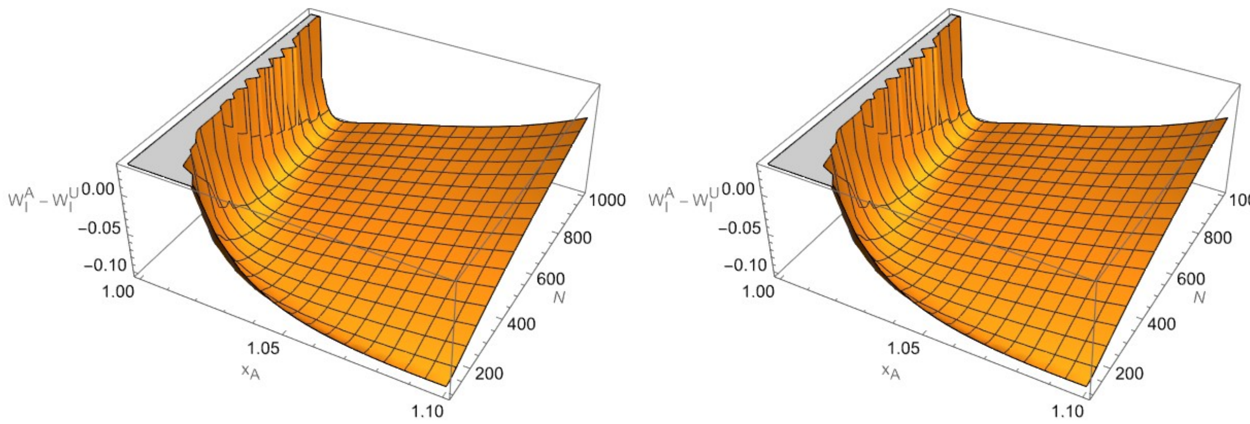
$$Q^T(N\theta_i)^T = \frac{a - b_i}{2}(N\theta_i)^T > \frac{a - b_i}{2}(N\theta_i)^U + \frac{a - b_j}{2}\left[(N\theta_i)^T - (N\theta_i)^U\right] = Q^U(N\theta_i)^T \tag{A.19}$$

This also holds at the aggregate level (note that we are integrating with respect to the shares determined after targeted repression, and not with respect to x):

$$Q^T = \int_{x_T}^{x_k} Q^T(N\theta_i)^T \, d(N\theta_i)^T > \int_{x_T}^{x_k} Q^U(N\theta_i)^T \, d(N\theta_i)^T = Q^U \tag{A.20}$$

Overall, it must hold $Q^A < Q^* < Q^U < Q^T$.

3. Simply revert all the arguments used in Part 2 of this Proposition with Specialization. Thus, under Complementarity it holds $Q^A > Q^* > Q^U > Q^T$.



(a) $W^A - W^U$

(b) $W^* - W^A$

Figure A1: Illegal profits under independence: anti-targeted vs un-targeted repression vs laisser faire.

Notes: Panel a plots the difference between illegal profits after anti-targeted and un-targeted repression. Since the number of surviving clans after anti-targeted repression is $N(x_A - 1)$, we compare it with an un-targeted repression of intensity $2 - x_A$ (so that the surviving clans are $N(x_A - 1)$, too). Panel b plots the difference between illegal profits in case of laisser faire and that after anti-targeted repression. Since $x_A < x_n$, the range of values of x_A is restricted to the interval 1-1.10.

Proof of Proposition 3

1. The first second equation (9), which shows that illegal profits are decreasing in N. It follows that $W_I^U = \frac{(a-b)^2}{3(1+\sqrt{1+2N\phi}} > W_I^*$. Likewise, for targeted repression the second equation (8) yields $W_I^T = \frac{(a-b)^2}{3(1+\sqrt{1+2Nx_T}} < W_I^*$. The same logic yields a more cumbersome expression for anti-targeted repression:

$$W_I^A = \frac{(a-b)^2}{4} \frac{4(1 + x_A + x_A^2) - 2(x_A - 1)^3 N + (x_A - 1)^4 N^2}{3(x_A - 1)(x_A + 1)^2 N^2} \tag{A.21}$$

   Our numerical simulations (Figure A1) who that $W_I^U > W_I^A > W^*$. The second part of this chain of inequalities is obvious, since anti-targeted repression reduces both the number of active clans and their military expenditure. The first one is less trivial, because $n^U < n^A$ and $G^U < G^A$ but this does not immediately translate into a reduction in military spending, since active clans after un-targeted repression are on average weaker and therefore pay a higher cost per units of military investment.

2. The case of Specialization yields far from conclusive results on illegal profits, with the remarkable exception of the comparison between W_S^U and W_S^*. We know that under Independence it holds un-targeted repression ensures higher illegal profits. Since under Specialization weaker clans are more productive, the previous result is simply reinforced irrespective of the functional form of $b(x_i)$. Turning to the other types of repression, we know that under Independence $W^U > W_I^A > W_I^* > W_I^T$. However, since under specialization $Q^T > Q^U > Q^* > Q^A$, all relations are in principle possible (provided that $W_S^U > W_S^*$). The only precise prediction that we can make is that for sufficiently steep function $b(x_i)$ the increase in production shall dominate i.e., $W_S^T > W_S^* > W_S^W > W_S^A$,

whereas for sufficiently flat functions we are back to the Independence case.

3. Here, it shall always hold $W_C^A > W_C^* > W_C * T$, as this already holds under Independence and the assumption of Complementarity further implies that $Q_C^A > Q_C^* > Q_C^T$. The only uncertain element is the illegal profit after un-targeted repression. Building upon the argument of Part 2 of this Proposition, we can state that if $b(x_i)$ is steep enough, then the quantity effect dominates ($W_C^A > W_C^* > W_C^U > W_C * T$). However, for sufficiently flat $b(x_i)$, illegal profits after un-targeted repression become higher than the laisser faire's ones. For even flatter functions (with the limit behaviour defined by the Independence Assumption), un-targeted repression shall maximize illegal profits.

Nash bargaining rule

Rewrite equation (10) as follows:

$$(s_n - w_n)\pi_n \prod_{k=1}^{n-1}(s_k - w_k)\pi_k = (1 - \sum_{k=1}^{n-1} s_k - w_n)\pi_n \prod_{k=1}^{n-1}(s_k - w_k)\pi_k \tag{A.22}$$

Maximization of expression (A.22) with respect to s_i, $i \in 1, n-1$ yields the following system of first order conditions:

$$-\pi_n \prod_{k=1}^{n-1}(s_k - w_k)\pi_k + (1 - \sum_{k=1}^{n-1} s_k - w_n)\pi_n\pi_i \prod_{k \neq i,n}(s_k - w_k)\pi_k = 0, \ i = 1, 2, .., n, \tag{A.23}$$

Divide both sides of equation (A.23) by $\pi_n\pi_i \prod_{k\neq i,n}(s_k - w_k)\pi_k$:

$$1 - s_i - \sum_{k=1}^{n-1} s_k - w_n + w_i = 0, \ i = 1, 2, .., n, \tag{A.24}$$

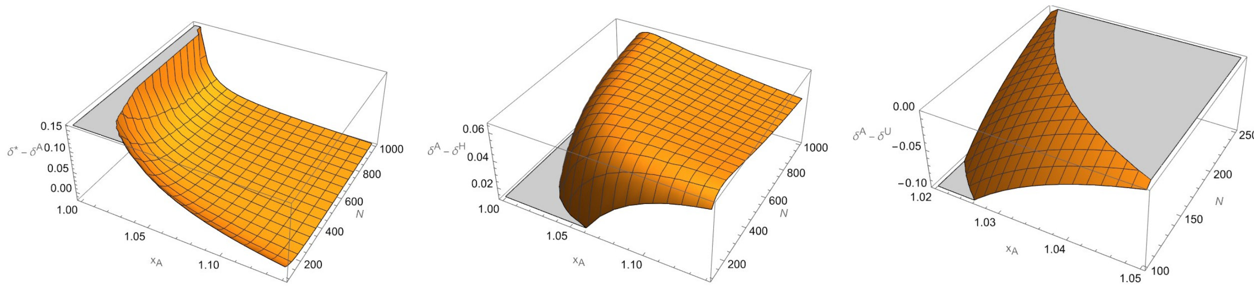
Subtracting from equation (A.24) the corresponding equation for player j, one gets:

$$s_j - s_i = w_j - w_i \tag{A.25}$$

Replicating the procedure for all $j \neq i$, solving for s_j and plugging the ensuing expressions into equation (A.24), one gets the following expression:

$$1 - s_i - \sum_{k=1}^{n-1}(s_i + w_j - w_i) - w_n + w_i = 0 \tag{A.26}$$

Let $\bar{w} = \frac{1}{n}\sum_{i=1}^{n} w_i$. Then, solving equation (A.26) for s_i, one gets expression (10) in the main text.



(a) $\tau^* - \tau^A$ (b) $\tau^A - \tau^U > 0$ (c) $\tau^A - \tau^U < 0$

Figure A2: Minimum discount factor sustaining collusion: anti-targeted vs laisser faire vs un-targeted repression.

Notes: Panel a plots the difference between the discount factor sustaining collusion in case of laisser faire and that after anti-targeted repression. Panels b and c plot the difference between the discount factor sustaining collusion after anti-targeted and un-targeted repression, distinguishing between the positive and negative region. Since the number of surviving clans after anti-targeted repression is $N(x_A - 1)$, we compare it with an un-targeted repression of intensity $2 - x_A$ (so that the surviving clans are $N(x_A - 1)$, too). Since $x_A < x_n$, the range of values of x_A is restricted to the interval 1-1.10. Note that if the number of clans surviving repression is below 4, then the entry condition does not apply to un-targeted repression because all clans would make positive profits as of the third equation (6). This means that τ^U would be actually lower than the depicted one (potentially reverting again the sign of $\tau^A - \tau^U$), since in our plot we have represented the case in which the marginal clan gets zero profit whereas instead $\tau^U = 1 - \frac{n^U - \tilde{w}^U}{1 - w_U}$. However, this limit case is not of particular interest for our purposes.

Proof of Proposition 5

Substituting the first equation (6) and the third equation (7) into the expression of τ, one gets:

$$\tau^* = \frac{6N + 7 + 3\sqrt{1 + 2N}}{6(N + 1 + \sqrt{1 + 2N})} \tag{A.27}$$

Since the RHS of expression (A.27) is increasing in N, it follows that $\tau^U < \tau^*$.
Likewise, substituting the first equation (A.3) and the third equation (A.4) into the expression of τ, one gets:

$$\tau^T = \frac{6Nx_T + 7 + 3\sqrt{1 + 2Nx_T}}{6(Nx_T + 1 + \sqrt{1 + 2Nx_T})} \tag{A.28}$$

Since the RHS of expression (A.28) is increasing in x_T, it follows that $\tau^T > \tau^*$.
By the same token, one gets the expression for τ^A:

$$\frac{(x_A - 1)\left[4 + N + 8x_A + Nx_A(10 + x_A)\right]}{12x_A\left[x_A + (x_A - 1)N\right]} \tag{A.29}$$

Numerical simulations (Figure A2) show that if the number of surviving clans ($N(x_A - 1)$) is below 6, then $\tau^A < \tau^U < \tau^*$, although in the general case in which more than 5 clans survive to repression it holds $\tau^U < \tau^A < \tau^*$

Proof of Proposition 6

First, we prove that peace generates an increase in production under Specialization and a decrease under Complementarity. From equation (11), we can compute the net change in the share of clan i from war to peace (dropping the apex T for the sake of the clarity of the exposition):

$$s_i - \theta_i = \frac{1}{n} - \frac{\sum_{i=1}^{n} \left(\frac{g_i}{G}\right)^2}{n} + \left(\frac{g_i}{G}\right)^2 - \frac{g_i}{G} \tag{A.30}$$

Differentiating the above expression with respect to $\frac{g_i}{G} = \theta_i$ and imposing the derivative greater than zero, one gets:

$$2\frac{n-1}{n}\theta_i - 1 > 0 \implies \theta_i > \frac{1}{2}\frac{n}{n-1} \tag{A.31}$$

However, since no clan gets a share higher than $\frac{1}{2}$, this means that $s_i - \theta_i$ is always decreasing in the share obtained after war (θ_i). Recalling that θ_i is a direct measure of the overall strength of a clan, that means that weaker clans obtain higher share in case of peace relative to what they get after a mafia war(indeed, clans with a war share of 0 obtain $\frac{1}{n} - \bar{w} > 0$ in case of peace.) This share gain gradually reduces as the strength of the clan i rises. At some point it must become negative since the share gain of the weak clans shall be equal to the share loss of the strong ones (as the sum of the shares is always 1). Thus, Nash bargaining transfers part of the share from the strong clans to the weak ones. From the previous Propositions, we can conclude that production shall necessarily increase under Specialization, that is $Q_P > Q$ for all considered policy. Obviously, under Complementarity the opposite holds i.e., $Q_P < Q$.
Next, we move to the analysis of the four possible sub-cases (where the fifth sub-case is the one shot game).

- In the first case, $\delta > \delta^T$. To compare Q_P^U and Q_P^*, we inspire to the demonstration of Proposition 2. Substituting equations (A.3), (7) and the definition of $\bar{w}$ into (11) and simplifying, one gets the share obtained by clan i in case of peace under laisser faire. We can therefore define Ω_i^* as the share held by all clans with an overall strength between $q \geq 1$ and $k \leq x_n$ in case of peace:

$$\Omega_i^* = \int_q^k \left[N\frac{3\sqrt{1+2N}-1}{6(1+N+\sqrt{1+2N})} + N\left(1 - \frac{x_i N}{(1+N+\sqrt{1+2N})}\right)^2 \right] dx_i \tag{A.32}$$

The proof of Proposition 2 already showed that the second term of the RHS of expression (A.32) is increasing in N. Differentiating the remaining part of θ_i^* with respect to N and simplifying, one gets:

$$2\sqrt{1+2N} + \frac{4N}{\sqrt{1+2N}} + \frac{3N^2}{\sqrt{1+2N}} + 2 + 6N > 0 \tag{A.33}$$

Since the latter expression is always true, we can conclude that the share held by all types of clan is increasing in N, that is $\frac{\partial \Omega_i}{\partial N} > 0$. Therefore, the share held by all clans of whatever type i shrinks after un-targeted repression, since clans with an overall

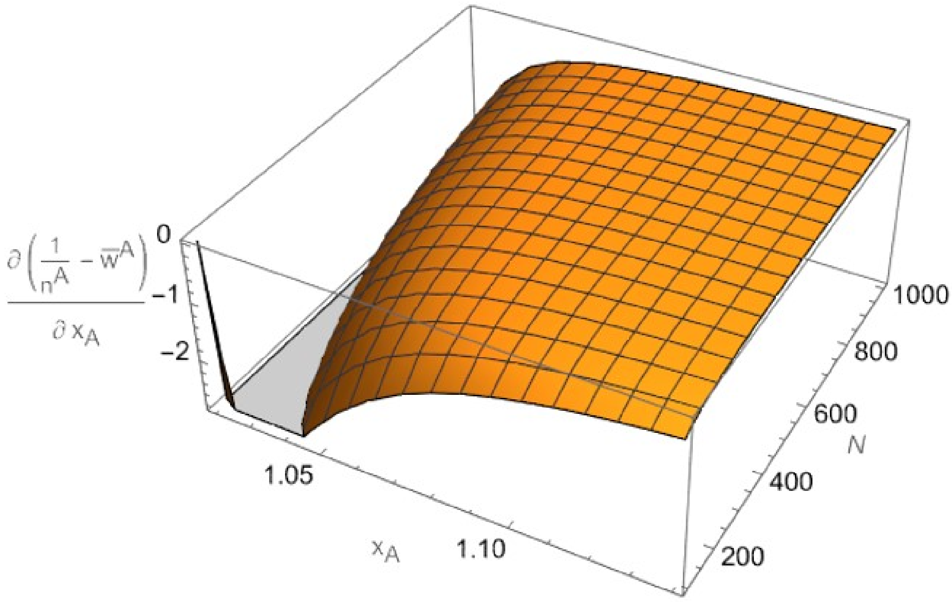


Figure A3: The impact of the survival rate x_A on the net gain $\frac{1}{n^A} - \bar{w}^A$ after anti-targeted repression.

Notes: The figure plots the derivative of the net gain $s_i^A - \theta_i^A$ obtained by each clan though Nash bargaining after anti-targeted repression.

strength between x_n and x_U becomes active. Since the new entrant clans are more productive, we can apply the logic of Proposition 2 to conclude that un-targeted repression increases illegal production, that is $Q_P^U > Q_P^*$.

By the same token, we know that $s_i^A = \frac{1}{n^A} - \bar{w}^A + w_i^A$, where $w_i^A = (1 - G^A x_i)^2$ is decreasing in x_A. Figure A3 shows that $\frac{1}{n^A} - \bar{w}^A$ is decreasing in x_A too i.e., s_i^A is increasing in the intensity $2 - x_A$ of anti-targeted repression. Exploiting the same logic of Proposition 2, we can conclude that under Specialization $Q_P^A < Q_P^*$, as anti-targeted repression leads to the assignment of higher shares (previously held by weaker and more productive clans) to stronger and less productive clans. Clearly, the opposite holds under Complementarity.

Moving to targeted repression, we can rewrite expression (A.32) as follows:

$$\Omega_i^T > N \int_q^k \left[\frac{3\sqrt{1+2Nx_T} - 1}{6(1 + Nx_T + \sqrt{1+2Nx_T})} + \left(1 - \frac{x_i N}{(1 + Nx_T + \sqrt{1+2Nx_T})}\right)^2 \right] dx_i \tag{A.34}$$

The second term of the RHS of (A.34) is clearly increasing in x_T. Differentiating the remaining term with respect to x_T, imposing the derivative greater than 0 and simplifying, one gets:

$$4N + 3N^2 - 3 - 6Nx_T + \sqrt{1 + 2Nx_T} > 0 \tag{A.35}$$

Rewrite inequality (A.35) as follows:

$$(N - 3) + 3N(1 + N - 2x_T) + \sqrt{1 + 2Nx_T} > 0 \tag{A.36}$$

A meaningful analysis of repression requires $N \geq 3$, so that both the first and the second term are non negative. Since the last term is strictly positive, inequality (A.36) is always verified. Therefore, all clans get a higher share after targeted repression i.e., $\frac{\partial \Omega_i^T}{\partial x_T} > 0$. Exploiting the same logic of Proposition 2, we can conclude that under Specialization $Q_P^T > Q_P^*$. Finally, since $x_T > 1$ and $x_k > x_U$, from Part (iv) of Proposition 2, we can conclude that $Q_P^T > Q_P^U$. Wrapping up, one gets $Q_P^T > Q_P^U > Q_P^* > Q_P^A$.

Note that, since in this case there is no violence irrespective of the policy implemented by the state, clans' expected payoff is equal to the operative profit, which is in turn the square of the quantity produced by each clan. Therefore, in this case a higher production directly translates into a higher payoff. Formally, building from the previous Propositions, we can rewrite the results of this Proposition as follows:

$$\begin{cases} Q_P^U (N\Omega_i)^* > Q_P^* (N\Omega_i)^* \\ Q_P^A (N\Omega_i)^A < Q_P^* (N\Omega_i)^A \\ Q_P^T (N\Omega_i)^T > Q_P^U (N\Omega_i)^T \end{cases} \tag{A.37}$$

The interpretation of the first two inequalities (A.37) is that production: (i) increases in each share previously controlled by clans of type i after un-targeted repression; (ii) decreases in each share controlled by clans of type i after anti-targeted repression; (iii) increases in each share controlled by clans of type i after targeted repression, compared to the production after un-targeted repression in the same share of territory. This clearly holds also at the aggregate level (i.e., summing over all the shares). Taking the square on both sides of inequalities (A.37), one still gets three true expressions (i.e., in each share, it holds that targeted repression ensures a higher payoff compared to un-targeted repression, which ensures a higher payoff compared to laisser faire which in turn ensures a higher payoff compared to anti-targeted repression) which aggregated over all shares yield $S^T > S^U > S^* > S^A$. Clearly, opposite results would hold under Complementarity.

- When $\tau^* < \tau < \tau^T$, building on the arguments of Proposition 2, we can state that under Specialization $Q^T > Q_P^U > Q_P^* > Q_P^A$. This is because, although un-targeted repression is followed by peace i.e., it leads to the assignment of a part of the share of the mightiest clans to the weaker (but more productive) clans (up to x_U), targeted repression assigns the entirety of the shares controlled by clans from 1 to x_T to weaker (but more productive) ones (up to $x_k > x_U$). The opposite holds under Complementarity.

- $\tau^A < \tau < \tau^*$, building on the arguments of Proposition 2, we can state that under Specialization $Q^T > Q_P^U > Q^U > Q^* > Q_P^A$. The latter inequality of the chain holds because under laisser faire a part of the shares held by the mightiest clans is transferred to more productive and weaker clans with overall strength between x_A

and x_n, whereas after anti-targeted repression followed by peace the shares' transfer would be towards less productive clans with overall strength below x_A. The opposite logic applies for Complementarity.

- From the discussion of the second sub-case, with $\tau^U < \tau < \tau^A$ and Specialization it holds $Q^T > Q_P^U (> Q^U) > Q^* > Q^A$, whereas the opposite would hold under Complementarity.

Note that, under Specialization, in sub-cases 2 and 3 it is not possible to determine which policy minimizes the aggregate expected payoff of the criminal organization, since targeted repression leads to an increase in both production and military spending compared to untargeted and anti-targeted repression. Specifically, in sub-case 2 we know that $S^U > S^* > S^A$ but we do not know whether $W^T > S^A$ or not, that is, both selective and anti-targeted repression could minimize violence. Likewise, in sub-case 3 we know that $S^U > S^A$ and $W^T > W^U$ but we do not know whether $W^* > S^A$ or not, that is, both laisser faire and anti-targeted repression could minimize violence (in general, the flatter b_i, the more likely $S^A > W^T$).
Conversely, in sub-case 4 it surely hold that for steep enough $b(x_i)$ it holds $W^T > W^* > W^A$ and $S^U > W^A$, so that anti-targeted repression minimizes the total net wealth of the criminal organization, whereas for flat enough $b(x_i)$ it holds $W^T < W^* < W^A < S^U$ and, so that targeted repression minimizes the total expected payoff of the criminal organization.
Finally, under Complementarity sub-case 2 implies $S^A > S^* > S^U > W^T$, as illegal profits are determined only by production with the expection of targeted repression, which would minimize production and maximize violence. By the same logic, sub-case 3 implies $S^A > S^U > W^* > W^T$ unless the function $b(x_i)$ is so steep that $S^A > W^* > S^U > W^T$. Last, sub-case 4 implies $S^U > W^A > W^* > W^T$, unless the function $b(x_i)$ is so steep that $W^A > S^U > W^* > W^T$ or even $W^A > W^* > S^U > W^T$.

The paradox of power play

Alessio Carrozzo Magli*†

Abstract

I present an asymmetric conflict model, revealing that, under fairly general conditions, economically disadvantaged factions derive the greatest benefits from warfare, even when they neither outnumber nor surpass their opponents in military strength. This is because, although less likely to emerge victorious, they have more to win and less to lose from the conflict. The resulting policy implication suggests that weakening the most aggressive belligerents could paradoxically fuel new conflicts, as the shift in the degree of asymmetry may further tempt the rival faction to attack.

I test the model predictions employing a database on militarized interstates disputes spanning the last two centuries and instrumenting countries' difference in GDP per capita with exogenous variations in rainfall.

*Dipartimento di Economia, Università di Bologna, Piazza Scaravilli 2, 40126 Bologna, ITALY, e-mail: alessio.carrozzo2@unibo.it

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1 Introduction

Understanding who has the incentive to initiate warfare is crucial for preventing and mitigating the significant economic and human costs associated with armed conflicts (Fearon, 1995). The debate on how the size of a faction, measured by its resources and population, influences its propensity to engage in war has been extensive. Wealthier belligerents, armed with greater resources, are often considered more likely to prevail in conflicts (Fearon, 1995). Conversely, poorer belligerents might have more to gain and less to lose from the dispute (Powell, 1999).

Support for the first hypothesis has been grounded in the idea that in highly costly conflicts, economically disadvantaged factions may grapple to match the investments made by their wealthier opponents (Hirshleifer, 1991; Garfinkel and Skaperdas, 2007; Franke and Öztürk, 2015). This allows the wealthier belligerents to enjoy a higher probability of victory and, consequently, a higher expected payoff from the dispute. Additionally, if the disputed resources are equally distributed in the absence of conflict, then the wealthier actors have a higher incentive for war relative to the initial resource allocation. Although the hypothesis of equal resource distribution is not always realistic in presence of wealth disparities, it is a quite common assumption in conflict models governed by the standard Contest Success Function[1] *à la Tullock* (Tullock, 1980).

Conversely, support for the second hypothesis is based on the idea that if conflicts are sufficiently cheap, then economically disadvantaged factions can invest resources comparable to those of wealthier factions, thereby roughly achieving a 50% probability of success (Hirshleifer, 1991). This probability may increase further if the poor faction is also stronger than the rich one in military terms (Herrera et al., 2022), e.g., because of specialization between production and predatory activities (Garfinkel and Skaperdas, 2007; Konrad and Skaperdas, 2012; Dal Bó and Dal Bó, 2011). In either cases, since the poor started with a lower initial endowment, it will enjoy at least the same expected payoff and a strictly greater relative incentive for war.

Motivated by this ongoing debate, this work aims to contribute, mostly theoretically but also empirically, to the cited literature on asymmetric conflicts.

From a theoretical perspective, I set up a game-theoretic framework supporting the hypothesis that economically disadvantaged factions have a greater incentive to wage war. Formally, I model a conflict within a network formed by two coalitions (Franke and Öztürk, 2015) of potentially different size whose members are characterized by heterogeneous military strength and resource endowments (Herrera et al., 2022).

From a methodological viewpoint, my setup inspires to and offers a generalization of two distinct classes of models widely adopted in the literature.

First, I contribute to the literature on conflicts with asymmetric initial endowments and/or

[1] A function mapping belligerents' effort into their winning probability.

military strength (Hirshleifer, 1991; Herrera et al., 2022). Whereas the generalization to $n > 2$ players (Corchón, 2007; Garfinkel and Skaperdas, 2007; Cornes and Hartley, 2005) leads to a single all against all war, reflecting the somewhat questionable postulate that "the enemy of my enemy is my enemy", I instead assume that agents sharing the same rivals do not attack each other, i.e., "the enemy of my enemy is my friend". This draws inspiration from a second relevant strand of the literature, modelling a multitude of simultaneous conflicts between the members of two or more coalitions (Alesina and Spolaore, 2005; Bloch, 2012; Franke and Öztürk, 2015), although with some distinctions. First, whereas models of group conflicts often consider and emphasize coalition size asymmetries, they commonly assume symmetry regarding initial endowments and military capability. In this context, my framework seeks to integrate these two model classes by introducing other sources of asymmetry, specifically in wealth and military power, in addition to coalition size. Second, and relatedly, previous studies highlighted the existence of negative network externalities from both enmity -in terms of higher conflict costs (Franke and Öztürk, 2015) and/or lower operational performance in the battlefield (König et al., 2017)- and friendship -in terms of monitoring the activity of the allies and/or suffering the cost of a political union (Alesina and Spolaore, 2005), as well as positive network externalities from friendship -in terms of higher operational performance in the battlefield (König et al., 2017). However, the existence of positive network externalities from enmity -in terms of higher spoils of war for smaller and/or poorer factions- has been largely overlooked. This is instead a crucial element of my setup, that, inspired to both the discussed classes of models, introduces wealth and size heterogeneity in the conflict between coalitions. Although the higher number and/or wealth of enemies reduces the chances of victory, smaller and/or poorer factions have more to win and less to lose. Briefly, I show that this effect generally dominates the others, thereby making the disadvantaged faction more war-seeking. My results hold under fairly general conditions on the three aforementioned sources of asymmetry that, if relaxed one by one, trace the model back to those of Hirshleifer (1991), Herrera et al (2022) and Franke & Öztürk (2015). However, an important caveat might lead to contrary outcomes. Specifically, the economically disadvantaged faction may be unable to afford the optimal military investment determined at the interior solution of the game, due to e.g., a binding budget constraint. In this scenario, the economic underdog is characterized by a higher probability of losing the war, which would diminish its net gains from the conflict—potentially turning them into net losses, as extensively discussed by Hirshleifer (1991). With heterogeneous probabilities of victory between rich and poor agents, the incentive to wage war is therefore determined by the disparity between the initial endowment (i.e., resources allocated in the absence of conflict) and actual military power (i.e., the real chances of winning the conflict). This concept is explored by (Herrera et al., 2022) for $n = 2$ and is somewhat extended to conflicts between alliances by Jackson and Morelli (2007). Next, unlike most asymmetric conflict models which focuses on one-shot interactions, I also extend the time horizon to an infinitely repeated game (Castillo and Kronick, 2020) to formalize some counter-intuitive policy implications. Specifically, I show that policies designed to reduce the likelihood of conflict by weakening the capabilities of the most aggressive faction could inadvertently backfire. This is due to the ensuing alteration of the former power balance, which may create an even stronger incentive for other factions to initiate attacks (Osorio, 2015). The latter finding appears to find support in the evidence presented by Dell (2015) regarding the effects of state crackdowns on the subsequent conflict intensity between Mexican drug cartels. Furthermore, under the plausible hypothesis that military effort is positively correlated with violence (Castillo and Kronick, 2020), a clear trade-off emerges: since, the most (least) aggressive faction generally invests more (less) in the conflict, weakening it reduces (increases) violence but also increases (decreases) the probability of conflict. The net effect on expected violence -i.e., the product between violence and the probability of occurrence of the dispute- is therefore ambiguous.

From an empirical perspective, I present the first evidence supporting the theoretical prediction that economically disadvantaged belligerents have a higher incentive for war. Specifically, employing the Correlates of War database (COW, 2021) on militarized interstates disputes over the years 1816-2014, I show that, if there is a conflict between countries i and j, the probability that i is the initiator decreases in the difference between its GDP per capita and that of country j, despite the richer country being more likely to win the dispute. The analysis excludes dispute events where the roles of attacker and defender are ambiguous, as such cases could undermine the validity of the results[2] (Caselli et al., 2015). We address major criticisms regarding the causal relationship between climatic conditions and conflicts, mediated through economic changes (Couttenier and Soubeyran, 2014; Sarsons, 2015), by conducting extensive robustness checks. These checks are informed by recent advances in the field (Berlemann and Wenzel, 2018; Devlin and Hendrix, 2014; Damania et al., 2020; Coulibaly and Managi, 2022; Kotz et al., 2022) and will be detailed in subsequent sections. To mitigate potential selection bias, the main results are also replicated using the Heckman two-step method (Heckman, 1979; Wooldridge, 2010). Further confirmation of these results is obtained by aggregating data at the coalition level, rather than by individual country pairs.

So far, scholars have found that wealth disparities play a crucial trigger role in triggering conflicts (Berman et al., 2021), especially when such disparities do not align with military capabilities (Herrera et al., 2022; Hong et al., 2022). However, to the best of my knowledge, this study is the first attempt to causally establish whether this wealth heterogeneity pushes the poor or the rich to initiate conflicts. Likewise, previous research has found that the network structures of alliances and enmities play a significant role in influencing the intensity of con-

[2]The rarity of using this approach in the literature, despite some exceptions like Colgan (2010) and De Soysa et al (2010), may be attributed to the challenges posed by ambiguously directed dyads.

flict, particularly in terms of the military effort exerted during disputes (König et al., 2017). However, no specific predictions have been empirically tested to determine whether conflicts are primarily initiated by large and/or powerful alliances as opposed to smaller and/or weaker ones. In this respect, I provide some evidence suggesting that what is found at the country-pair level holds also between coalitions, namely that disadvantaged coalitions are more likely to be the initiator of a dispute.
The rest of the article is organized as follows. In section 2 I present and solve the model. Data and the empirical strategy are discussed in section 3, whereas the empirical results are shown in section 4. Concluding remarks follow.

2 The model

In section 2.1 I describe the assumptions of the model, whereas in section 2.2, I solve the one-shot game. Finally, in section 2.3 I allow the game to be repeated infinitely (or indefinitely) many times to derive some counter-intuitive policy implications.

2.1 Model setup

Consider a conflict game between two coalitions whose total population is $N \geq 2$. Coalition I has m members, whereas coalition J has $n = N - m$ members, with $min[n, m] \geq 1$. The network structure is a complete bipartite network with bidirectional links (Franke and Öztürk, 2015): all members of a given coalition are simultaneously in war against all members of the rival alliance.
Each bilateral conflict is governed by a standard ratio contest success function à la Tullock (1980), which gives the probability that player i wins over j:

$$p_{ij} = \frac{g_{ij}}{g_{ij} + g_{ji}}, \tag{1}$$

where g_{ij} is military effort of player i against j. The winner temporarily occupies a portion of the opponent territory extracting its resources, but no player ceases to exist after the war. Formally, if player $i \in I$ defeats player $j \in J$, player j will pay a sum π_j to player i. If, on the contrary, j defeats i, she will obtain a sum π_i from player i. In other words, for any battlefield:

- if no conflict occurs, player i keeps π_I and player j keeps π_J;
- if i defeats j, she keeps $\pi_I + \pi_J$ minus the military investment;
- If i loses against j, she loses its resources and also pays the military investment.

The presence of network negative externalities from being involved in several conflicts is captured by a convex cost function (Franke and Öztürk, 2015):

$$\begin{cases} C(G_i) = G_i^2, \ G_i = \sum_{j=1}^{n} g_{ij} \\ C(G_j) = G_j^2, \ G_j = \sum_{i=1}^{m} g_{ji} \end{cases} \tag{2}$$

For the sake of analytical tractability, all members of the same coalitions are assumed to be identical, i.e., $\pi_i = \pi_I \ \forall i \in I$ and $\pi_j = \pi_J \ \forall j \in J$. However, we allow for heterogeneity across coalitions in three ways. First, one coalition may be formed by wealthier members, i.e., π_I may differ from π_J. Second, one coalition may be more numerous, i.e., m may differ from n. Third, players pay a coalition-specific fixed cost to enter the war, which we denote by c_I and c_J for members of coalition I and J respectively. Overall, the payoff functions of the generic players $i \in I$ and $j \in J$ are defined as follows:

$$\begin{cases} W_i = \sum_{j=1}^{n} \frac{g_{ij}}{g_{ij}+g_{ji}}(\pi_I + \pi_J) - \left(\sum_{j=1}^{n} g_{ij}\right)^2 - c_I \\ W_j = \sum_{i=1}^{m} \frac{g_{ji}}{g_{ij}+g_{ji}}(\pi_I + \pi_J) - (\sum_{i=1}^{m} g_{ji})^2 - c_J \end{cases} \tag{3}$$

Note that the theoretical predictions of this model can be applied to any conflict between two coalitions of any size, therefore including also the specific case of a two players contest ($n = m = 1$).

2.2 The one shot game

Simultaneous maximization of equations (3) yields the following system of first order conditions:

$$\begin{cases} \frac{g_{ji}}{(g_{ij}+g_{ji})^2}(\pi_I + \pi_J) - 2\sum_{j=1}^{n} g_{ij} = 0 \\ \frac{g_{ij}}{(g_{ij}+g_{ji})^2}(\pi_I + \pi_J) - 2\sum_{i=1}^{m} g_{ji} = 0 \end{cases} \tag{4}$$

Exploiting symmetry within each coalition, we can write $g_{ij} = g_i \ \forall j \in J$ and $g_{ji} = g_j \ \forall i \in I$. Therefore, it shall also hold that $G_i = ng_i$ and $G_j = mg_j$. Then, dividing the two equations (4) one gets:

$$g_{ji} = g_{ij}\sqrt{\frac{n}{m}} \tag{5}$$

Note that substituting equation (5) into (1) yields the probability that player i wins over j. This probability is independent on the initial endowments π_I and π_J only under the implicit assumption that the poorest players can afford the optimal military investment determined in (5), i.e., the game has an interior solution. The possibility that the poorest players reach the corner solution, not showed here but discussed by Hirshleifer (1991), would instead establish a

positive relation between the wealth of a player and its winning probability.
Now, plugging equation (5) into the second equation (4), solving for g_{ij} and substituting again into (5), exploiting (2), yields players' optimal military effort per battlefield and in aggregate terms:

$$\begin{cases} G_i^* = ng_i^* = \frac{1}{(\sqrt{n}+\sqrt{m})}\sqrt{\frac{\pi_I+\pi_J}{2}\sqrt{\frac{m}{n}}} \\ G_j^* = mg_j^* = \frac{1}{(\sqrt{n}+\sqrt{m})}\sqrt{\frac{\pi_I+\pi_J}{2}\sqrt{\frac{n}{m}}} \end{cases} \tag{6}$$

Plugging equations (6) into (4), one gets players' expected payoff:

$$\begin{cases} W_i^* = \frac{(2\sqrt{m}+\sqrt{n})(n\sqrt{m})}{2(\sqrt{m}+\sqrt{n})^2}(\pi_I+\pi_J) - c_I \\ W_j^* = \frac{(2\sqrt{n}+\sqrt{m})(m\sqrt{n})}{2(\sqrt{m}+\sqrt{n})^2}(\pi_I+\pi_J) - c_J \end{cases} \tag{7}$$

In what follows we will assume that all players will enjoy a war payoff greater than their outside option ($-n\pi_I$ for $i \in I$ and $-m\pi_J$ for $j \in J$). Alternatively, we shall simply reinterpret m and n as the number of players of the two coalitions which do not prefer to surrender and will therefore be active.
Comparing the two equations (7), one can determine which coalition benefits the most from war in absolute terms:

$$W_i^* > W_j^* \iff \frac{(n-m)(\sqrt{nm})}{2(\sqrt{m}+\sqrt{n})^2}(\pi_I+\pi_J) > c_I - c_J \tag{8}$$

Moreover, subtracting from the war payoff the corresponding peace payoff ($P_i = n\pi_I$ for player i and $P_j = m\pi_J$ for player j), one can compare also the net incentive to engage war (defined as $I_h = W_h^* - P_h$, $h = i, j$), which will be useful for the subsequent analysis:

$$I_i - I_j > 0 \iff \frac{(n-m)(\sqrt{nm})}{2(\sqrt{m}+\sqrt{n})^2}(\pi_I+\pi_J) - n\pi_I + m\pi_J > c_I - c_J \tag{9}$$

Both conditions (8) and (9) depend on three different sources of asymmetry, namely the number, wealth and military power of the members belonging to the two coalitions. As a convenient shortcut, we start by separately looking at the effects of each type of asymmetry imposing symmetry on the other two.

Case 1: $n = m$, $\pi_I = \pi_J$

If coalitions are homogeneous in terms of population and wealth, conditions (8) and (9) simplify to:

$$W_i^* > W_j^* \iff c_I < c_J \iff I_i > I_j \tag{10}$$

Intuitively, *ceteris paribus*, stronger players benefit more from war both in absolute and in relative terms. This is a standard result of asymmetric conflicts (Corchón, 2007).

Case 2: $c_I = c_J$, $\pi_I = \pi_J = \pi$

If coalitions are homogeneous in terms of wealth and military strength, condition (8) simplifies to:

$$W_i^* > W_j^* \iff n > m \tag{11}$$

In contrast, condition (9) simplifies to:

$$I_i > I_i \iff n < m \tag{12}$$

The intuition behind condition (11) is that, *ceteris paribus*, smaller coalition fight for higher spoils of war as they are involved in more battlefields. The higher revenues more than offset the higher costs of engaging the war. Notice that condition (11) derives the opposite result of Franke and Öztürk (2015), who instead claimed that smaller coalitions pay higher military costs and are therefore worse off. However, this difference simply stems from the fact that they are measuring the net incentive to wage war relative to peace, and not the absolute payoff stemming from war. Indeed, since the two coalitions are equally wealthy, the less populated faction is in fact richer in per capita terms ($n\pi > m\pi \ \forall \ n > m$). Thus, smaller coalitions have less to gain (or more to lose) from a conflict, compare to the initial allocation of resources. Formally, condition (12) essentially captures the results of Franke and Öztürk (2015).
In other words, in this simplified scenario there are few rich players who benefit from war more than the many poor agents in absolute terms but less in relative terms. As I will discuss in section 2.3, this means that poorer players are more likely to engage war.

Case 3: $n = m$, $c_I = c_J$

If coalitions are homogeneous in terms of population and military strength, condition (8) is always satisfied as a strict equality because all players enjoy the same expected payoff from war. Indeed, since the two coalitions are equally mighty and populated, each of their members will win on each battlefields with probability one half. However, (9) simplifies to:

$$I_i > I_i \iff \pi_I < \pi_J \tag{13}$$

Intuitively, poorer players have a higher incentive for war, *ceteris paribus*, because, though their expected wealth at the end of the conflict is the same of their rivals, they compare it with a lower initial endowment. In other words, they extracted resources from a richer opponent.

Assuming $n = m = 1$, this simplified model replicates the results of Hirshleifer (1991).
Note that the number of members of a coalition is an important feature of the model only when the contest is not excessively asymmetric. In fact, a super strong player would still be advantaged against a coalition made of a higher number of super weak players. Pairwise, even if in numeric disadvantage, very poor coalitions would enjoy the conflict more than the rival faction because they would have more to win and less to lose. Therefore, without loss of generality, we can reformulate conditions (8) and (9) imposing $n = m$ but preserving the asymmetry in wealth and military power.

Case 4: $n = m$

In a contest between two equally populated coalition with heterogeneous wealth and military power, condition (8) will simplify again to (10). In other words, the strongest coalition benefits the most from war in absolute terms. In contrast, condition (9) becomes:

$$I_i > I_i \iff \pi_J - \pi_I > \frac{2(c_I - c_J)}{N} \tag{14}$$

Inequality (14) represents the main testable prediction of the model, namely that what matters in determining the incentive for war is the relation between the difference in wealth and that in military power. In particular, players of a given coalition benefit more from war if at least one of the conditions below is satisfied:

- they are poorer and stronger than their opponent;
- they are poorer and not excessively weaker than their opponent;
- they are richer and sufficiently stronger than their opponent.

Therefore, even if one assumes a positive correlation between wealth and military strength, poorer (and weaker) players may nevertheless be advantaged in a conflict if they are "sufficiently poorer than weaker".
Notably, in a two players contest, condition (14) simplifies to $\pi_J - \pi_I > c_I - c_J$, which essentially replicates the results of Herrera et al (2022). In contrast, in a contest with many players ($N \to \infty$) it becomes $\pi_J - \pi_I > 0$.
In other words, for low N, wealth and military power are equally important in determining the incentive to engage war. However, the higher the number of belligerents, the more the difference in wealth remains the only relevant dimension.

2.3 Policy implications in the repeated game

Assume that the game described in the previous section is repeated infinitely many times. Then, the Folk theorem (Friedman, 1971) states that players can avoid the war provided that they are patient enough by playing the classic grim trigger strategy (i.e., players stick to the peace agreement as long as it is respected by all players, but they engage war forever at the first defection). Formally, the discounted present value of peace shall exceed the discounted present value of starting a war for all members of both coalitions. Denote by $\delta \sim U[0,1]$ the discount factor common to all agents. Then, for player $i \in I$, the following inequality shall hold:

$$\frac{n\pi_I}{1-\delta} > n\pi_I + m\pi_J - c_I + \frac{\delta}{1-\delta}\frac{(2\sqrt{m}+\sqrt{n})n\sqrt{m}}{2(\sqrt{m}+\sqrt{n})^2}(\pi_I + \pi_J) \tag{15}$$

Solving inequality (15) for δ yields the minimum discount factor such that player $i \in I$ will stick to the peace agreement:

$$\delta > \frac{n\pi_J - c_I}{n(\pi_J + \pi_I)\left[1 - \frac{2m+\sqrt{nm}}{2(\sqrt{m}+\sqrt{n})^2}\right] - c_I} = \delta_i^* \tag{16}$$

In contrast, for player j it shall hold:

$$\frac{m\pi_J}{1-\delta} > n\pi_I + m\pi_J - c_J + \frac{\delta}{1-\delta}\frac{(2\sqrt{n}+\sqrt{m})m\sqrt{n}}{2(\sqrt{m}+\sqrt{n})^2}(\pi_I + \pi_J) \tag{17}$$

Solving inequality (17) for δ, one gets the minimum discount factor such that player $j \in J$ will stick to the peace agreement:

$$\delta > \frac{m\pi_I - c_J}{m(\pi_J + \pi_I)\left[1 - \frac{2n+\sqrt{mn}}{2(\sqrt{m}+\sqrt{n})^2}\right] - c_J} = \delta_j^* \tag{18}$$

Notably, given the hypothesis on the distribution of the discount factor, δ_i^* and δ_j^* respectively denote the probability that i and j deviate from the peace agreement. It therefore follows that the probability that a war occurs is equal to $p = max[\delta_i^*, \delta_j^*]$.
Simple inspection of conditions (16) and (18) reveal that $\frac{\partial \delta_i^*}{\partial c_I} < 0$ and $\frac{\partial \delta_j^*}{\partial c_J} < 0$. In other words, *ceteris paribus*, stronger players are also more impatient. Without loss of generality, we can therefore assume $c_I = c_J = 0 \; \forall \; i \in I, j \in J$ and focus on the effects of wealth heterogeneity on the sustainability of the peace agreement.
Then, comparing the RHS of (16) and (18), one can find the conditions such that player $i \in I$ is more impatient than $j \in J$, i.e., $\delta_i^* > \delta_j^*$. In particular, note that:

- the numerator of (16) is greater than that of (18) if $\pi_J > \pi_I$, i.e., i is poorer than j

- The denominator of (16) is lower than that of (18) if $m > n$, i.e., if i is in numerical advantage

In other words, poorer players that are not excessively in numeric disadvantage (otherwise, they would become richer in per capita terms) will be more likely to deviate from a peace agreement. Note that if the two coalitions are homogeneous in terms of military power and population, the above conditions simplify to $\pi_I > \pi_J$, i.e., the poorer coalition will be more likely to deviate first, i.e., $p = \delta_i^*$.

Moreover, under symmetry in military power, the policy implications are far from irrelevant. Indeed, it is easy to note that:

$$\begin{cases} \frac{\partial \delta_i^*}{\partial n} < 0 < \frac{\partial \delta_i^*}{\partial m} \\ \frac{\partial \delta_j^*}{\partial m} < 0 < \frac{\partial \delta_j^*}{\partial n} \end{cases} \tag{19}$$

Inequalities (19) highlights the following trade-off: whereas eliminating some players of the most aggressive coalition (say, I) reduces its members' incentive to deviate ($\frac{\partial \delta_i^*}{\partial m} > 0$), it also increases the incentive to engage war for the rival coalition ($\frac{\partial \delta_j^*}{\partial m} < 0$). Eventually, the rival coalition J may be even more aggressive than what was I before its partial annihilation. Likewise, the elimination of a subset of the more "peaceful" coalition (say, J) increases the incentive to wage war for coalition J, but it reduces that of the most aggressive coalition I. In other words, a partial elimination of the most pacific (aggressive) coalition may result in a decrease (increase) in the probability of a war A numerical example is provided in Appendix A.

Notably, the probability of a war is not the only relevant factor. Define violence as an increasing function (Castillo and Kronick, 2020) $V(G)$, where G is total military investment according to:

$$G^* = mG_i^* + nG_j^* = \sqrt{\sqrt{mn}(mn)\frac{\pi_I + \pi_J}{2}} \tag{20}$$

It is immediate to note that aggregate military investment is more sensitive to changes in the number of members of the smaller coalition.

Now, define expected violence can be defined as follows:

$$EV = pV(G^*) = max[\delta_i^*, \delta_j^*]V(G^*) \tag{21}$$

Two possibilities emerge. First, if coalition I is both the smallest and the most aggressive, its partial elimination produces three effects:

- members of coalition i become less aggressive
- members of coalition j become more aggressive
- aggregate military investment decreases

In contrast, under the same set of hypotheses, the elimination of some members of the rival coalition J produces the following consequences:

- members of coalition i become more aggressive
- members of coalition j become less aggressive
- aggregate military investment decreases by a lower amount

In other words, in the first sub-case, military investment falls by a higher amount, whereas the probability of a conflict may either go down or up, depending on whether coalition J becomes or not sufficiently aggressive. In contrast, in the second sub-case the probability of a war surely goes up, and military investment goes down by a lower amount.

If, on the contrary, coalition I is the biggest and the most aggressive, then its partial elimination reduces military investment and produces ambiguous effects on the probability of a conflict, whereas the elimination of some members of coalition J increases the probability of a conflict but reduces aggregate military investment by a greater amount.

Overall, the net impact of any policies attempting to eliminate some members of either coalition depends on which of the two effects (that on aggregate military investment *vis à vis* that on the discount factor threshold) dominates. Specifically, eliminating m' members of coalition I reduces expected violence if:

$$EV(m,n) - EV(m-m',n) < 0 \iff \frac{p(m,n)}{p(m-m',n)} < \frac{V(G,m-m',n)}{V(G,m,n)} \tag{22}$$

Likewise, eliminating n' members of coalition J reduces expected violence if:

$$EV(m,n) - EV(m,n-n') < 0 \iff \frac{p(m,n)}{p(m,n-n')} < \frac{V(G,m,n-n')}{V(G,m,n)} \tag{23}$$

2.4 Summing up: from theory to empirics

The presented model yields a wealth of theoretical predictions, some of which can be tested at the belligerent level, some other only at the coalition one. At the present time, I will only test the main result of Section 2.2[3]. In particular,let $\Delta\pi = \pi_I - \pi_J$ and $\Delta c = c_J - c_I$. Then, the main testable hypothesis under $N = 2$ and given the level of Δc is that the probability that i attacks j is decreasing in $\Delta\pi$.

Among the robustness checks presented in section 4.3, I test the above mentioned hypothesis also at the coalition level, i.e., showing that poorer coalition are more likely to attack first.

[3]I plan to test the predictions of section 2.3 in the close future.

1 No military action =	1021729			
Sample (2-5)	Full		Only certain initiator	
Hostility level of MID	N	%	N	%
2 Threat to use force	231	4.45	215	5.54
3 Display of force	1245	28.43	1160	29.88
4 Use of force	2994	57.67	1966	50.64
5 Interstate war	722	13.91	541	13.94
Total	5192	100	3882	100

Table 1: Conflict intensity (1816-2014).

3 Data and empirical strategy

The data employed to test my theoretical predictions come from the Correlates of War (COW) project (Correlates of War, 2021). Specifically, I employ country-pair data on militarized interstates disputes (MID) over the years 1816-2014. Each MID is coded with a hostility level ranging from 1 to 5, whose description and frequency is shown in Table 1 for the whole database as well as for the subsample for which the initiator of the dispute is clearly identified, which is the main object of interest for the present analysis. Given the low frequency of interstate wars, I use a broader definition of MID (Martin et al., 2008), ranging from level 2 to 5 (summary statistics in Appendix B), further restricting it in the robustness checks section (4.3).

I define $\Delta\pi_{i,j,t}$ as the difference in real GDP per-capita (in 1990 International Geary-Khamis dollars) between country i and j at time t (Bolt and van Zanden, 2020). Likewise, $\Delta c_{i,j,t}$ denotes the difference in military spending[4] between country i and j at time t. Following the gravity literature (Martin et al., 2008), I control for bilateral distance (between borders and capitals), contiguity, similarity in languages, colonial links as well as whether the pair has ever formed (or forms) a unique country[5] (Mayer and Zignago, 2011). Finally, I add a dummy taking value one in case of positive difference between countries i and j's scores in the democracy index (Polity V). As a first step, I test my theoretical prediction adopting the following empirical strategy:

$$Pr(i\ attacks\ j \mid dispute_{i,j})_t = \beta\Delta\pi_{i,j,t} + \delta\Delta c_{i,j,t} + \gamma X_{i,j,t} + \alpha_T + \eta_{i,j} + \varepsilon_i + \xi_j + u_{i,j,t}, \quad (24)$$

where ε_i and ξ_j denotes the country-specific fixed effects, $u_{i,j,t}$ is the error term and α_T controls for time fixed effects. In particular, given the long time span, I will also use decade fixed effects, although in the most demanding specifications I substitute them with year fixed effects. Finally,

[4] Notably, a higher $\Delta c_{i,j,t}$ (i spends more than j) corresponds to a higher $\Delta c = c_{jt} - c_{it}$ (j is weaker than i) as defined in section 2.4.

[5] Note that the rich set of FE included in equation (24) essentially absorbs the impact of these control variables, which are almost time-invariant. Nonetheless, these control variables will be useful in the upcoming sections.

since there are probably other unobserved determinants of international relations (Head and Mayer, 2013) and conflicts (Caselli et al., 2015), I also add country-pair fixed effects ($\eta_{i,j}$). The coefficient of interest is β (expected to be negative), capturing the impact of a change in country i GDP per capita relative to that of country j on the probability that i attacks j conditional on the occurrence of a dispute between the two[6]. Secondarily, I will also comment on the size and sign of the coefficient δ, capturing the impact of the difference in military spending between countries i and j on the probability that the former attacks the latter.

Notably, equation (24) raises two main concerns, namely endogeneity and selection bias. As for endogeneity concerns, there are serious issues of simultaneity and reverse causality, as international conflicts and militarized disputes affect both GDP and military spending for obvious reasons. The two main regressors are also likely to be excessively correlated. Moreover, there might be also measurement errors in both the dependent and the explanatory variables, as well as potential omitted variables that may affect conflict dynamics. To address these issues, I adopt the following IV strategy. First, after showing some suggestive correlations coherent with my predictions, I drop $\Delta c_{i,j,t}$ (and the score difference in the democracy index) from the regressions, thereby focusing solely on the effect of GDP per capita differentials on the likelihood of being the initiator of a militarized dispute. Second, I instrument $\Delta\pi_{i,j,t}$ exploiting exogenous variations in the difference between rainfall in countries i and j. Specifically, for both country I divide the year-average precipitation (in mm) by the size of agriculture land (in squared km). Data (available only from 1961 onward for agriculture land) are respectively taken from Harris et al (2020) and from the World Development Indicators (World Bank). The intuition behind the identification strategy is that rainfall should be an exogenous shock that affects GDP by increasing agricultural productivity (Harari and La Ferrara, 2018; König et al., 2017) and impact conflicts only by this channel. There has been an extensive debate upon the use of rainfall variations to instrument for income when the outcome variable is conflict occurrence. Couttenier and Soubeyran (2014) argue that the relationship between rainfall and civil war in Sub-Saharan Africa is driven by global climate shocks, whereas Barrios et al (2010) find a positive effect of rainfall on GDP only for African countries. Relatedly, Dell et al (2012) and Burke et al (2015) find little (strong) evidence of an impact of rainfall (temperature), although their dependent variable is GDP growth and not level. Furthermore, Sarson (2015) finds that rainfall has a negative impact on religious conflicts in India also in areas downstream of dams even though irrigation makes agricultural production less sensitive to rain shocks, thereby questioning the validity of the exclusion restriction hypothesis. Overall, key criticisms regarding the use of rainfall as an instrument for GDP center on its weak predictive power for GDP in wealthy economies and its potential to influence conflicts through channels other than the income one.

[6]Thus, the dependent variable does not measure the probability that i initiates a dispute with j. Rather, it measures the probability that, if there is a dispute between the two countries, the initiator of this dispute was i.

Addressing these concerns, several studies have sought to refine the empirical strategy to mitigate these issues. Berlemann and Wenzel (2018) highlight that, as also suggested by Dell et al (2012), the comprehensive set of control variables typically employed in such studies may be influenced by climate variables, potentially leading to biased outcomes. Using a two-way fixed effects model, they demonstrate a significant long-term impact of rainfall on GDP growth in underdeveloped countries (not only the African ones), although their dependent variable is GDP growth and not level. Expanding on this theme, Devlin and Hendrix (2014) find that long-term effects of water scarcity and variability contribute to fueling militarized interstate disputes, a finding more closely aligned with the framework of my study. In further support, studies that disaggregate data at the subnational level, such as those by Kotz et al (2022) and Damania et al (2020), report a nonlinear and robust effect of rainfall averages and variations on GDP growth. Most pertinent to my analysis, Coulibaly and Managi (2022) demonstrate that the impact of rainfall on conflicts via the income channel is more pronounced when analyzed at a more granular, monthly level.

Building on these recent developments, I plan to conduct a series of robustness checks to strengthen the validity of my findings. These checks include: (i) disaggregating rainfall and conflict data at the quarterly level; (ii) examining non-linear effects of precipitation, (iii) focusing on a sub-sample of less developed countries, (iv) excluding extreme values by dropping the top and bottom 5% of the differences in GDP per capita, and (v) incorporating medium-run effects of rainfall. The latter exercise also provides additional evidence in support of the exclusion restriction hypothesis. In this sense, König et al (2017) provide relevant insights by discussing the minimal impact of rainfall shocks on conflict decisions in the Congo, considering potential secondary channels such as migration, terms of trade, spatial correlation in rainfall, and measurement errors. Their findings suggest that in a single-country context, these secondary channels have negligible effects, which reassures their likely minimal impact in my broader, international setting. Moreover, concerns about the direct influence of rainfall on conflicts—such as the reduced likelihood of people participating in riots under severe weather conditions (Sarsons, 2015)-, are primarily relevant for studies on civil conflicts rather than international ones. Still, to further mitigate any direct impact of rainfall on conflicts, I will also utilize lagged variables of rainfall.

As for selection bias, this analysis might be flawed due to its focus on conflicting dyads rather than considering the complete matrix of observations for each pair of countries per year. Moreover, including non-conflicting dyads presents significant interpretative challenges for the dependent variable, which should be zero if country i is the defender and one if it is the attacker in a militarized interstate dispute. A third value would be needed if countries i and j are not incurring in a dispute.For these reasons, I retain equation (24) as my baseline, testing for potential selection bias using the Heckman two-step method (Heckman, 1979; Wooldridge, 2010).

In the first step, I regress the probability that two countries will enter into conflict on a set of exogenous regressors. I then compute the inverse Mills ratio, which I use as a control variable in the second step (i.e., the restricted-sample regressions). The results indicate that the inverse Mills ratio is not statistically significant, suggesting that selection bias is not a concern in the model. Notably, the set of exogenous regressors used in the first step of the Heckman procedure should include at least one variable that is not included in the second step (Wooldridge, 2010). This requires identifying an exogenous variable that influences the likelihood of conflict between countries i and j but does not affect the GDP per capita of the two countries or the probability of either being the attacker or defender in a dispute. While the variable contiguity and the other controls seem appropriate for this purpose, their temporal variability is very limited, which means they are partially absorbed by the fixed effects included in the model. To address this, I also incorporate data on interstate alliances (Correlates of War, 2021). The presence of an alliance between two countries at time t is likely independent of their economic status and does not directly influence whether one country is the attacker or defender in the event of a conflict. However, the existence of an alliance can significantly influence the general likelihood of a dispute occurring between the two countries.

4 Empirical results

In section 4.1 I present the OLS estimations of equation (24), whereas IV estimations are discussed in section 4.2. Finally, in section 4.3 I present a wealth of robustness checks to further validate the findings from the main analysis.

4.1 OLS results

The OLS estimations of equation (24) are reported in Table 2. In the first column, I regress the probability that i attacks j (conditional on a dispute between the two countries) on the difference between the GDP per capita of countries i and j.The second column adds control for the difference in military expenditure between countries i and j ($\Delta c_{i,j}$). In the third column, I add countries, country pairs and decades fixed effects, whereas in the fourth column I substitute decades with year fixed effects. In the fifth and sixth columns, I further augment the models with a comprehensive set of geographic, ethnic, and political controls outlined in section 3, accompanied by decade and year fixed effects, respectively. Across all specifications, a negative and statistically significant effect of $\Delta\pi_{i,j}$ on the conditional probability of i attacking j is observed. Similarly, a positive and strongly significant effect of $\Delta c_{i,j}$ is consistently found. Note that the coefficients are comparable across all specifications and increase in size as more demanding models are estimated. While the statistical significance slightly diminishes in the

y=	Pr(i attacks j | dispute$_{i,j}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\pi_{i,j}$	-.002***	-.003***	-.006**	-.005*	-.005*	-.004*
	(.001)	(.001)	(.003)	(.002)	(.002)	(.002)
$\Delta c_{i,j}$		.004***	.005***	.003***	.005**	.005**
		(.001)	(.002)	(.001)	(.002)	(.002)
Full set of controls					✓	✓
Country-pair FE			✓	✓	✓	✓
Single country FE			✓	✓	✓	✓
Decade FE			✓		✓	
Year FE				✓		✓
Observations	3257	3172	3172	3172	2969	2969
Country-pairs			675	675	610	610
R-squared	.004	.02	.63	.70	.61	.68

Table 2: The impact of differences in GDP per capita on the probability of initiating a militarized disputes-OLS results.

Notes: Robust standard errors (columns 1-2) clustered at the country-pair level (columns 3-6) in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. The variable $\Delta c_{i,j}$ is expressed in thousands current dollars.

most complex specifications, it remains below the 10% confidence level. The magnitude of the impact is far from negligible. With the inclusion of time, country and country pair fixed effects (columns 3-6), a 2000\$ in country i's GDP per capita relative to country j is associated with an approximately 1 percentage point increase in the conditional probability of i attacking j. The interpretation of the coefficient requires careful consideration. Specifically, the effect of a one-unit change in GDP differentials on the probability of country i attacking j is the product of two probabilities: the likelihood of i attacking j and the probability that any conflict occurs between the two countries.

4.2 IV results

The IV estimations of equation (24) are presented in Table 3. This analysis replicates the specifications in Table 2, excluding the variable $\Delta c_{i,j}$ and the democracy index from all regressions, as they are potentially affected by conflict engagement. Accordingly, the second column of Table 2 is not presented here, since it differed from the first one only because of the inclusion of $\Delta c_{i,j}$. In all specifications, the Kleibergen-Paap F statistics suggests that the instrument is not weak (see Appendix B for the first stage results). The coefficient of interest gains a remarkable increase in the statistical significance (far below 1% level of confidence even in the most demanding specifications) and up to a one order of magnitude increase in the size: a 200\$ decrease in country i's GDP per capita *vis à vis* that of country j is associated with a

y=	Pr(i attacks j $\vert$ dispute$_{i,j}$)				
	(1)	(2)	(3)	(4)	(5)
$\Delta\pi_{i,j}$	-.005***	-.044***	-.031***	-.042***	-.031***
	(.001)	(.008)	(.007)	(.008)	(.007)
Full set of controls				✓	✓
Country-pair FE		✓	✓	✓	✓
Single country FE		✓	✓	✓	✓
Decade FE		✓		✓	
Year FE			✓		✓
Observations	1665	1665	1665	1599	1599
Country-pairs		405	405	387	387
R-squared	-.03	-.43	-.25	-.13	-.24
Kleibergen-Paap F statistics	299.75	196.87	77.05	190.46	75.45

Table 3: The impact of differences in GDP per capita on the probability of initiating a militarized disputes-IV results.

Notes: Robust standard errors (columns 1) clustered at the country-pair level (columns 2-5) in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars.

more than 10 percentage point increase in the conditional probability of i attacking j. This substantial discrepancy suggests a significant downward bias in the OLS estimates, likely due to the correlation between $\Delta\pi_{i,j}$, and $\Delta c_{i,j}$, as well as that between $\Delta\pi_{i,j}$ and the democracy index. Additionally, the negative impact of conflicts on GDP, primarily through the destruction of resources, may contribute to this bias (Fearon, 1995; Garfinkel and Skaperdas, 2007). The variation in OLS and IV coefficients mmay also be attributed to the fact that the IV regressions are limited to the years 1961 to 2014, a subset of the overall period covered by the OLS analysis.

4.3 Robustness checks

In this section, I conduct five sets of robustness checks. The initial two sets aim to reinforce my interpretation of the results presented in Tables 2 and 3. The third and fourth sets are designed to further enhance the instrumental variable (IV) strategy. The final set addresses potential selection bias.

First (Table 4), I regress the probability that country i wins the dispute against j conditional on i being the initiator. I start again from a simple regression of the conditional probability that i defeats j on the difference in the two countries GDP per capita. In column 2, I include the difference in military expenditure between the two countries. In columns 3 and 4, I include country and country pair FE, as respectively with decade and year FE, further including the full set of controls described in Section 3 in the last two columns. The coefficient

y=	Pr(i defeats j ∣ i attacks j)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\pi_{i,j}$	.003***	.004***	.003	.001	.004*	.002
	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
$\Delta c_{i,j}$		-.002**	-.002	-.001	-.002	-.001
		(.001)	(.001)	(.001)	(.001)	(.002)
Full set of controls					✓	✓
Country-pair FE			✓	✓	✓	✓
Single country FE			✓	✓	✓	✓
Decade FE			✓		✓	
Year FE				✓		✓
Observations	3128	3128	3045	3045	2859	2859
Country-pairs			661	661	598	598
R-squared	.01	.01	.35	.51	.33	.49

Table 4: The impact of differences in GDP per capita on the probability of winning a militarized dispute-OLS results.

Notes: Robust standard errors (columns 1-2) clustered at the country-pair level (columns 3-6) in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. The variable $\Delta c_{i,j}$ is expressed in thousands current dollars.

of $\Delta\pi_{i,j}$ is positive and strongly significant across the first two specifications, although after including decade, country and country-pair fixed effects it loses its statistical significance. After the inclusion of the full set of controls, the coefficient becomes statistically significant in the specification with decade FE, though it remains insignificant with the inclusion of year FE. Surprisingly, the coefficient of $\Delta c_{i,j}$ is negative (although not always statistically significant), possibly because of the correlation with $\Delta\pi_{i,j}$. Overall, this evidence suggests that the poorer, rent-seeker, initiator is not more likely to win. If anything, there is moderate evidence that it is more likely to lose. Since the expected spoils of war are given by the actual revenues times the probability of winning, the presented evidence suggests that the paradox of power play is driven by the fact that the poorer belligerent has more to win and less to lose from the dispute, although it wins with lower probability. Moreover, the lower statistical power of this finding is coherent with the prediction of equation (5). Indeed, since the wealth of a belligerent affects its winning probability only when the poor opponent reaches the corner solution where its budget constraint is binding, the richer agent has not necessarily a higher likelihood of victory.

In the second set of robustness checks, I collapse disputes data at the coalition level (Table 5). Note that country and country-pair fixed effects cannot be used, although the rest of the control variables and time fixed effects are employed. I start by a basic regression without controls, adding decade and year fixed effects in columns 2 and 3 respectively. In the last two columns, I include the full set of controls, again separately employing decade and year fixed effects. As expected, the coefficient of interest is negative and strongly significant across all

y=	Pr(i attacks j | dispute$_{i,j}$)				
	(1)	(2)	(3)	(4)	(5)
$\Delta\pi_{i,j}$	-.037***	-.037***	-.037***	-.038***	-.038***
	(.005)	(.005)	(.005)	(.005)	(.005)
Full set of controls				✓	✓
Decade FE		✓		✓	
Year FE			✓		✓
Observations	2440	2440	2440	2440	2440
R-squared	-.52	-.52	-.52	-.54	-.54
Kleibergen-Paap F statistics	239.52	239.00	234.30	217.66	213.15

Table 5: The impact of differences in coalitions' GDP per capita on the probability of engaging militarized disputes-IV results.

Notes: Robust standard errors in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. The variable $\Delta c_{i,j}$ is expressed in millions current dollars.

specifications, and the first stage Kleibergen Paap statistics suggests that the instrument is not weak. This evidence substantiate the hypothesis that poorer coalitions are generally the initiator of militarized interstates disputes.

In the third set of robustness checks, I come back to the country-pair level of analysis to further refine the empirical strategy. First, I drop disputes of low intensity (Martin et al., 2008), specifically those with a value of 2 (Threat to use force), thereby focusing solely on actual conflicts. The IV regression is shown in the first column of Table 6. In order to further increase the precision of the dependent variable, in the next column I restrict the focus to the sub-sample of disputes where the attacked countries does not react more than proportionately to the offender. In particular, if, say, country i threatens to use force (hostility=2) and, as a reaction, country j declares war to country i (hostility=5), the COW database considers country i as initiator of the conflict, although the highest hostility level is reached by country j. This somewhat creates uncertainty on which side is the real conflict-seeker. In column (2) I therefore replicate the regression of (5) of Table 3 considering only the observations in which the highest hostility reached by the initiator (H_I) is not lower than that of the target (H_T). In the third column, I further restrict the sample to disputes of maximum hostility higher than 2 where the target does not react more than proportionately to the offender. In all cases, the coefficient of interest is negative and strongly significant, being also very close to the estimations of the last two columns of Table 3. All six regressions include the full set of controls, with country, country-pair and year fixed effects.

Next, I refine the analysis from the first three columns by excluding conflicts where both countries are ranked in the bottom quintile in terms of the share of value added in the primary sector relative to GDP. This adjustment narrows the focus to conflicts involving at least one

y=	Pr(i attacks j | dispute$_{i,j}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\pi_{i,j}$	-.032***	-.026***	-.058***	-.059***	-.038***	-.041***
	(.007)	(.0006)	(.007)	(.020)	(.014)	(.015)
Full set of controls	✓	✓	✓	✓	✓	✓
Country-pair FE	✓	✓	✓	✓	✓	✓
Single country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Only $H_I \geq H_T$	✓		✓	✓		✓
Observations	1497	1322	1265	726	661	628
Country-pairs	372	358	348	220	213	205
R-squared	-.25	-.16	.20	-.18	-.08	-.10
Kleibergen Paap F-statistics	69.92	85.44	82.22	41.01	54.35	35.50

Table 6: The impact of differences in GDP per capita on the probability of engaging a highly hostile militarized dispute for different levels of economic developments- IV results.

Notes: Robust standard errors clustered at the country-pair level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. In all columns I restricted the sample to the disputes of hostility level between 3 and 5.

country where the economy is predominantly agricultural, making it more susceptible to rainfall variations (Berlemann and Wenzel, 2018). Although this may seem paradoxical at first, it is explained by the fact that the endogenous variable represents the absolute difference in GDP per capita—not its growth rate—which is susceptible to scale effects. Indeed, the second stage coefficients are generally higher in the final columns, indicating that the influence of rainfall on GDP per capita has a more pronounced effect on the conditional probability of a country attacking another when the economy is heavily reliant on the primary sector.

In the fourth set of robustness tests (Table 7), I further refine the IV strategy, aligning with the latest advancements in the literature. Each regression maintains the full set of controls. Initially, I disaggregate both the dependent and instrumental variables to the quarterly level.[7]. nterestingly, the findings align closely with those presented in Table 3, lending support to the assertion by Coulibaly and Managi (2022) that the relationship between rainfall and conflicts, which I contend operates through the income channel, is predominantly a short-term phenomenon. In the second column I lag my instrumental variable by two years. This adjustment yields a second stage coefficient of similar magnitude and Kleibergen-Paap F statistics nearly identical to those in previous models, supporting the hypothesis that rainfall variations have a longer-term effect on interstate conflicts via the income channel (Devlin and Hendrix, 2014). In the subsequent two columns, I explore rainfall's potentially non-linear impact (Kotz et al., 2022; Damania et al., 2020) by employing a parabolic and a square root specification. Consis-

[7]Quarterly data on GDP for the past decades are available only for advanced economies, thereby compelling me to use annual GDP data.

y=	Pr(i attacks j $\mid$ dispute$_{i,j}$)				
	(1)	(2)	(3)	(4)	(5)
$\Delta\pi_{i,j}$	-.031***	-.031***	-.023***	-.023***	-.043***
	(.007)	(.007)	(.009)	(.008)	(.009)
Full set of controls	✓	✓	✓	✓	✓
Country-pair FE	✓	✓	✓	✓	✓
Single country FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	1599	1533	1599	1599	1380
Country-pairs	387	376	387	387	354
R-squared	-.24	.18	-.14	-.13	-.17
Kleibergen Paap F-statistics	76.22	71.00	38.43	19.37	51.67

Table 7: Alternative specifications of the main empirical strategy- IV results.

Notes: Robust standard errors clustered at the country-pair level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. In the first column Δ rainfall$_{i,j} is computed at the lagged quarterly level (Dec-Jan-Feb and so on), whereas$ Pr(i attacks j $\mid$ dispute$_{i,j}$) is computed at the quarterly level (Jan-Feb-March and so on).

tent with predictions, the sign of the coefficient of the linear difference in rainfall is positive, while the quadratic term exhibits a negative relationship (Table B5). The results hold when using the square root of rainfall as the instrumental variable. In the fifth column of my analysis, I exclude the top and bottom 5% of the values from the distribution of the difference in GDP per capita. This modification leads to a significant increase (approximately 33%) in the estimated coefficient compared to both the original specification in the fifth column of Table 3 and other models. This finding indicates that the negative impact of GDP per capita differences on the likelihood of a country being the aggressor in a dispute is more pronounced when these income disparities are not overly large. Theoretically, this suggests that nations with similar levels of wealth are able to sustain the optimal level of military effort as determined by equations (6). On the other hand, when the income disparity is too great, poorer nations may reach a limiting condition where they can no longer compete effectively, thereby diminishing the predictive power of my proposed theoretical framework. This observation lends support to the complementarity between the theory I propose and the mismatch theory discussed by Herrera et al. (Herrera et al., 2022) and documented in (Hong et al., 2022).

Finally, I utilize the Heckman two-step method to address concerns regarding potential selection bias in previous results. Table 8 shows the outcomes of both the first step (odd columns) and the second step (even columns) of this method. Additionally, the first stage of the instrumental variable (IV) regressions from the second step is detailed in the Table Appendix B6. The analysis begins with a basic regression model devoid of controls. Notably, due to STATA

17.0's limitation of handling a maximum of 32,767 variables, I am unable to include the complete set of country-pair dummies[8]. To circumvent this limitation, I have utilized the United Nations classification (United Nations Statistics Division, 2024) of countries into sub-regions and further divided it into smaller areas, thereby generating 40 sub-regions (see Table B7) for a total of $40 \times 39 = 1560$ sub-region pairs. In comparison to earlier regressions, the importance of including a comprehensive set of controls is notably magnified, especially in the first step of the analysis. Accordingly, column 3 of the results includes a probit regression with a complete set of controls, year, country, and sub-region pair fixed effects. The results are presented using a concave measure of rainfall, specifically the natural logarithm[9]. In all cases, the coefficient of interest is negative and statistically significant. The magnitude of the coefficient is consistent across all specifications, aligning with results from regressions conducted on the restricted sample. Although the Kleibergen-Paap F statistics are lower in magnitude compared to previous analyses, they confirm that the instrument is not weak. Notably, all measures of rainfall prove insignificant in the first step, indicating that rainfall does not influence the likelihood of a militarized interstate dispute. This finding is crucial as it validates the use of rainfall as a credible exogenous instrument in the second step. Finally, the coefficient of the Inverse Mill ratio is consistently not statistically significant, reinforcing the hypothesis that there is no selection bias (Heckman, 1979; Wooldridge, 2010).

Conclusions

In this paper I study the effect of power, size and especially wealth heterogeneity on the incentive to engage war. Building on a game-theoretic model, I show that, under fairly general conditions, economically disadvantaged factions exhibit a higher incentive to wage war, even when they do not possess neither numerical nor military superiority. I test the theoretical predictions of the model on data on militarized interstates dispute spanning the last two centuries (1816-2014), at both the country and coalition levels. The findings indicate a positive correlation between the relative wealth of two countries (or coalitions) and the likelihood that the economically disadvantaged entity initiates a militarized dispute between them. Moreover, I also show that, despite being the primary instigator, the economically disadvantaged faction typically faces a higher probability of defeat. This evidence substantiates the hypothesis that, despite lower odds of victory, the greater spoils of war enjoyed by the poor belligerent more than compensate

[8]Which consists of approximately 200×200 countries, i.e., around 40,000. Dummies must be included manually because some country-pair has experienced more than one dispute per year. This prevents me from using the "xtset" command. Nor can I ignore repeated conflicts within the same year, since the objective of this exercise is exactly to tackle the selection bias.

[9]Results using the square root (available upon request) are very similar in magnitude, though the second stage coefficients display slightly lower statistical significance, close to the 10% confidence level. Therefore, I present the specification with the most reliable outcome directly.

y=	Pr(dispute$_{i,j}$)	Pr(i attacks j | dispute$_{i,j}$)	Pr(dispute$_{i,j}$)	Pr(i attacks j | dispute$_{i,j}$)	
	(1)	(2)	(3)	(4)	(5)
$\Delta\pi_{i,j}$		-.042***		-.037**	-.038**
		(.001)		(.017)	(.017)
Inverse Mill ratio		.014		.013	.040
		(2.323)		(.043)	(.058)
Alliance	.636***		-.163***		
	(.039)		(.056)		
Δ rainfall$_{i,j}$	0				
	(.001)				
$ln\Delta$ rainfall$_{i,j}$			-.002		
			(.041)		
Full set of controls			✓	✓	✓
Sub-region pair FE			✓	✓	✓
Single country FE			✓	✓	✓
Year FE			✓	✓	✓
Observations	1447514	3304	482933	3054	3054
Subregion-pairs	27722	810	11220	768	768
Pseudo R-squared	.03		.45		
R-squared		-.85		-.11	-.11
Kleibergen Paap F-statistics		28028.31		27.91	27.10

Table 8: The impact of differences in GDP per capita on the probability of engaging a highly hostile militarized dispute for different levels of economic developments- IV results.

Notes: Robust standard errors clustered at the country-pair level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars.

for the reduced chances of winning, resulting in a higher expected benefit from the conflict. The magnitude of the impact is considerable: under my IV specification, a difference in GDP per capita of 200$ between two countries is associated with a more than 10 percentage point increase in the conditional probability that the poorer entity is the initiator of a dispute. To the best of my knowledge, this is the first empirical estimate of side of the wealth distribution becomes more inclined toward initiating conflicts in response to increased heterogeneity.

References

A. Alesina and E. Spolaore. War, peace, and the size of countries. *Journal of Public Economics*, 89(7):1333–1354, 2005.

S. Barrios, L. Bertinelli, and E. Strobl. Trends in rainfall and economic growth in africa: A neglected cause of the african growth tragedy. *The Review of Economics and Statistics*, 92 (2):350–366, 2010.

M. Berlemann and D. Wenzel. Precipitation and economic growth. 2018.

N. Berman, M. Couttenier, and R. Soubeyran. Fertile ground for conflict. *Journal of the European Economic Association*, 19(1):82–127, 2021.

F. Bloch. Endogenous formation of alliances in conflicts. In M. R. Garfinkel and S. Skaperdas, editors, *The Oxford Handbook of the Economics of Peace and Conflict*. Oxford Handbooks, 2012. Online edition, Oxford Academic, 21 Nov. 2012.

J. Bolt and J. L. van Zanden. Maddison style estimates of the evolution of the world economy. a new 2020 update, 2020. Version 2020.

M. Burke, S. M. Hsiang, and E. Miguel. Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239, 2015.

F. Caselli, M. Morelli, and D. Rohner. The geography of interstate resource wars. *The Quarterly Journal of Economics*, 130(1):267–315, 2015.

J. C. Castillo and D. Kronick. The logic of violence in drug war. *American Political Science Review*, 114(3):874–887, 2020.

J. D. Colgan. Oil and revolutionary governments: Fuel for international conflict. *International organization*, 64(4):661–694, 2010.

L. C. Corchón. The theory of contests: a survey. *Review of economic design*, 11:69–100, 2007.

R. Cornes and R. Hartley. Asymmetric contests with general technologies. *Economic theory*, 26:923–946, 2005.

Correlates of War, 2021. URL https://correlatesofwar.org/.

T. Y. Coulibaly and S. Managi. Identifying the impact of rainfall variability on conflicts at the monthly level. *Scientific reports*, 12(1):18162, 2022.

M. Couttenier and R. Soubeyran. Drought and civil war in sub-saharan africa. *The Economic Journal*, 124(575):201–244, 2014.

E. Dal Bó and P. Dal Bó. Workers, warriors, and criminals: social conflict in general equilibrium. *Journal of the European Economic Association*, 9(4):646–677, 2011.

R. Damania, S. Desbureaux, and E. Zaveri. Does rainfall matter for economic growth? evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, 102:102335, 2020.

I. De Soysa, E. Gartzke, and T. Lie. Oil, blood, and strategy how petroleum influences interstate disputes. 04 2010.

M. Dell. Trafficking networks and the mexican drug war. *American Economic Review*, 105(6): 1738–1779, 2015.

M. Dell, B. F. Jones, and B. A. Olken. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95, 2012.

C. Devlin and C. S. Hendrix. Trends and triggers redux: Climate change, rainfall, and interstate conflict. *Political Geography*, 43:27–39, 2014.

J. D. Fearon. Rationalist explanations for war. *International organization*, 49(3):379–414, 1995.

J. Franke and T. Öztürk. Conflict networks. *Journal of Public Economics*, 126:104–113, 2015.

J. W. Friedman. A non-cooperative equilibrium for supergames. *The Review of Economic Studies*, 38(1):1–12, 1971.

M. R. Garfinkel and S. Skaperdas. Economics of conflict: An overview. *Handbook of defense economics*, 2:649–709, 2007.

M. Harari and E. La Ferrara. Conflict, climate, and cells: a disaggregated analysis. *Review of Economics and Statistics*, 100(4):594–608, 2018.

I. Harris, T. J. Osborn, P. Jones, and D. Lister. Version 4 of the cru ts monthly high-resolution gridded multivariate climate dataset. *Scientific data*, 7(1):109, 2020.

K. Head and T. Mayer. What separates us? sources of resistance to globalization. *Canadian Journal of Economics/Revue canadienne d'économique*, 46(4):1196–1231, 2013.

J. J. Heckman. Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161, 1979.

H. Herrera, M. Morelli, S. Nunnari, et al. A theory of power wars. *Quarterly Journal of Political Science*, 17(1), 2022.

J. Hirshleifer. The paradox of power. *Economics & Politics*, 3(3):177–200, 1991.

L. Hong, M. Morelli, L. Ogliari, et al. Power mismatch and civil conflict: an empirical investigation. *CERP (Centre for Economic Policy Research) DISCUSSION PAPER SERIES*, 2022.

M. O. Jackson and M. Morelli. Political bias and war. *American Economic Review*, 97(4): 1353–1373, 2007.

M. D. König, D. Rohner, M. Thoenig, and F. Zilibotti. Networks in conflict: Theory and evidence from the great war of africa. *Econometrica*, 85(4):1093–1132, 2017.

K. A. Konrad and S. Skaperdas. The market for protection and the origin of the state. *Economic Theory*, 50:417–443, 2012.

M. Kotz, A. Levermann, and L. Wenz. The effect of rainfall changes on economic production. *Nature*, 601(7892):223–227, 2022.

P. Martin, T. Mayer, and M. Thoenig. Make trade not war? *The Review of Economic Studies*, 75(3):865–900, 2008.

T. Mayer and S. Zignago. Notes on cepii's distances measures: The geodist database. 2011.

J. Osorio. The contagion of drug violence: spatiotemporal dynamics of the mexican war on drugs. *Journal of Conflict Resolution*, 59(8):1403–1432, 2015.

Polity V project. URL https://www.systemicpeace.org/polityproject.html.

R. Powell. *In the shadow of power: States and strategies in international politics*. Princeton University Press, 1999.

H. Sarsons. Rainfall and conflict: A cautionary tale. *Journal of development Economics*, 115: 62–72, 2015.

G. Tullock. Efficient rent seeking. *In Buchanan, James M and Tollison, Robert D and Tullock, Gordon: Toward a theory of the rent-seeking society*, pages 97–112, 1980.

United Nations Statistics Division. Standard country or area codes for statistical use (m49), 2024. URL https://unstats.un.org/unsd/methodology/m49/overview. Accessed: 2024-05-03.

J. M. Wooldridge. *Econometric analysis of cross section and panel data*. MIT press, 2010.

World Bank. World development indicators (wdi). URL https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators.

Appendix A

In this section, I provide a numerical example showing that eliminating some members of the most aggressive coalition I may backfire in terms of a higher probability of war afterwards. Consider the case $\pi_J > \pi_I$ and just replace $m = n = \frac{N}{2}$ and $c_I = 0$ into (16) to obtain:

$$\delta_i^* = \frac{8\pi_J}{5(\pi_J + \pi_I)} \tag{A.1}$$

Now, assume that the number m of members of coalition I is exogenously reduced to 1. Expression (18) becomes:

$$\delta_j^* = \frac{\pi_I}{(\pi_J + \pi_I)\left[1 - \frac{N+\sqrt{\frac{N}{2}}}{2(1+\sqrt{\frac{N}{2}})^2}\right]} \tag{A.2}$$

Notably, the above expression is increasing in N. In plain words, if the number of eliminated the members of coalition I is sufficiently high, the equilibrium of power is altered and the rival coalition J may be even more encouraged to engage a new war.

Appendix B

Table B1 reports the summary statistics of the variables employed for the analysis in the main text. Then, I show the first stage results of the IV estimations of Tables 3, 5, 6 and 7. Results are respectively reported in Tables B2, B3, B4 and B5. Table B7 lists the sub-regions adopted in the regressions of Table 8, whose first stage results are reported in Table B6.

Variable	Observations	Mean	Std. Deviation	Min	Max
MAIN VARIABLES					
Pr(i attacks j $\vert$ dispute$_{i,j}$)	5192	0.565	0.496	0	1
Pr(i defeats j $\vert$ i attacks j)	5192	0.085	0.278	0	1
$\Delta\pi_{i,j}$	4179	465949.1	1374329	-4611551	9475792
$\Delta c_{i,j}$	4911	3773367	42800000	-174000000	692000000
Δ rainfall$_{i,j}$	2153	-0.005	0.086	-2.494	0.577
Value added in the primary sector over GDP	1883	17.824	14.841	0.268	76.534
CONTROL VARIABLES					
Distance	4714	3415.092	3749.606	85.941	18824.75
Contiguity	4714	0.428	0.495	0	1
Common languages	4714	0.290	0.454	0	1
Colonial relationship	4714	0.090	0.286	0	1
Actors were previously the same country	4714	0.094	0.292	0	1
Distance between capitals	4714	3421.675	3767.737	85.941	18587.08
Δ Democracy index$_{i,j}$	5192	.515	.500	0	1

Table B1: Descriptive statistics

y=			$\Delta\pi_{i,j}$		
	(1)	(2)	(3)	(4)	(5)
Δ rainfall$_{i,j}$	.043***	.035***	.079***	.035***	.079***
	(.003)	(.003)	(.009)	(.003)	(.009)
Full set of controls				✓	✓
Country-pair FE		✓	✓	✓	✓
Single country FE		✓	✓	✓	✓
Decade FE		✓		✓	
Year FE			✓		✓
Observations	1665	1665	1665	1599	1599
Country-pairs		405	405	387	387
R-squared	.002	.96	.96	.96	.96

Table B2: The impact of differences in GDP per capita on the probability of initiating a militarized disputes-IV first stage results.

Notes: Robust standard errors (columns 1) clustered at the country-pair level (columns 2-5) in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars.

y=	$\Delta\pi_{i,j}$				
	(1)	(2)	(3)	(4)	(5)
Δ rainfall$_{i,j}$	.051***	.053***	.047***	.051***	.048***
	(.007)	(.006)	(.012)	(.006)	(.010)
Full set of controls				✓	✓
Decade FE		✓		✓	
Year FE			✓		✓
Observations	1193	1193	1193	1193	1193
R-squared	.00	.001	.05	.12	.15

Table B3: The impact of differences in coalitions' GDP per capita on the probability of engaging militarized disputes-IV first stage results.

Notes: Robust standard errors in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars.

y=	$\Delta\pi_{i,j}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ rainfall$_{i,j}$	.077***	.081***	.080***	.031***	.033***	.032***
	(.009)	(.009)	(.009)	(.005)	(.005)	(.005)
Full set of controls	✓	✓	✓	✓	✓	✓
Country-pair FE	✓	✓	✓	✓	✓	✓
Single country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Only $H_I \geq H_T$	✓		✓	✓		✓
Observations	1497	1322	1265	726	661	628
Country-pairs	372	358	348	220	213	205
R-squared	.96	.97	.97	1	1	1

Table B4: The impact of differences in GDP per capita on the probability of engaging a highly hostile militarized dispute for different levels of economic developments- IV first stage results.

Notes: Robust standard errors clustered at the country-pair level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. In all columns I restricted the sample to the disputes of hostility level between 3 and 5.

y=	$\Delta\pi_{i,j}$				
	(1)	(2)	(3)	(4)	(5)
Δ rainfall$_{i,j}$	.225***		4.415*		.066***
	(.026)		(.002)		(.009)
Δ rainfall$_{i,j}(t-2)$		.085***			
		(.010)			
Δ^2 rainfall$_{i,j}$			-.007*		
			(.004)		
$\Delta^{\frac{1}{2}}$ rainfall$_{i,j}$				3.214***	
				(.730)	
Full set of controls	✓	✓	✓	✓	✓
Country-pair FE	✓	✓	✓	✓	✓
Single country FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	1599	1533	1599	1599	1380
Country-pairs	387	376	387	387	354
R-squared	.96	.97	.96	.96	.96

Table B5: Alternative specifications of the main empirical strategy- IV results.

Notes: Robust standard errors clustered at the country-pair level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. In the first column Δ rainfall$_{i,j} iscomputedatthequarterlylevel (Dec - Jan - Febandsoon)$.

y=	$\Delta\pi_{i,j}$	
	(2)	(4)
Δ rainfall$_{i,j}$	.040***	
	(.002)	
$ln\Delta$ rainfall$_{i,j}$		2.812***
		(.530)
Inverse Mill Ratio	.000	-.068
	(45.006)	(.692)
Full set of controls		✓
Subregion-pair FE		✓
Single country FE		✓
Year FE		✓
Observations	3304	3054
Country-pairs	810	768
R-squared	.002	.94

Table B6: The impact of differences in GDP per capita on the probability of engaging a highly hostile militarized dispute for different levels of economic developments- IV first stage results.

Notes: Robust standard errors clustered at the country-pair level in parentheses. $***$, $**$ and $*$ respectively denote $p < 0.1$, $p < 0.05$ and $p < 0.01$. The variable $\Delta\pi_{i,j}$ is expressed in thousands 1990 International Geary-Khamis dollars. In all columns I restricted the sample to the disputes of hostility level between 3 and 5.

Subregion	Frequency	Percent	Cumulative %
Andes	42,184	2.53	2.53
Central Asia	60,104	3.60	6.12
Australia and New Zealand	20,954	1.25	7.38
Balkans	20,544	1.23	8.61
Baltic Republics	11,017	0.66	9.27
Benelux	25,311	1.52	10.78
Brazil	8,436	0.51	11.29
British Isles	16,877	1.01	12.30
Caribbean	77,872	4.66	16.96
Caucasus	11,027	0.66	17.62
Central Africa	41,036	2.46	20.08
Central America	64,301	3.85	23.93
Continental Europe	38,672	2.32	26.25
East Africa	16,546	0.99	27.24
Eastern Europe	44,492	2.66	29.90
Far East	112,898	6.76	36.66
Former Yugoslavia	33,272	1.99	38.65
Great Lakes	33,263	1.99	40.65
Guiana	13,802	0.83	41.47
Guinea	73,829	4.42	45.89
Hellenic Peninsula	16,873	1.01	46.90
Horn of Africa	26,117	1.56	48.47
Iberian Peninsula	16,875	1.01	49.48
Indochina	99,335	5.95	55.43
Insulindia	73,777	4.42	59.84
Italian Peninsula	16,381	0.98	60.82
Maghreb	16,709	1.00	61.82
Middle East	131,799	7.89	69.72
Melanesia	7,178	0.43	70.15
Micronesia	4,075	0.24	70.39
North Africa	16,884	1.01	71.40
North America	16,903	1.01	72.41
Arabian Peninsula	126,126	7.55	79.97
Scandinavia	42,188	2.53	82.49
Southern Africa	85,459	5.12	87.61
Southern Cone	33,751	2.02	89.63
Indian Subcontinent	105,722	6.33	95.96
Sudan	25,930	1.55	97.51
West Africa	41,527	2.49	100.00
Total	1,670,046	100.00	

Table B7: Frequency and percentage distribution of country-pairs by sub-region.