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Summary

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JELClassification: C25, D73, D78, I38, K42

Keywords: Organized Crime, Violence, Anti-corruption measures, Spillovers

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Abstract

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1 Introduction

Organised crime influences politics by bribery and threats to "induce a given policy maker to change his action from that preferred by society to that preferred by the group" (Dal Bó and Di Tella, 2003, p. 1128). For instance, in El Salvador, Mexico and Colombia politicians are often physically attacked by criminal gangs (see for instance Melnikov et al., 2020; Sviatschi, 2019; Blattman et al., 2020; Daniele et al., 2020). Studies on developed countries have shown that criminal organizations use violence strategically in the post-electoral period, in view of the potential "moral hazard" inherent in politicians' bargaining with clans (Daniele and Dipoppa, 2017; Dell, 2015); also, organised crime can attack politicians before elections, in order to redirect votes to the candidate they back (Olivieri and Sberna, 2014; Alesina et al., 2019; Acemoglu et al., 2020). In general, in the period around elections local governments are called on to make important decisions, such as appointments and political programs, so this is the time when criminal influence is likely to have the highest return. The violence perpetrated during the electoral mandate to induce politicians to divert public resources to the advantage of local clans results in significant losses in social welfare and economic development (Pinotti, 2015).

This pervasive phenomenon thus demonstrates the need for empirical assessment of the efficacy of government anti-mafia policies, also from the standpoint of public safety.

Over the last thirty or forty years mafia organizations have influenced politics mainly through corruption (bribes), but violence is still present, not only in its most visible and disruptive forms but also in the form of threats and intimidation. Corruption is a victimless crime, while violence is visible and frightening, leaving a trail of blood and death and compelling the central government to react. Recent Italian measures against mafia infiltration on politics have aimed at combating bribery. These measures can be defined as non-repressive in that they are directed to cutting off the economic resources of organised crime, not engaging in an explicit battle against local clans through stepped-up deployment of law enforcement bodies (Daniele and Dipoppa, 2022). Nonetheless, non-repressive measures can reduce the expected overall payoff to organised crime from influencing political decisions. This in turn will affect the profitability of resort to violence.

Dal Bó et al. (2006) has developed one of the most influential theoretical frameworks for studying how pressure groups (in our case, criminal organizations) maximize the expected payoff to political influence thanks to an optimal mix of bribery and threats of violent punishment, which determines the level of "state capture". These actions entail costs, whose magnitude depends on institutional factors, including the quality of law enforcement. For instance, non-repressive measures can be thought of as a sort of intensified law enforcement that increases the costs of corruption and reduces the amount of public resources that corrupt politicians can redirect to pressure groups. These measures lower the expected payoffs and so may well induce pressure groups to modify the mix of bribery and violence.

More specifically, measures that lower the profitability of bribery but do not directly increase the cost of violent intimidation by expanding police forces have an ambivalent effect on organised criminal violence. On the one hand, they may lead criminal organizations to discard bribery in favor of intimidation, raising the level of violence (a sort of retaliation for the anti-bribery measure). Consistently with this line of reasoning, a recent study by Pulejo and Querubín (2023), although not specifically focused on the effect of anti-crime measures, shows that an increase in the cost of bribes due to higher remuneration of politicians in more populated municipalities induces a substantial increase in violent attacks by organised crime. On the other hand, however, an increase in the costs of corruption due to non-repressive measures is also likely to stiffen the entry barrier to political influence, so that some criminal groups might actually refrain from their illicit activities and go "out of business", lowering the level of violence and the overall degree of "state capture". Hence, Dal Bó et al. (2006)'s model does not offer a definite prediction about the effect of non-repressive measures.[1] Which of the two effects prevails is ultimately an empirical question; to answer it is the aim of this paper.

The Italian institutional framework is particularly well suited to this purpose. To counter the political influence of criminal organizations, in 1991 Parliament passed Decree Law 164/1991 (converted with amendments as Law 221 of 22 July 1991, but still known as Law 164). Law 164 prescribes, where there is evidence of organised criminal infiltration of a municipality, the dismissal of the elected officials and the institution of "compulsory administration" by three external commissioners designated by the Prefect, the central government representative in the province.

The application of this measure can be interpreted as an unexpected increase in the cost of corruption to local clans, because the replacement of corrupt politicians by trusted commissioners should presumably cut funding for public projects, especially in the sectors targeted by organised crime, such as manufacturing, waste management and construction (Acconcia et al., 2014). Moreover, the enforcement of Law 164 has been shown to increase the quality of public resource allocation (Di Cataldo and Mastrorocco, 2022), and also to reduce irregularities in the public procurement award procedure (Ravenda et al., 2020). Hence, in the logic of Dal Bó et al. (2006)'s model, the enforcement of Law 164 increases the cost of corruption, by reducing the amount of public resources that corrupt or complicit politicians had previously diverted to criminal clans and by increasing the quality of public policies.

However, city council dissolution is an exclusively administrative act, entailing neither an expansion of police forces nor increased allocations for public safety during the compulsory administration (Mete, 2009; Cavaliere, 2004).

To gauge how increasing the cost of corruption affects the level of violence, here we estimate the causal effect (unexplored to date) of the enforcement of Law 164 on acts of violent intimidation against politicians by organised crime. We adopt a difference-in-differences approach, comparing the change in the number of attacks against local politicians in dissolved and undissolved municipalities after the city council dissolution.

Our empirical analysis relies on several data sources: municipal data on the attacks against local politicians from 2010 to 2019 in the regions of Calabria, Campania, Apulia and Sicily (where practically all the city council dissolutions occurred) provided by the NGO "Avviso Pubblico"; municipal data on the time and date of city council dissolution for mafia

[1] The paragraph of the "Conceptual framework" in Appendix A provides formal derivation of the Dal Bó et al. (2006)'s model hypothesis we are dealing with.

infiltration as well as for all other reasons; the municipal data provided by the Italian Ministry of Interior from which we derived the composition of city councils by gender, age, level of education and kind of position; and provincial data from the Ministry of Interior on a number of crimes reported to the judicial authorities by police forces.

The main challenge for our diff-in-diff analysis is to validate the key identification assumption, namely the exogeneity of the treatment to the outcome. Following the normative prescriptions, city council dissolution itself can only be ordered if evidence of the collusion of local politicians with organised crime emerges from investigations: a municipal council can never be dissolved owing to violence against politicians; attacks on politicians might trigger an investigation, but evidence of a link between politicians and mafia must be found in order for the Prefect to order council dissolution. Such attacks can nevertheless be a warning sign, inducing suspicion of collusion and therefore increasing the probability of initiating the investigation that will lead to dissolution. To address this potential reverse causality, we have used the reports of the Prefects who urged city council dismissal for mafia infiltration in 22 sample dissolved municipalities in which the evidence of collusion was accompanied by evidence of violent intimidation. We then excluded these municipalities from the treatment group in the main analysis. Moreover, in order to check the validity of the Stable Unit Treatment Value Assumption (SUTVA) in the diff-in-diff design (Rubin, 1980), namely that the status of treated municipalities does not affect the outcomes for the untreated, following a well published literature, we detected spillover effects in municipalities that share borders with those dissolved but not in the case of cities distant less than 20km, 30km, 40km; accordingly, in the main analysis we excluded from the control group any neighboring municipalities.

The estimation results show that after the period of compulsory administration there was a considerably sharper reduction in attacks against politicians in the treatment group of dissolved municipalities than in the undissolved control group. The results are robust to Poisson and linear FE specifications. The dynamic of the attacks under our preferred Poisson FE specification shows pre-treatment coefficients that are not significant (corroborating the common trend assumption) and a sine curve of the post-treatment coefficients. The enforcement measure affects the number of attacks through the first two elections after compulsory administration, or over a period of 6-7 years or more. The drop in the number of attacks after compulsory administration is sharp: 82% at the first year after election and about 73% and 57% at the second and third, respectively, with an overall mean effect (over the entire period after compulsory administration) of 55%. These results are confirmed by several tests supporting the exogeneity of dissolution for mafia infiltration with respect to the number of attacks against local politicians, as well as by a series of robustness checks.

As regards the ambivalent effect of an increase in the cost of corruption on organised criminal violence highlighted in Dal Bó et al. (2006), our findings indicate that the enforcement of Law 164 has in fact proved to be effective in stiffening the barriers to political influence (by lowering the mafia's expected profits from infiltration), thus reducing the violent activity of criminal organizations and the overall degree of "state capture".

We consider some possible mechanisms that might be driving this outcome. Investigating the effect of anti-mafia dissolution on the sub-samples of both municipal and non-municipal entities, we were able to exclude as mechanisms increases in police forces and also *perceived* *deterrence*. As a consequence, the most likely mechanism is that proposed by Dal Bó et al. (2006): a non-repressive anti-crime measure reduces the expected profitability of corruption, thereby also decreasing the overall use of violence against politicians. We further support this mechanism by showing that the decrease in violence after compulsory administration relates *only* to politicians on the city council. We refer to robust evidence that the reduction in the profitability of corruption is a consequence of the renewal of the pool of politicians in office, which following compulsory administration tends to consist of more highly qualified individuals with a larger proportion of well-educated women (Daniele and Dipoppa, 2017, Baraldi and Ronza, 2022), who are typically less inclined to corruption and criminal activities (Lochner, 2004), as well as reflecting a new awareness on the part of citizens that the mafia is not invincible (Baraldi et al., 2022b).

This study contributes to the abundant literature on the effects of Law 164/1991, producing novel empirical evidence that its enforcement reduces mafia violence against politicians. Our results thus complement and extend other recent work that documents the effectiveness of city council dissolution in favoring better local economic performance (Fenizia and Saggio, 2022), fostering women's political empowerment (Baraldi and Ronza, 2022), enhancing the quality of elected politicians (Daniele and Geys, 2015), and improving tax collection and the allocation of public funds (Di Cataldo and Mastrorocco, 2022). Moreover, since some studies have shown that repressive policies trigger violent reprisals from criminal organizations (e.g., Calderón et al., 2015; Castillo and Kronick, 2020), our analysis contributes to the literature studying the effectiveness of non-repressive government measures in fighting organised crime activities (Daniele and Dipoppa, 2022).

The rest of the paper is organised as follows. Section 2 describes the institutional framework to show that Law 164/1991 can be taken as a legitimate treatment and presents the data and the variables used in the empirical analysis. Section 3 describes the empirical design and discusses selection bias as a possible threat to our identification strategy. Section 4 reports the results of our baseline analysis. Section 5 details the econometric analyses we use to address concerns over treatment endogeneity. Section 6 reports robustness checks. Section 7 deals with possible driving mechanism; Section 8 proposes a new methodological approach to the analysis of spillover effects and Section 9 concludes.

2 Institutional background and data

2.1 The anti-mafia measure

Law 164/1991 prescribes the dissolution of a city council upon evidence of direct or indirect links with organised crime that compromise the local administration's neutrality and autonomy, and more generally public safety. Introduced in response to the growing influence of organised crime on local administrations in the 1980s, the Law was designed to prevent or reverse criminal control of public procurement, public works, urban plants, and housing.

Dissolution entails the replacement of the mayor, the city council, and the executive board with commissioners appointed by the central government and drawn from outside the local area. They run the municipality for 12 to 24 months before new elections are held to reinstate a legal city council and restore public safety. In detail, the activity of the compulsory administration consists in an unexpected reduction in public investment projects, chiefly in the sectors targeted by organised crime (manufacturing, waste management, construction).

The Law lays down a rigid procedure from the initial discovery of evidence of mafia infiltration to the dissolution decree. Typically, there is some advance warning in the form of independent judicial or police inquiries.[2] This evidence is reported to the Prefect, the provincial representative of the Ministry of the Interior, who, by virtue of powers of inquiry, can name a commission (*Commissione d'Accesso*) to investigate the extent of permeability of the local government to organised crime.

This investigation is kept secret until completed, or for a maximum of three months. That is, the conduct of local administrators and criminal organizations cannot be influenced by the procedure while it is under way. Once the investigation is concluded, the report of the *Commissione d'Accesso* will form the basis of the Prefect's proposal for city council dissolution, which is submitted to the Ministry of the Interior for final decision. The outcome of the procedure, in other words, is independent of the partisan political dynamics of the municipality (Mete, 2009).

The dissolution provision is preventive, in that the replacement of local politicians by outside commissioners is intended to prevent future crimes in the public administration rather than prosecute past ones. Thus the evidence of links between civil servants and organised crime does not necessarily have to show a crime in order to trigger the procedure. In fact, the reports of the Prefect with a view to dissolution decrees very commonly involve evidence not of crimes but of personal relationships of kinship or friendship between local politicians and members of criminal organizations. The main triggers of the inspection procedure by the *Commissione d'Accesso* turn out to be electoral agreements, electoral participation of individuals linked to local clans, the exchange of packets of votes, and shared economic interests between politicians and criminal organizations.

For the purposes of our study, the intimidation of local politicians by organised crime — killings, physical attacks, threatening letters — may be a factor in activating the *Commissione d'Accesso*'s inquiry. This is plainly a threat to our identification strategy, as municipalities dissolved owing to evidence of violent intimidation are self-selected into the treatment group, creating a problem of reverse causation, since we may be unable to determine the causal link between the council dissolution and the variation in the number of attacks against local politicians.[3]

However, violent intimidation certainly cannot be taken as unequivocal evidence of collusion with local clans like the above-mentioned cases of electoral agreement, the delivery of packets of votes, and shared economic interests. Indeed, as the administrative courts have rightly pointed out, the simple fact of local roots of organised crime and criminal violence does not prove a connection with the local government such as to trigger an inspection procedure. Intuitively, in fact, one might well consider violence as an alternative to corruption as a way of influencing political action. Thus, acts of intimidation can be considered as a sign of city council permeability to mafia infiltration only insofar as they are combined with

[2]This is the reason for controlling for repressive action by government (Section 5.2.2).

[3]We will address the issue of reverse causality in sub-section 3.1.1.

evidence of collusive behaviour. For example, the municipalities of Bagnara Calabra and Delianuova were dissolved because local clans repeatedly attacked the majority of the city council with the complicity of its minority.[4]

As a consequence, relatively few of the municipalities where attacks against local administrators occur undergo an inspection procedure.

On the empirical level, this means that there should be no correlation between the regional distribution of the dissolutions (concentrated in the South) and that of per capita attacks on politicians (widespread throughout Italy). We test this hypothesis in Section 2.2. For more thorough statistical analysis of this issue, we conduct endogeneity tests (Sections 5).

2.2 Data

We construct a dataset of threats and violence against local politicians in Italy from 2010 to 2019. Official sources of data about attacks against politicians are not available; like Daniele and Dipoppa (2017), we use the yearly reports of "Avviso Pubblico", a non-governmental organization that collects daily media reports of threats and attacks directed against Italian politicians. The violent actions are sorted by type of attack and type of politician, in each of the municipalities where they occur.

"Avviso Pubblico" distinguishes 20 types of attack[5] and 11 types of politician targeted for attack.[6]

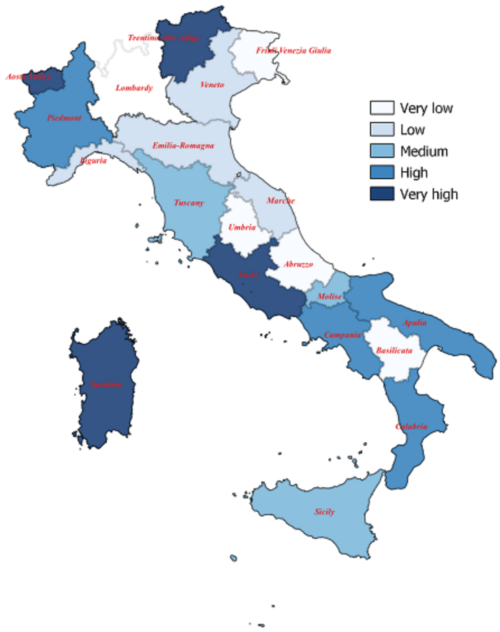
According to this source, Italy counted 4448 attacks against politicians from 2010 to 2019. Considering only city council politicians (deputy mayor, former mayor, relative of politician, candidate, alderman, city councillor, city or municipal company manager, mayor) the total is 3857. Figure 1 shows the geographical distribution of the attacks by region. For each region we calculate the mean number of attacks in the period 2010-2019. This mean is divided by the average regional population in the same period to produce the average number of attacks per capita, shown in Figure 1, which groups regions in classes from very low to very high (see the note on Figure 1 for details).

[4]Similar cases can be found in a number of other reports on dissolved municipalities. On this issue see Marotta (2019).

[5]1) Setting car on fire, 2) Setting City Hall or municipal property on fire, 3) Threatening letter, 4) Threatening letter containing bullets, 5) Verbal or telephone threats, 6) Physical assault, 7) Setting home on fire, 8) Shootings against City Hall, 9) Homicide, 10) Threatening messages on the family tomb, 11) Killing of domestic animals, 12) Delivery of an animal head in a box, 13) Shootings against car, 14) Leaving dead animals or their parts in front of home, 15) Damage or robbery in City Hall, 16) Felling of trees on private property, 17) Physical assault in public places, 18) Bullets left in front of home or City Hall, 19) Threatening messages on walls of home or City Hall, 20) Bombing of home or City Hall.

[6]1) Regional councillor, 2) Regional president, 3) Deputy mayor, 4) Former mayor, 5) Relative of politician, 6) Candidate, 7) Alderman, 8) City councillor, 9) City or municipal company managers, 10) Mayor, 11) Representative of other institutions or entities.

Figure 1: Geographical distribution of attacks against politicians



Notes. The figure shows the regional averages of attacks against local politicians per capita. Regions are grouped according to the following range of values: Very Low: 0.00063-0.00190; Low: 0.00210-0.00229; Medium: 0.00271-0.00229; High: 0.00312-0.00370; Very High: 0.00454-0.01572.

The per capita measure allows a more meaningful comparison of the intensity of the attacks between regions of differing population. Figure 1 shows that attacks against politicians are widespread throughout the country. That is, organised crime is now active well beyond the southern regions where it originated. For instance, northern regions like Valle D'Aosta have become a strategic territory for the business of the *'ndrangheta*, a criminal organization that originated in Calabria.

Table 1: City council dismissal by regions

Region	City council dismissals
Calabria	59
Campania	21
Sicily	25
Apulia	10
Piedmont	2
Lombardy, Emilia Romagna, Liguria	1
Rest of Italy	0
Total	120

Note. The table displays the number of administrations dissolved in the period 2010-2019 by region. Lombardy, Emilia Romagna, and Liguria had 1 dissolution each.

Table 1 shows the distribution of city council dismissals by region: from 2010 to 2019 they totalled 120. The regions of Campania, Calabria, Sicily and Apulia count 115 dismissals (in 108 municipalities),[7] or 95.8% of the total. In line with the relevant literature analysing the effectiveness of Law 164, we focus our analysis on these four regions where city council dissolution are concentrated in order to achieve the highest homogeneity between treatment and control groups (e.g., Daniele and Geys, 2015; Galletta, 2017, Di Cataldo and Mastrorocco,

[7] 7 municipalities in our database were dissolved more than once.

2022;Baraldi et al., 2022a; Baraldi et al., 2022b; Baraldi and Ronza, 2022).[8]

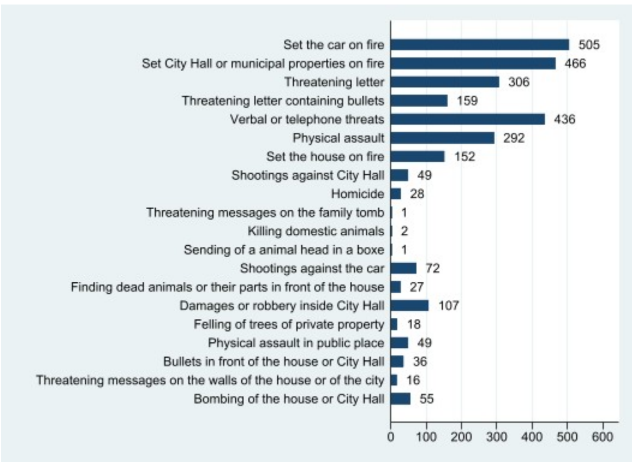
As noted, the possible reverse causality between the number of attacks and dissolution for mafia infiltration is a serious concern. The issue of endogeneity will be treated extensively in the next sections, but we begin to address this concern here with a t-test comparing the per capita mean of attacks in Calabria, Campania, Apulia and Sicily (group 1) and in the rest of the country (group 2). The results (in Table A.1 in Appendix A) show that there is no statistical difference between the means of the two sets of regions. Further corroboration comes from re-scaling the mean number of attacks against local politicians (by region) by the mean number of local politicians in charge (by region) in order to capture the number of potential mafia targets. The last column of Table A.1 shows, once again, that there is no statistical difference between the means of the two sets of regions.

This suggests that while city council dissolutions for mafia are concentrated in Calabria, Campania, Apulia and Sicily, no such concentration is found for attacks on politicians, which precludes correlation between the two variables.

2.3 Variables

The dependent variable in this empirical analysis is the number of attacks against local politicians as reported by "Avviso Pubblico". Figures 2 and 3 sort the data by type of attack and type of politician in our four regions.

Figure 2: Types of attacks. 2010-2019



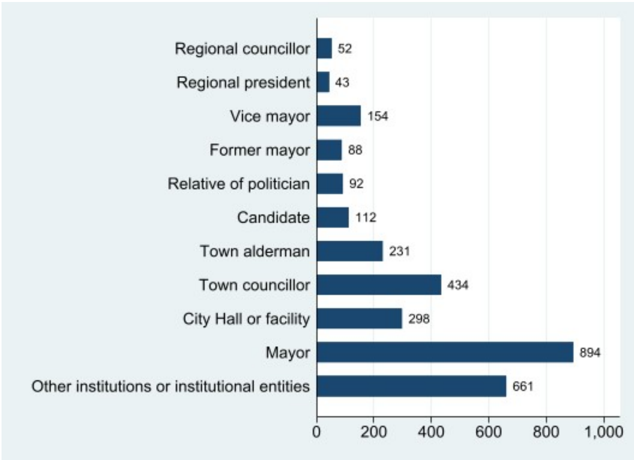
Notes. The Figure shows the types of attack against politicians. 2010-2019.

From 2010 to 2019, the most common types of attack were arson targeted at cars (505) or the City Hall or other municipal properties (466), followed by verbal or telephone threats (436). A non-negligible number of cases also involved threatening letters (306 + 159). Physical assaults and arson against politicians' homes too were reported in a substantial number of cases (respectively 292 and 152). Other types of attack are not so frequent; the worst, homicide, registered 28 victims. In the baseline specification of our empirical model, the

[8]Focusing our analysis on this specific sample allows us also to control for economic shocks due, for example, to the Great Recession in 2009-2010, which is unlikely to have affected differently the four regions under analysis. However, in Section 4, we control for this aspect by including in the regression equation the interaction of Region and year FE.

dependent variable is the total number of attacks against politicians; we provide further evidence of the findings in the sub-samples of threats and violent intimidation.

Figure 3: Victims of attack. 2010-2019



Notes. The Figure shows the types of victim of mafia attacks. 2010-2019.

Figure 3 shows 894 attacks against mayors (almost 30% of the total). City Councilors, aldermen and deputy mayors display lower risk. The last category in the figure, namely policemen and managers in city government or other public facilities, counts about 21% of the attacks. Attacks against regional presidents and Councilors are far less frequent. As is observed by Daniele and Dipoppa (2017), national politicians are not targeted by organised criminal violence, presumably thanks to their stronger protection owing to their greater public exposure.

Figure B.1 in Appendix B shows the trend in the mean number of attacks over the years. The Figure shows a downward spike of the attacks in 2012. As the National Coordinator of "Avviso Pubblico" explains, however, this is deceptive. The low value actually reflects the organization's lack of human resources that year, so that the data were collected ex-post via internet search only. Given this problem, we provide further evidence of findings by excluding the year 2012 from the analysis.

As Daniele and Dipoppa (2017) observes, the number of attacks on local politicians surveyed by "Avviso Pubblico" could be affected by a measurement error, in that the violence reported might be the work of private citizens and not necessarily organised crime. However, the parliamentary report by Moro et al. (2015), which documents the connection between attacks on politicians and organised crime using both open-source and restricted-access data, estimates that attacks driven by personal motives constitute a tiny fraction of the total.

Moreover, since organised crime deploys violence either to affect election results or for bargaining with the politicians elected, the attacks cannot be random but should be concentrated at election times. And research provides robust evidence that violent intimidation by organised crime is in fact concentrated around elections (Daniele and Dipoppa, 2017; Alesina et al., 2019). The strategic use of violence around elections corroborates the hypothesis that attacks are actually perpetrated by organised crime rather than private citizens.[9] Therefore,

[9] "Data provided by the Prefectures show that less than 8% of the acts of intimidation to which a moti-

the estimates of the models of attacks against politicians are robust to (consistent with) this kind of measurement error in the dependent variable.

Our regressor is the application of Law 164/1991 to dissolve a city council upon evidence of the infiltration of local politics by organised crime. Figure B.2 in Appendix B shows the number of dissolutions for mafia by year (graph B.2a) and by province (graph B.2b).

Except in 2012 and 2017, dissolutions are fairly evenly distributed; the same goes for provincial distribution in the four regions of interest: only the province of Reggio Calabria counts more than 30 dissolutions, while 4 provinces had none. We take this into account in the empirical analysis.

3 Empirical strategy

We create a yearly panel of all the municipalities in Calabria, Campania, Apulia and Sicily from 2010 to 2019. This panel structure, together with the exogeneity of the shock for organised crime due to the application Law 164/1991, makes it possible to isolate the effect of the measure from any time-specific features. Further, the municipal-level fixed effects account for possible local factors. We take a difference-in-differences approach. We record the number of attacks before and after city council dissolutions for mafia infiltration, which is our treatment, in both dissolved and undissolved municipalities (i.e. in the treated and control groups). The baseline specification is the following event study model (subscript i for municipalities, t years):

$$Y_{it} = \sum_{n=-m}^{+m} \nu_t \cdot D_{i,t-n} + \alpha_i + \delta_t + Pop_{it} + \epsilon_{it} \tag{1}$$

Y_{it} is the outcome variable in municipality i at year t. D_t is the set of event-time dummies, which take the value of 1 only for dissolved municipalities if year t is k periods before/after the dissolution. The omitted category, D_{-1}, is the year before the dissolution; the remaining ν_t coefficients measure the effects in the period before and after the application of Law 164 (t_0). In all the estimations we control for 1) municipality fixed effects (α_i); 2) time fixed effects (δ_t); 3) municipal population (Pop_{it}). ϵ_{it} is the idiosyncratic error term.

Since the dependent variable is the occurrence of an attack, the count of events has a large portion of 0 and a skewed distribution as shown in Table A.2 (Appendix A). We specify the outcome variable as the total number of attacks in municipality i in year t and we estimate eq. 1 by: 1) a Poisson model with fixed effects and standard errors clustered at the municipality level, which is more suitable for count data; 2) a linear model. Clustered standard errors are robust to heteroscedasticity and serial correlation, and they allow for consistent inference in a diff-in-diff framework (Bertrand et al., 2004).

Assuming the exogeneity of the explanatory variables, the conditional quasi-maximum likelihood estimation of Poisson models (Wooldridge, 2010; Cameron and Trivedi, 2013) is consistent even when the assumption of a Poisson distribution of events is not correct

vation could be attributed refers to personal motives, private disputes that fall outside of the political and administrative engagement of the victim, and 3% are vandalism" (Moro et al., 2015).

(i.e. over- or under-dispersion). Municipality FE control for heterogeneity in the cross-section dimension and account for unobserved time-invariant factors that could engender omitted-variable bias. Time FE account for unobserved year-specific events that affect all municipalities. In Poisson FE estimations, the coefficients are interpreted as an elasticity, according to the following expression: $Exp(coef) - 1$ (Cameron and Trivedi, 2013).

The validity of the empirical design requires satisfaction of the common trend assumptions, which can be tested by analysis of the pre-treatment dummies of the event study model in eq. 1 (Mora and Reggio, 2019). The event study estimates also permit assessment of the dynamic effect of the measure, i.e. the trajectories of the attacks in treated and untreated municipalities in each year after the dissolution.

We also estimate the mean impact of the measure using the following specification:

$$Y_{it} = \beta_1 Policy_{it} + \alpha_i + \delta_t + Pop_{it} + \lambda' X_{it} + \epsilon_{it} \tag{2}$$

where Y_{it} is, as above, the number of attacks in municipality i in year t. The regressor of interest is $Policy_{it}$, which is equal to 1 for treated municipalities in all the years between compulsory administration and 2019 and to 0 in the period from 2010 to the year of the dissolution; for municipalities in the control group, it is 0 for the entire period 2010-2019. β_1 in eq. 1 measures the average treatment effect on the number of attacks against politicians. Since municipalities are defined as receiving treatment in the year they are dissolved, we need to exclude the 5 municipalities whose administrations were dissolved in 2010 in order to have at least one observation (a 0) before the dissolution.

For our analysis it is important to control for the characteristics of the politicians in office, such as education, because these help determine whether and how the mafia affects politicians (see, among others, Daniele and Geys, 2015). Since the education level is a proxy of quality, highly qualified politicians are more likely to manage a higher amount of public resources that organised crime can be interested to reap by attacking local administrators (Dal Bó et al., 2006). The vector of control variables (X_{it}) consists of a dummy for university degree of the mayor (*Mayor degree*) taking the value of 1 if the mayor has at least a university degree and 0 otherwise; a dummy taking value 1 if at least one city councillor has a university degree and 0 otherwise (*Councilors degree*); a dummy taking value 1 if at least one alderman in the executive board has a university degree and 0 otherwise (*Aldermen degree*); and the number of female Councilors (*Female councilors*) and aldermen (*Female aldermen*).[10]

The inclusion of control variables offers an indication of the relevance of omitted-variable bias: where these additional controls have only marginal impact on the treatment coefficient (*Policy*), a causal interpretation of the results is justified. Moreover, the possible endogeneity of government dissolution with respect to the number of attacks is controlled for by covariates as well as municipality and time fixed effects.

[10] In Table A.3 in the Appendix A there are the descriptive statistics. Data show that the 57% of mayors in our sample of municipalities has an university degree; this percentage steeply fall looking at the Councilors and aldermen.

3.1 About the validity of the diff-in-diff research design

The diff-in-diff research design is based on two assumptions: 1) the exogeneity of the measure with respect to the outcome variable and 2) the validity of the "Stable Unit Treatment Value Assumption" (SUTVA).

3.1.1 Reverse causality

To address a possible concern of reverse causality, in this section we will clarify that, although a city council can be dismissed only because of evidence of a collusive agreement between local clans and politicians, violent intimidation might be a hint triggering a procedure of investigation. We will, then, illustrate the main reasons motivating the Prefect's choice of city council dissolution to identify those municipalities whose motivation of dissolution was accompanied, among other reasons, *also* by episodes of violence against local politicians. Therefore, for the purpose of our analysis we will *drop* these municipalities altogether from our sample.

In principle, any policy intervention whatever should be the response to some problem of public life. So while as we have seen the reasons for dissolution are much more wide-ranging, the procedure for city council dissolution can sometimes be triggered by violent acts against local politicians. However, Section 2.1 makes it clear that violent intimidation *per se* is not conclusive evidence of infiltration by organised crime; it can only activate an investigation by the *Commissione d'Accesso* insofar as acts of intimidation are combined with evidence of collusion. Therefore, on the normative level, the decision to dissolve a city council depends exclusively on evidence of collusive behaviour. Nonetheless, since violent intimidation itself can be a warning sign of collusion and thus increase the probability of dissolution, a problem of endogeneity may arise, in this instance one of reverse causality.

The Prefects' reports on the investigations of the *Commissione Parlamentare d'Inchiesta* on the municipalities dissolved for mafia infiltration in our sample (in 2010-2019) make it possible to identify five main motivations for dissolution: (i) *Politicians' crimes*: investigations on crimes committed by administrators or politicians, not necessarily linked to their official functions;[11] (ii) *Extortion/irregular markets*: investigations on practices of extortion, illegal trafficking in arms and drugs, as well as wars among rival clans for the control of local territory; (iii) *Politicians' resignation*: inquiries prompted by the early dissolution of the city council due to the resignation of the mayor or of city council members, possibly indicating pressure from organised crime; (iv) *Shared economic interests*: investigations into irregularities in public procurement or the systematic distortion of public expenditure in sectors targeted by organised crime, indicating shared economic interests between local politicians and criminal clans; (v) *Violent intimidation*: investigations into attacks and threats against politicians.[12]

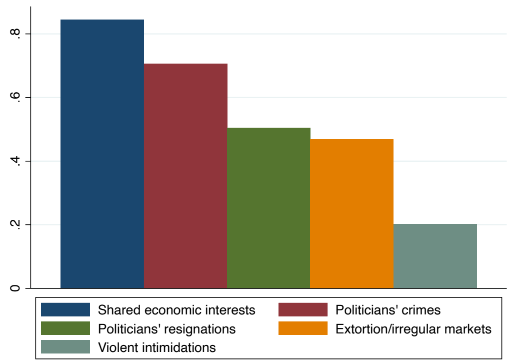
The histogram in Figure 4 gives an intuitive picture of the frequency of these five types of reasons for city council dissolution. The most common – found in 84% of the cases – is evi-

[11] This category comprises also investigations triggered by whistleblowers, informing on politicians' crimes not necessarily linked to organised criminal infiltration.

[12] This definition is in line with the relevant juridical literature on this issue (e.g., Marotta, 2019).

dence of shared economic interests, followed closely by crimes committed by local politicians (70%). Resignation and extortion or irregular markets are relatively less frequent. Consistently with its ancillary nature, violent intimidation is the least common type of grounds for dissolution, occurring in 20% of the cases.[13]

Figure 4: Reasons for City council Dismissals. Percentage



Notes. The histogram reports the percentage of occurrence (on the y axis) of all five categories of reason motivating the Prefect's decision for city council dissolution. Time-span 2010-2020.

Further corroboration that violence against politicians alone does not suffice to justify a dissolution decree can be found in Table 2, which bears on the 22 municipalities whose Prefect reports featured evidence of violent intimidation against politicians among other reasons (see the flags in Column 1). The Table clearly shows that this violence must be accompanied by other evidence that demonstrates some kind of collusive agreement between local clans and politicians. For example, for the dissolution of Cellino San Marco (Apulia) in 2011, the Prefect's report refers to "Repeated episodes of intimidation perpetrated against the directors of the entity", together with evidence that "the mayor's behavior was reprehensible and indicative of proximity to the local criminal milieu, such as his attendance at the funeral of a convicted criminal known to be part of the local clan", which indicates the existence of "long-standing relationships between the administration and the local clan that made the institution permeable to organised crime." This confirms that violence against local politicians is strictly ancillary as a type of motivation for city council dissolution.

However, since intimidatory violence might be a factor that increases the probability of dissolution, in order to support the assumption of exogeneity of the law's application with respect to mafia violence against politicians, we estimate the baseline models as in eq. 1 and 2 excluding the 22 municipalities listed in Table 2. Therefore, the remaining sample comprises those municipalities whose reasons of city council dissolution (e.g., extortion/irregular markets, politicians' crime, shared economic interests and politicians resignation) are not correlated in any way with clans' violence against politicians.

[13]The sum of the percentages in Figure 4 is more than 100% because the Prefect's reports often give more than one reason for the inquiry.

Table 2: Dissolved municipalities *also* because of violent intimidation against politicians

Municipality	(1) Violent intimidation	(2) Politicians' crimes	(3) Extortion/irregular markets	(4) Shared economic interests	(5) Politicians' resignations
Altavilla Milicia	✓		✓	✓	✓
Bagnara Calabra	✓			✓	
Borgetto	✓		✓	✓	✓
Brancaleone	✓	✓			✓
Camastra	✓	✓		✓	
Carmiano	✓	✓		✓	
Cellino San Marco	✓	✓	✓	✓	
Corleone	✓	✓	✓	✓	
Crispano	✓	✓	✓		
Manduria	✓	✓	✓	✓	✓
Mazzarrà Sant'Andrea	✓	✓	✓	✓	✓
Monte Sant'Angelo	✓	✓	✓	✓	✓
Montelepre	✓	✓	✓		
Plati'	✓		✓	✓	✓
Rizziconi	✓	✓			✓
San Ferdinando	✓	✓	✓		✓
Scafati	✓	✓	✓	✓	✓
Scicli	✓	✓	✓		✓
Siderno	✓		✓		✓
Strongoli	✓	✓		✓	✓
Surbo	✓	✓	✓	✓	✓
Tropea	✓			✓	

Note. The table reports the reasons for city council dismissals in the 22 municipalities where such reasons accompanied the evidence of attacks against politicians.

3.1.2 SUTVA

The "Stable Unit Treatment Value Assumption" (SUTVA) (Rubin, 1980), requires that the treatment status of one municipality does not affect outcomes for untreated municipalities. Since mafias often operate in areas larger than a single town, the shock to mafia infiltration due to the enforcement of Law 164 in one municipality may generate spillover effects on neighboring municipalities. For example, Galletta (2017) shows the presence of spillover effects in neighboring towns due to the dissolution for mafia infiltration in Calabria, Campania and Sicily in 1998-2013 in terms of a reduction in public investment. In the same spirit, Cingano and Tonello (2020) show spillover effects on the local petty crimes in municipalities in the neighborhood of the dissolved ones. According to the literature just cited, we can likely consider that the enforcement of Law 164 may generate spillover effects in neighboring towns.

In this respect, we estimate a Poisson FE model as in eq. 1, taking as treated municipalities those with at least one neighbor experiencing a city council dissolution in the period 2010-2019; the control group comprises all the other municipalities except the dissolved ones that are excluded from the analysis.[14] The neighboring municipalities are assumed to start receiving the treatment in the year of the first dissolution of a contiguous municipality. The results are shown in Figure B.3, where the dependent variable is the total number of attacks against politicians by year.

Figure B.3 shows the event study estimates of the Poisson FE model with standard errors clustered at municipal.[15] The coefficients for the pre-treatment period are not significantly different from zero, corroborating the validity of the common trend assumption for neighboring municipalities.

[14] Our source for selection of the neighboring municipalities is the "Matrici di contiguità, distanza e pendolarismo" database provided by the Italian Institute of Statistics (*ISTAT*).

[15] We also perform the same estimation by clustering standard errors at provincial level; results are unchanged and available upon request. Clustering at province level could improve the estimation of standard errors when spatial spillovers are significant.

The dynamic of the number of attacks suggests that for neighboring municipalities the measure substantially reduces organised criminal violence against politicians. Interestingly, the trajectory of the attacks in neighboring municipalities displays a lagged response to the dissolution. Although all the post-treatment coefficients are negative, they are not significant until $t_0 + 3$ and $t_0 + 4$. For neighboring municipalities, the effect of the measure is persistent through time, as documented by the strongly significant coefficients up to $t_0 + 9$.

The presence of municipality spillovers means the SUTVA assumption is probably violated, so the baseline estimates could be biased, because these neighboring municipalities are part of the control group. In order to correct for this potential bias in the estimates, in the empirical analysis, following Kline and Moretti (2014a), we exclude these neighboring municipalities from the control group.

However, spillover effects could extend beyond the neighboring municipalities. Therefore, bias in the estimate will likely remain even after dropping neighboring municipalities. Thus, we will check for spillover effects in a more rigorous manner. Figure B.4 in the Appendix B shows the municipalities in the control group according to the distance (based on the scale of blue) from the dissolved municipalities (the red points). Among such distances, for each treated (dissolved) municipality, we select all the never-treated municipalities in a 20, 30 and 40 km radius. As for the neighboring municipalities, the treated municipalities are those with at least one experiencing a city council dissolution in a radius of 20/30/40 km in the period 2010-2019 (hereafter *new treated*). The *new treated* municipalities are assumed to start receiving the treatment in the year of the municipality's dissolution in the 20/30/40 km radius. The control group comprises all the other municipalities except the dissolved ones.

Figure B.11 reports the results for the Poisson estimation of eq. 1 where the dependent variable is the total number of attacks against politicians by year. Graphs B.11a, B.11b and B.11c show the event study estimates with standard errors clustered at municipal level. For any radius in between 20 and 40 km, the event study graphs suggest the absence of any anticipatory effect of the anti-mafia measure as well as of any the spillover effects.

4 The results

4.1 Baseline results

We first estimate eq. 1 and calculate the trajectory of the attacks on politicians year-by-year before and after city council dissolution. In the baseline specification, the dependent variable is the total number of attacks against all the categories of politician reported by "Avviso Pubblico", in each municipality and in each year from 2010 to 2019. That is, in this specification the treatment group drops the 22 municipalities where violence against politicians was accompanied, in the Prefect's dissolution decree, by evidence of collusion with mafia clans; and the control group excludes municipalities neighboring those dissolved. Moreover, we also remove from the sample the municipalities dissolved because of mafia infiltration before 2010.

The results are displayed in Figure 5 and Table 3 (to save space, the latter shows only the significant coefficients). As mentioned in Section 3, the excluded category in the baseline regressions is the year before the dissolution of the council. Depending on the month of the dissolution, the year of the city council dismissal might be partially treated. For example, if the council is dismissed in January the whole event year t_0 would be treated; instead, if the council is dismissed in December the whole event year t_0 would be untreated. To account for this monthly-staggered treatment we multiply the event dummy t_0 by the fraction of the year that is treated.[16]

Table 3 display a Poisson FE model where the dependent variable is the total number of attacks against local politicians.[17] All regressions present robust standard errors, which are clustered at municipal level.[18]

The graphs 5a and 5b in Figure 5 depict the results reported Columns 1 and 2 in Table 3 respectively. Overall, the coefficients for the pre-treatment period are not significantly different from zero, suggesting the absence of any anticipation effect and of divergent patterns between the two groups before the treatment. Hence, the parallel trend assumption is empirically satisfied. A rapid examination of the Graphs in Figure 5 shows that at t_0, given that only a fraction of the year is treated (i.e., the fraction of the year after the dissolution), the coefficient is noisily estimated delivering a null effect. The coefficient immediately after the dissolution at $t_0 + 1$ (corresponding to the year when compulsory administration ends and a new elected local government takes office) is negative and strongly statistically different from zero, estimating a 81.3% ($e^{-1.680}$ - 1) reduction in the number of attacks (see Column 1 Table 3). However, the strength of the estimated reduction at $t_0 + 1$ can be the sum of three effects: i) the mechanical reduction in threats and violence against local politicians as most of them are out of office during compulsory administration; ii) the effect of the enforcement of Law 164 in reducing the incentive to use violence by mafia, well shown by the statistically significant coefficients in the following years; iii) the incentive of organised crime to attack politicians at the time of elections, well documented by Daniele and Dipoppa (2017), to affect the policy of the new local government, which tend to dissolve the effects of the Law 164.

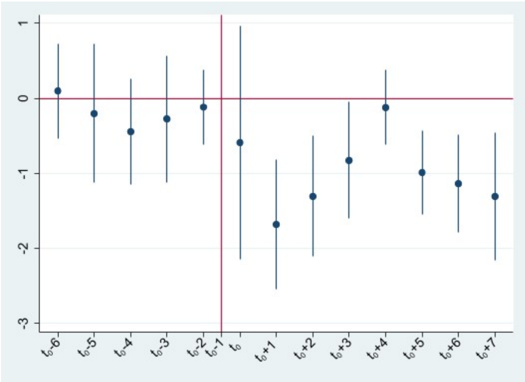
[16] Therefore, in the event study graphs, the event dummy t_0 is no more equal to 1 but to the fraction of the year that is treated.

[17] Although the number of municipalities in the full sample is $1,015$ (with a total number of observations of more than $10,000$), in Table 3 the Poisson fixed effects model determines a substantial reduction in the number of municipalities and observations, because the log-likelihood maximization excludes the units that always have zero values of the dependent variable for the entire period. In this restricted sub-sample the number of city council dismissal is 57 instead of 85 as in the full sample. Nevertheless, while in the full sample of municipalities the dissolved municipalities are the 8% of the total, in the Poisson sample they are the 21%. Table A.4 presents the t-test on the mean difference between treated and untreated units according to the covariates.

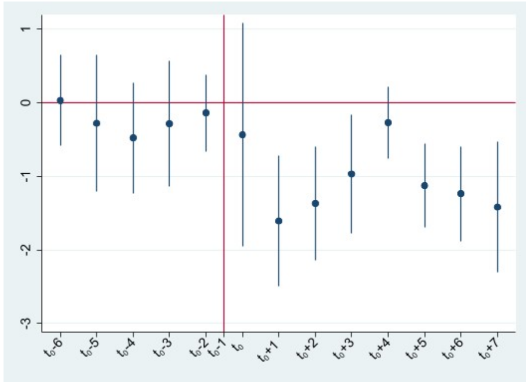
[18] To compute these clustered robust standard errors at municipal level in the Poisson FE model we use the Stata command *xtpqml*. We also perform estimations with standard errors clustered at provincial level. They confirm the previous and are available upon request.

Figure 5: Event study graphs

(a) *Poisson-cluster city*



(b) *Poisson-controls*



Note. The graphs report coefficients and confidence intervals estimated according to eq. 1. The dependent variable is the total number attacks against local politicians. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. We include event-time dummy variables for 6 years before and 7 years after the dissolution. In all regressions we control for municipality FE, year FE and the log of resident population. In Graph 5b we also control for *Mayor degree*, *Councilors degree* and *Aldermen degree*. Period: 2010-2019.

A clearer effect of the anti-mafia measure appears at $t_0 + 2$ and at $t_0 + 3$, respectively with a decrease of 73% and 56% in the number of attacks after compulsory administration compared to the control group of never-dissolved municipalities.[19] The effect of the measure then weakens, and is not statistically significant, up to $t_0 + 4$, when new elections are held. Indeed, even if the law prescribes municipal elections have to be held every five years, specific circumstances may lead to the early termination of the local government and anticipated elections are called. In our sample a local government lasts 2.5 years on overage. Hence, it is reasonable to expect that the second electoral round after compulsory administration occurs in the event-time $t_0 + 4$. Consistently with the results of Daniele and Dipoppa (2017), the null effect of the anti-mafia measure is likely due to the fact that, when the second electoral round is approaching, organised crime has an incentive to attack politicians to affect the policy of the new local government.

Our main result refers to the persistence of the effect of the measure after the second electoral round following the compulsory administration. Indeed, between $t_0 + 5$ and $t_0 + 7$, the attacks still decrease more in the treatment than in the control group; the estimated effect shows a decrease in the number of attacks against local politicians of 63% at $t_0 + 5$, 68% at $t_0 + 6$ and 73% at $t_0 + 7$. As we will detail in Section 7, these effects point to the effectiveness of Law 164 in reducing the profitability of collusion between politicians and organised crime. On the one hand, the costs associated to the city council dissolution (e.g., the costs of being caught by police) should induce politicians to step away from colluding with mafias, thereby being less a target of attacks. On the other hand, since the city council dismissals reduce the amount of public resources to be redirected to local clans, they lower the profitability for organised crime to attack local politicians in order to have favorable policies.

[19] As said above, clustering the standard errors at provincial level does not alter the significance of the coefficients.

Table 3: Baseline estimates

Dep. Var.: No. Attacks	(1)	(2)	(3)	(4)
t_0+1	-1.680***	-1.606***		
	(0.528)	(0.542)		
t_0+2	-1.306***	-1.367***		
	(0.490)	(0.471)		
t_0+3	-0.825*	-0.968**		
	(0.471)	(0.487)		
t_0+5	-0.988***	-1.126***		
	(0.341)	(0.348)		
t_0+6	-1.138***	-1.236***		
	(0.398)	(0.392)		
t_0+7	-1.306**	-1.417***		
	(0.518)	(0.540)		
Policy			-0.795***	-0.810***
			(0.257)	(0.282)
Ln(pop)	0.657	0.824	0.965	1.049
	(2.705)	(2.517)	(2.938)	(2.659)
Mayor degree		0.273**		0.271**
		(0.138)		(0.130)
Councilors degree		0.584		0.593
		(1.155)		(1.127)
Aldermen degree		0.00666		-0.0239
		(0.182)		(0.173)
Observations	3,174	3,174	3,174	3,174
No. Municipalities	319	319	319	319
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note. The table reports coefficients estimated according to eq. 1 (Columns 1 - 4) and eq. 2 (Columns 5 - 8). Columns 1, 2, 3, 5, 6 and 7 show the Poisson FE model estimates; Columns 4 and 8 show the linear model estimates; The dependent variable is the total number attacks against local politicians. Standard errors are clustered at municipal level except for the estimations in Columns 2 and 6 where they are clustered at provincial level. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 in previous years. In estimating eq 1 we include event-time dummy variables for 6 years before and 7 years after the dissolution; the omitted category is the year before the dissolution ($t_0 - 1$). In linear estimation we include the resident population; in Poisson estimations we include the log of resident population. All regressions include municipality FE and year FE (coefficients not reported). Standard errors are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

In Section 3 we underscored the importance of controlling for the education of local politicians. The theoretical model of Dal Bó et al. (2006) and its empirical testing by Daniele and Geys (2015) show how organised crime worsens the quality of politicians, as proxied by their education. Accordingly, we re-estimate eq. 1 and 2, now adding the following control variables: *Mayor degree*, *Councilors degree* and *Aldermen degree*, capturing whether these local administrators have a University degree or not. The Poisson FE estimation results, reported in graph 5b in Figure 5 and in Column 2 of Table 3, show, again, that city council dissolution reduces acts of mafia violence sharply in the period following the election of the first new government after compulsory administration (between $t_0 + 2$ and $t_0 + 3$) and following the next election as well (between $t_0 + 5$ and $t_0 + 7$). Importantly, controlling for politicians' characteristics does not alter the dynamics of the dependent variable. Only the dummy for the mayor's education appears to have a positive and significant impact.
The effect (at least for the first two council terms after compulsory administration), as shown by the U-shaped curve of the attacks, means that the average impact of the policy can be examined by estimating eq. 2; the results are displayed in Columns 3 and 4, Table 3.

One sees at a glance that the negative sign of the treatment coefficient (*Policy*) is robust across specifications, confirming that the dissolution of a local administration for mafia infiltration reduces attacks against local politicians. The Poisson coefficients suggest that the measure diminishes the occurrence of attacks by 54.8% (Column 3). Column 4 shows the mean impact of the measure when the relevant controls are included: the coefficient of *Policy* remains negative and highly significant.

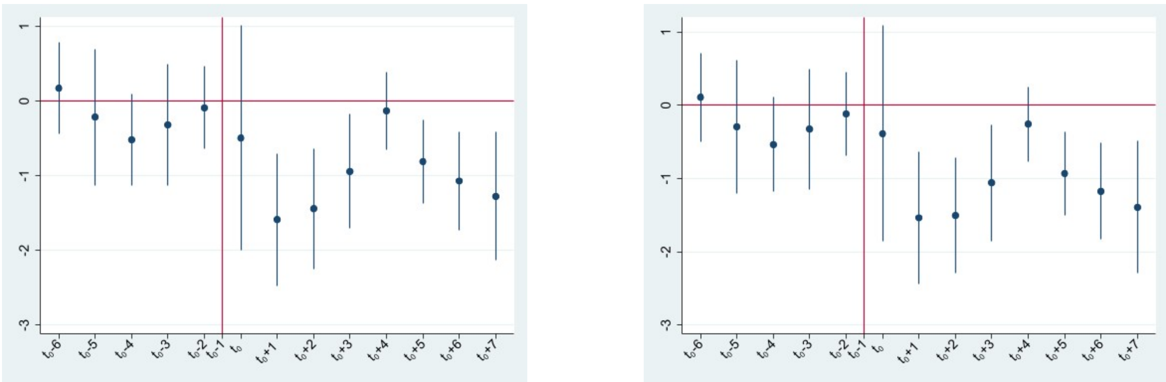
Finally, in order to control for economic shocks in 2009-2010 which could differently affected the four regions under analysis, we include in eq. 1 the interaction between Region and year FE; the related results, displayed in Figure B.5 in Appendix B, confirm the dynamic pattern of the anti-mafia measure as in the main analysis.

4.2 Electoral cycle

The dismissal is de-facto aligning the electoral cycle of all treated municipalities, while the elections in control municipalities are likely distributed uniformly over the event time range. Treated municipalities vote around in event time $t_0 + 1$ as well as in $t_0 + 4$. This implies that treatment is correlated with the electoral cycle, and this correlation has to be taken into account. Therefore, we control for the possible importance of the electoral cycle via a set of dummy variables from the election years up to the three years after,[20] for all municipalities in the sample.[21] The results are displayed in Figure 6 and Table 4.

Figure 6: Event study graphs - Electoral cycle

(a) *Poisson-cluster city* (b) *Poisson-controls*



Note. The graphs report coefficients and confidence intervals estimated according to eq. 1. The dependent variable is the total number attacks against local politicians. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. We include event-time dummy variables for 6 years before and 7 years after the dissolution. In all regressions we control for municipality FE, year FE, the four dummies for electoral cycle and the log of resident population. In Graph 6b we also control for *Mayor degree*, *Councilors degree* and *Aldermen degree*. Period: 2010-2019.

The coefficients of the electoral cycle dummies in Table 4 are never significant (except for a weak significance of *Electoral cycle_0*), indicating no electoral cycle effect on the level of violence. This result is as expected, given the findings of Daniele and Dipoppa (2017) that

[20] Considering that the whole electoral cycle lasts up to five years, we include four dummies to avoid the dummy variable trap.

[21] The four dummies are the following: *Electoral cycle_0* taking the value of 1 in election year and 0 in other years; *Electoral cycle_1* taking the value of 1 in the first year after the election year and 0 in other years; *Electoral cycle_2* taking the value of 1 in the second year after the election year and 0 in other years; *Electoral cycle_3* taking the value of 1 in the third year after the election year and 0 in other years.

in the same sample of municipalities in Campania, Calabria and Sicily, the mafia violence against local politicians increases only in the first month after an election; this result precludes any annual electoral cycle effect. Figure 6 confirm the dynamic pattern of the measure against organised crime depicted in Figure 5.

Table 4: Baseline estimates - electoral cycle

Dep. Var.: No. Attacks	(1)	(2)	(3)	(4)
$t_0 + 1$	-1.588***	-1.535***		
	(0.539)	(0.551)		
$t_0 + 2$	-1.442***	-1.505***		
	(0.493)	(0.481)		
$t_0 + 3$	-0.941**	-1.058**		
	(0.467)	(0.480)		
$t_0 + 5$	-0.809**	-0.929***		
	(0.343)	(0.346)		
$t_0 + 6$	-1.070***	-1.172***		
	(0.398)	(0.400)		
$t_0 + 7$	-1.275**	-1.392**		
	(0.522)	(0.549)		
Policy			-0.798***	-0.818***
			(0.266)	(0.286)
Ln(pop)	0.832	0.951	1.119	1.162
	(2.592)	(2.437)	(2.794)	(2.576)
Electoral cycle_0	0.273*	0.236	0.277**	0.236*
	(0.148)	(0.152)	(0.139)	(0.142)
Electoral cycle_1	0.119	0.0828	0.168	0.125
	(0.174)	(0.174)	(0.162)	(0.162)
Electoral cycle_2	0.00132	-0.0213	0.107	0.0803
	(0.154)	(0.158)	(0.144)	(0.146)
Electoral cycle_3	-0.209	-0.237	-0.194	-0.224
	(0.172)	(0.174)	(0.161)	(0.164)
Mayor degree		0.246*		0.239*
		(0.137)		(0.130)
Councilors degree		0.655		0.649
		(1.099)		(1.084)
Aldermen degree		-0.0125		-0.0517
		(0.185)		(0.175)
Observations	3,174	3,174	3,174	3,174
No. Municipalities	319	319	319	319
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note. The table reports coefficients estimated according to eq. 1 (Columns 1 and 2) and eq. 2 (Columns 3 and 4). The dependent variable is the total number attacks against local politicians. Standard errors are clustered at municipal level. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 in previous years. *Electoral cycle_0* takes the value of 1 in each election year and 0 otherwise. *Electoral cycle_1* takes the value of 1 in the year after the election year and 0 otherwise. *Electoral cycle_2* takes the value of 1 in the second year after the election year and 0 otherwise. *Electoral cycle_3* takes the value of 1 in the third year after the election year and 0 otherwise. In estimating eq 1 we include event-time dummy variables for 6 years before and 7 years after the dissolution; the omitted category is the year before the dissolution ($t_0 - 1$). All regressions include municipality FE, year FE (coefficients not reported) and the log of resident population. Standard errors are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

4.3 Further results

In a further analysis of our main findings, we investigate whether Law 164 is effective in reducing both threats and actual violence as detailed in Figure 2, splitting the total number of attacks into the two categories of *Threats* and *Violence*. We define as *Violence*: set the car on fire, set City Hall on fire, set the house on fire, physical assault, homicide and physical assault in public places. We define as *Threats* all the remaining attacks.

Given that the "Avviso Pubblico" data on threats and attacks against politicians are drawn from media reports, this distinction allows us to mitigate two possible measurement errors of the dependent variable. First, since we rely on attacks that are denounced by politicians, a bias due to media under-reporting could be a concern. Second, not all the reported attacks could be imputed to organised crime. The first kind of measurement error, as Daniele and Dipoppa (2017) note, is not a serious danger: as in most cities attacks against politicians are uncommon, we can assume that when they occur, they generally do get reported. For while threats may be hidden, outright violence is visible and, thus, unlikely to go unreported. As for the second measurement error, we have already clarified that attacks driven by personal motives constitute a tiny fraction of the total (Moro et al., 2015). Furthermore, this issue mainly concerns threats rather than violence. Indeed, the sub-sample of threats is likely to include also online threats that are unlikely to be perpetrated by organised crime. Unfortunately, we are not able to distinguish between these two types of threats in our data. Nonetheless, the sub-sample of violence is mainly constituted by types of attacks (e.g., set the car on fire, set City Hall on fire, set the house on fire, shootings against the city hall and/or the politicians' car) that are typical of organised crime intimidation strategy and are less likely to be perpetrated by private citizens.

Graphs B.6a and B.6b of Figure B.6 (in Appendix B) show the effect of the measure for the two categories of attacks respectively. The dynamic pattern of the number of threats against local politicians after the enforcement of Law 164 is very similar to that of violence. The persistence of the measure's effect after the second electoral round after the city council dissolution is confirmed for both the subgroups of attacks. Columns 1 and 2 of Table A.5 (in the Appendix A) show the average effect of the measure for the two categories of attacks. Both coefficients are highly significant: the Law's application reduced both subsets of attacks in the treated compared with the untreated municipalities. The decrease in *Violence* was greater than that in *Threats*: the elasticity of the average treatment effect over the entire period is about 52% for *Threats* and 58.6% for *Violence*.

4.4 Negative weights

The most recent econometric literature has shown that in a staggered diff-in-diff design, when the effects of the measure are dynamic (as in our setting), the coefficient of the average treatment effect (*Policy* in Table 3) represents a weighted average of these dynamic effects; and some of the weights can be negative, generating possible bias in the estimates (Goodman-Bacon, 2021). When the treatment effect is not constant over time, negative weights arise because the already-treated units move into the control group, so that changes in their treatment effects over time are no longer factored into the diff-in-diff estimate. De Chaisemartin and d'Haultfoeuille (2020) propose a test to compute the number of negative weights in this setting.[22] The test shows that the number of negatively-weighted Average Treatment Effects on the Treated (ATTs) is 0, suggesting that the heterogeneity is chiefly between treated and never-treated municipalities. Therefore, this statistical inference supports the hypothesis

[22] We use the *twowayfeweights* Stata command, developed by De Chaisemartin and d'Haultfoeuille (2020), for linear estimations.

that our initial estimates are not biased due to the negative weight issue.

5 Checking for the exogeneity of the dissolution measure

The main assumption of the diff-in-diff methodology is the strict exogeneity of the policy with respect to the dependent variable.

In this section, we tackle this methodological issue by addressing two important threats to our identification strategy: reverse causality and omitted variable bias. All Tables with the prefix “A.” are in Appendix A. All Figures with the prefix “B.” are in Appendix B.

5.1 Granger causality

As noted above, the procedure for city council dissolution can also be triggered by violent acts against local politicians. The event study as in eq. 1 already addresses the concern of reverse causality. It is suitable for a first check of the exogeneity of the treatment through a test of the Granger causality hypothesis (Granger, 1969).

Granger causality implies that the treatment is not caused by current attacks on politicians. Hence, city council dissolution should come before violence and threats, not after. The estimation of the dynamic model in eq. 1 shows that the coefficients of the event time dummies t_0, $t_0 - 1$, $t_0 - 2$ are not statistically significant.

Hence, the evidence supports the hypothesis that city council dissolution has not been anticipated by organised crime.

However, even under Granger causality, the dissolultion could be endogenous with respect to violence if the decision is influenced by the expectation of future attacks against politicians. In this case, the central government would justify the dissolution of a municipal council on the grounds of expected future violence.

However, such behavior on the part of the institutions in charge of the decision is readily ruled out. In fact, council dissolution means that the mayor and Councilors suffer the damage of being deprived of legally held offices, and in democracy the rule of law does not admit any role for expectations in legal decisions. Further, as noted above, the estimates refer to council dissolutions in which the relevant documents do not refer to violence against politicians in the past or in the future.

The exogeneity of policy further implies that current and past values of the outcome do not explain the policy intervention. Table A.6 shows results of the regression of the dummy *Policy* on the total number of attacks in municipality i at times t, $t-1$ and $t-2$ (in Column 1) and at times $t-1$ and $t-2$ (in Column 2). The coefficients indicate that the *historical* number of attacks has no significant effect on the probability that a municipality will be dissolved.

We also estimate a linear probability model for the *hazard rate* of the policy, that is the probability of a municipality's being dissolved at time t when it has never been dissolved until then, as is common in duration analysis.

In this case, the dependent variable *Policy* is a dummy that for treated municipalities takes the value of 0 in the years before the city council dissolution and 1 in the year of dissolution, while it is always 0 for the control municipalities.

Accordingly, in these estimates we remove all the observations of treated municipalities after the year of dissolution. The results in Columns 3 and 4 of Table A.6 show that mafia-related violence has no effect on the conditional probability of a municipality's being dissolved.

5.2 Omitted variable bias

Strict exogeneity of the treatment requires that the timing of treatment exposures in the diff-in-diff design must be statistically independent of the potential outcome distributions, conditional on the group and time fixed effects. We provide evidence of robustness to omitted variable bias with a propensity score matching analysis and controls for important variables that proxy for the level of government public security intervention.

5.2.1 Propensity score matching

In the matching procedure, the first step is to estimate the propensity score corresponding to the probability of each municipality's being treated, which is then regressed on covariates at the municipal level: population, average female and male educational attainment, female and male unemployment rates, a dummy for mayor's gender (1 if female) and the share of female politicians within the city council.[23]

The goodness of the match for constructing a suitable control group is confirmed in Figure B.7, which shows the distributions of the estimated propensity scores for the treated municipalities (right-hand side) and the matched control municipalities (left-hand side).

Figure B.8 and Table A.7 show the estimation results of eq. 1 and eq. 2 by the Poisson FE procedure. The baseline findings are confirmed despite the substantial reduction in the number of observations, inevitable in propensity score matching. First of all, the common trend assumption is definitely corroborated, as is shown by the insignificance of the coefficients before the dissolution. The post-dissolution dynamic shows a significant negative effect just after compulsory administration ($t_0 + 2$ and $t_0 + 3$). The estimates also display a durable effect of the measure, lasting at least until the second election afterwards.

Column 2 of Table A.7 shows that after a city council dissolution the number of attacks decreases on average by 48% more in the treatment than in the control group. The coefficient is smaller (in absolute value) than that in the full sample estimates.

5.2.2 Controlling for government repressive action

According to the theoretical argument set out in Section A, the reduction in violence against politicians is an indirect effect of the measure under examination, which is designed to increase the cost of corruption (i.e., bribes) but not that of violent punishment, which would require an expansion of law enforcement bodies. Thus government repression of criminal activities through police forces could be an important source of omitted variable bias in our analysis. The greater reduction in attacks in the treated than in the untreated municipalities

[23] We use the Stata command *psmatch2* developed by Leuven and Sianesi (2003).

after city council dissolution could be due to an increase in the police presence rather than to the application of Law 164/1991.

To address this concern, let us note first that the application of the Law does not entail police control of the city government in territories where organised crime is especially active. Previous studies clearly show that owing to stringent budget constraints, neither police forces nor funds for public safety are increased during compulsory administration (Mete, 2009; Cavaliere, 2004). In fact, examination of the national data reveals that both the number of policemen and national expenditure for public safety declined between 2010 and 2019.[24]

In any case, we address the concern over omitted variable bias statistically by controlling for government repressive action. Data on central government control of the territory at municipal level are not available,[25] so we looked at the data of the Ministry of Interior on a large number of crimes reported by police to the judicial authorities at provincial level from 2006 to 2019. These crimes – homicides, sexual abuses, fencing of stolen goods, extortion, smuggling, drug trafficking, etc. – can be considered as a good proxy for central government repressive action against criminality (Cingano and Tonello, 2020).

However, the number of crimes reported can be a good proxy for government action against crime only if it is not affected by the treatment itself (Wooldridge, 2005). To verify this basic condition, we regress all of these crimes on our treatment variable. Since the number of crimes is reported at province level, following Acconcia et al. (2014) we define as composing the treatment group the Italian provinces with at least one dissolved municipality and as the control group all other Italian provinces. Accordingly, we construct the treatment variable as taking value 1 if at least one municipality has been dissolved in the province, from the year of dissolution onward, and 0 for all the other Italian provinces.

We estimate a panel FE model for all provinces (with both year and province FE and the provincial population), where the 55 crimes recorded by the Ministry of the Interior are regressed one-by-one on the treatment variable defined above. The estimates, reported in Tables A.8 - A.14,[26] allowed us to pick out 34 crimes that are not affected by the treatment. We then estimated the Poisson FE model of attacks of local politicians in the four regions of Calabria, Campania, Apulia and Sicily as in eq. 2, controlling for each of the crimes selected. The coefficients associated with the treatment variable *Policy* remain negative and highly significant when the 34 felonies are added, one-by-one, as controls. Here, for brevity, we show only those that have a statistically significant correlation with our outcome variable.[27] These number 11 and are reported in Table A.15 one-by-one and in Table A.16 all together, with their sum as well. The magnitude of the coefficient associated with the variable *Policy* is very close to that given in Table 3, further supporting the hypothesis that the treatment variable is exogenous with respect to the outcome variable.

[24] See the Eurostat website: http://ec.europa.eu/eurostat.

[25] For example, national expenditure for police and number of policemen are confidential information, not available at lower levels of government.

[26] In the notes to Tables A.8 - A.14 we report the designation of each crime.

[27] The results for all 34 felonies are available upon request.

6 Robustness

This section presents additional evidence in support of our findings. First of all, we test the validity of our main result on the full sample of municipalities in the treatment and control groups by Poisson RE estimates. To assess the overall efficacy of Law 164 as an anti-mafia measure, we refine the analysis by excluding the year 2012, the municipalities that underwent multiple dissolutions for mafia infiltration, and the municipalities dissolved for mafia infiltration before 2010. We also seek to determine whether the political orientation of the local government has an impact on the effect of dissolution on the number of attacks. Finally, we test whether dissolution unrelated to mafia infiltration affects our dependent variable.

6.1 Poisson RE estimates

In Section 3 we well documented the validity of the Poisson empirical model to estimates count data. Indeed, with count data, applying an ordinary linear regression model can lead to two kinds of problems. First, being our distributions of count data positively skewed with many observations having a value of 0, it prevents the transformation of a skewed distribution into a normal one. Second, it is quite likely that the regression model will produce negative predicted values, which are theoretically impossible.[28]

However, as pointed out, in the model that controls for any omitted time-invariant variables, Poisson log-likelihood maximization excludes the units that always have zero values of the dependent variable for the entire period, leading to a substantial reduction in the number of observations. To face this issue, in this section, for robustness we present Poisson RE estimations (Table A.17 and Figure B.9). The results are similar but less strong than those with fixed effects.

6.2 Excluding year 2012

As noted in Subsection 2.3, the downward spike in attacks for 2012 simply reflects the lack of data collection by "Avviso Pubblico" for that year. Accordingly, 2012 is excluded from the analysis, but the results are unchanged (see Table A.18 and Graph B.10a of Figure B.10).

6.3 Multiple dissolution for mafia infiltration

As is observed in the previous Section 2.2, 7 municipalities were dissolved more than once. To avoid post-treatment bias, in Table A.19 and in Graph B.10b of Figure B.10 we exclude them; again the findings are unchanged.

[28] An alternative linear estimation specification in case of count data with skewed distribution around 0 is to define a binary variable 0/1 equal to 1 when one or more events occurred in municipality i at year t. However, this recommendation holds when the case of more than 1 occurrence of the event is less than 1%. In our case, the cases of more than 1 attacks occurred have a frequency of 3.14%, as Table A.2 in Appendix A shows.

6.4 Political party in power

In view of the literature that has documented that mafias are more connected with center-right parties Buonanno et al. (2016), we assess whether our results are affected by the political orientation of the victims. In Italy, at local level, only in the largest municipalities is the electoral competition between national parties with a well-defined political orientation. In most municipalities, instead, it is between civic lists, often with no clear political orientation.

Applying a broader code of center-right and center-left parties, we divide the parties in local government into three categories: parties and civic lists of right and center-right (i.e., all those whose names contain words clearly ascribable to a rightist political group - *Center-right*), parties and civic lists of left and center-left (i.e., those with names containing words clearly ascribable to a leftist political group - *Center-left*), and parties and civic lists with no definite political orientation (*Civic lists*). In our sample of municipalities, 83.74% of municipal administrations are headed by civic list mayors, 9.63% by center-left mayors and the remaining 6.57% by center-right mayors.

According to this broader coding, in the Poisson FE estimations as in eq.1 and 2 we control for the dummies *Center-right*, *Center-left* and *Civic lists*.[29] The results (Graph B.10c of Figure B.10 and Table A.20) are consistent with the baseline, and they indicate that the mayor's political orientation does not affect the outcome variable.

6.5 Placebo test on governments dissolved for reasons unrelated to mafia infiltration

As a further check of our findings, we run a placebo test on municipalities dissolved for reasons other than mafia infiltration, which is a common occurrence. The regular term in office of the mayor and the council is five years;[30] under certain circumstances — permanent impediment, removal, lapse of appointment, or death preventing the mayor or the majority of the council from performing their duties; violation of the Constitution or national law; failure to pass the budget — the mandate may be terminated early and new elections held.

We estimate Poisson FE as in eq. 1, considering the dynamics of the number of attacks in municipalities dissolved for non-mafia reasons before and after the city council dismissal. Obviously municipalities dissolved for mafia infiltration are excluded. Graph B.10d of Figure B.10 shows the year-by-year Poisson FE estimated coefficients, which are not statistically different from zero.[31] In short, the number of attacks against local politicians is plainly not significantly affected by city council dissolution *per se*.

7 Discussion on possible mechanisms

The evidence set forth to this point is broadly consistent with Dal Bó et al. (2006)'s conceptual framework, in which non-repressive measures (Law 164) reduce the profitability of

[29] Given that the Poisson FE algorithm does not estimate the constant term, we can add all the dummies without falling into the dummy variable trap.

[30] Until 2000, shortened to four years by Law 81/1993, Art.2; restored to five by Legislative Decree 267/2000, Art.51).

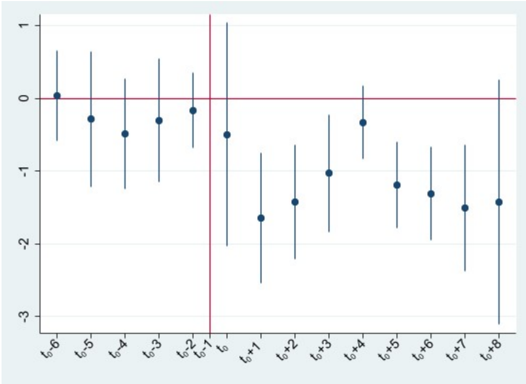
[31] In our sample, 420 municipalities were dissolved for reasons unrelated to mafia infiltration.

corruption and with it the overall resort to violence. However, the recorded decrease in violent intimidation of politicians might also be due to 1) greater attention of police forces to defending the territory after the city council dissolution; or 2) *perceived deterrence*; that is, criminal behavior can be influenced by the perception of more certain or more severe punishment (Sah, 1991; Lochner, 2007).

From the perspective of local clans, this alternative mechanism entails an increase in the level of risk associated to political infiltration. If this was the case, we should observe a decline in the number of attacks roughly uniformly distributed in the post-treatment period. However, the estimated sine curve of Law 164's effect on clans' violence is inconsistent with this alternative mechanism. Indeed, as shown in Figure 7, the estimated effect of the measure is insignificant when the second and third electoral rounds after compulsory administration are held, presumably at $t_0 + 4$ and $t_0 + 8$ (with the latter being the last lead that we can estimate), documenting an attempt of local clans to affect the electoral outcomes through violence against politicians.

Moreover, the argument based on organised crime perceived risk of political infiltration would entail that local clans should refrain from violence after the city council dissolution to reduce the probability of further dismissals in the future. So, the more local clans reduce violence after the city council dissolution, the lower the probability of future dismissals should be. This would imply that in the sub-sample of municipalities dissolved *only once* — i.e., where the probability of future dissolution is zero — the negative effect of the anti-mafia measure on the number of attacks against politicians should be stronger compared to whole sample including municipalities that underwent multiple dissolution — i.e., where the probability of future dissolution is greater than zero. However, the comparison of the estimates where we include exclusively municipalities dissolved only once (Table A.19) and our baseline estimates (Tables 3 and 4) does not deliver any appreciable differences neither in the size nor in the significance of the estimated coefficients. This makes unlikely that the reduction in the number of attacks is due to the increase in organised crime's perceived risk of political infiltration after city council dissolution.

Figure 7: Third Electoral Round



Notes. The graph reports coefficients and confidence intervals estimated according to eq. 1. Poisson FE model estimates, dependent variable is total number attacks against politicians. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. We include event-time dummy variables for 6 years before and 78 years after the dissolution. All regressions include municipality FE, year FE, the log of resident population. Period: 2010-2019.

To further support the previous argument, as discussed in subsection 2.1, the enforcement of Law 164 does not directly imply an increase in actual deterrence through stiffer sanctions or stepped-up police deployment. Subsection 5.2.2 addressed this issue from the statistical standpoint (controlling for the repressive action of the state as proxied by the number of crimes at province level). Here we further investigate the alternative mechanism based on the perceived deterrence by exploiting the information given in Figure 3: the targets of mafia attacks are municipal politicians/institutions as well as politicians/institutions outside local government. We then replicate the analysis dividing politicians and institutions into two groups: *Municipal*, including deputy mayors, mayors, Councilors, aldermen, former mayors, relatives, and the city hall building; and *other politicians/institutions*, comprising regional Councilors, regional presidents and other institutions and institutional entities. If the observed reduction in violence against politicians was due to closer attention on the part of law enforcement bodies or the perception of greater enforcement, then we should observe a decrease in the number of attacks in the municipality as a whole, that is, in *both* the sub-samples of politicians.

Table 5: Types of politician

	(1)	(2)
No. Attacks	Municipal politicians/institutions	Other politicians/institutions
Policy	-0.602**	-0.416
	(0.280)	(0.293)
Observations	3,304	1,817
Number of new_id	332	182
Municipality FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to eq. 2 by a Poisson FE model. *Policy* is a dummy taking the value of 1 for all the years from the first after compulsory administration to the end of the period and 0 for previous years. We control for the log of resident population, municipality FE and year FE whose coefficients are not reported. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

The estimation results are given in Columns 1 and 2 of Table 5 respectively for the *municipal* and *other* politicians/institutions. The measure strongly affects municipal entities, and attacks on them after compulsory administration declined on average by 44% more in the treatment than in the control municipalities (Column 1). By contrast, the measure has no effect on politicians and institutional entities outside the municipality (Column 2).

This evidence suggests that neither increased police deployment nor *perceived deterrence* is a likely driver of our results. In short, the mechanism analysed in Dal Bó et al. (2006) would appear to correspond more closely to our results. The application of Law 164 increases the costs of corrupting city council politicians (by ousting them from office). Therefore, the Dal Bó et al. (2006) model would predict a complementary or a substitution effect on mafia violence against the *same* target of bribery (now more costly). Accordingly, we estimate the relationship of interest as in eq. 1, distinguishing between members of the city council (mayor, deputy mayor, Councilors and aldermen) and other figures within the municipality but *outside* the city council (former mayor, relatives of politicians, the city hall). As we are interested in the post-treatment dynamic, we show only the event-time coefficients after city council dissolution. The results are reported in Figure 8, comparing the dynamic effect of the enforcement of Law 164 on attacks against city council members (Graph 8a) and other political figures or institutions (Graph 8b).

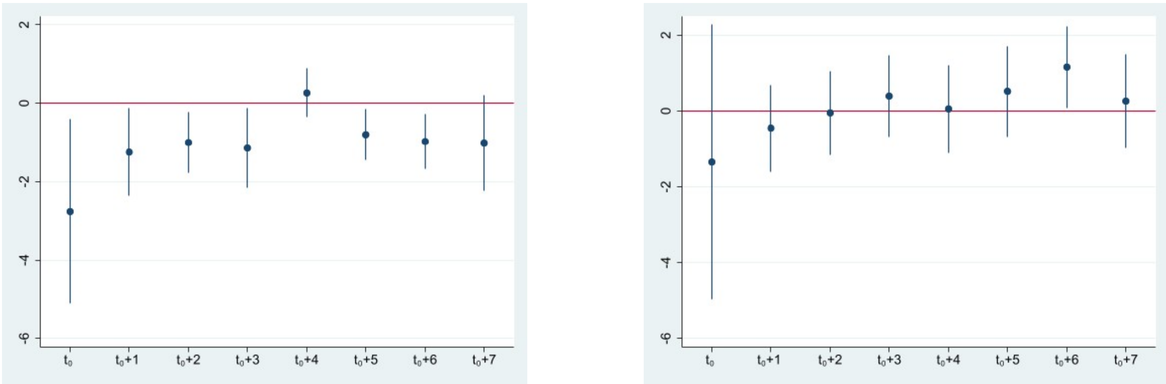
The analysis clearly shows that the reduction in violence against politicians is driven mainly by a decrease in attacks against city council members (Graph 8a); except for those at $t_0 + 4$ and $t_0 + 7$, all the coefficients are statistically significant. No significant coefficients, instead, appear after the compulsory administration period for politicians outside city council (Graph 8b). This further corroborates the unlikeliness of both stepped-up police deployment and *perceived deterrence* as drivers.

Interestingly, the coefficient associated to the event-time t_0 in Figure 8a is negative and statistically significant, while it resulted not significantly different from zero in estimates shown in Figure 5. This difference is due to the fact that in the baseline estimates we pooled together all types of politicians, while in Figure 8a we only consider those in the city council. Therefore, the estimated negative coefficient is likely to be driven also by a mechanical effect since during compulsory administration city council politicians are out of office. Moreover, when dealing with only city council politicians, the magnitude of the coefficient at $t_0 + 1$ becomes smaller with respect to that in Graph 5a and significant at 10%, providing a reliable estimate of the three effects discussed in subsection 4.1 (i.e., the mechanical reduction in attacks due to politicians out of office, the reduction in attacks due to the effect of the measure, the increase in the number of attacks during elections). Specifically, it is likely that the increase in violence against city council politicians due to the upcoming elections after compulsory administration (Daniele and Dipoppa, 2017) tends to outweigh the reduction in the number attacks due to the mechanical effect and to the effect of the policy.

Figure 8: Dynamic city-council politicians - no city-council politicians

(a) City-council politicians

(b) No city-council politicians



Note. The graphs report coefficients and confidence intervals estimated according to eq. 1. Graph 8a shows the Poisson FE model estimates where the dependent variable is the total number attacks against city-council politicians; Graph 8b shows the Poisson FE model estimates where the dependent variable is the total number attacks against other politicians or institutions. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. All regressions include municipality FE, year FE, the log of resident population. Period: 2010-2019.

7.1 Renewed pool of politicians

Why might the enforcement of Law 164 induce organised crime to complement bribery and corruption with violence? As we have seen, this measure is intended primarily to break the ties between organised crime and corrupt local politicians by replacing the latter with external commissioners. In this regard, Di Cataldo and Mastrorocco (2022) show that city council dissolution entails a reallocation of public funds away from sectors targeted by organised crime (e.g. construction and waste management) and an increase in tax collection. Moreover, Ravenda et al. (2020) show that the city council dismissal significantly reduces irregularities in public procurement, a widely accepted proxy for bribery by organised crime. This evidence documents how the city council dissolution entails a substantial reduction in the amount of public resources redirected to local clans, as complicit politicians are no longer in a position to influence appropriations.

These results indicate the efficacy of city council dissolution in renewing the pool of elected politicians, who now systematically implement policies hostile to organised crime. The newly elected councils following compulsory administration have been shown to be made up of more highly educated politicians (see, for instance, Daniele and Geys, 2015; Baraldi et al., 2022a) and with a larger number of women (Baraldi and Ronza, 2022), who are typically less inclined to corruption (e.g., Eagly and Crowley, 1986; Eckel and Grossman, 1998; Glover et al., 1997; Goertzel, 1983; Ones and Viswesvaran, 1998), as well as younger politicians at their first term in office (Daniele and Geys, 2015; Fenizia and Saggio, 2022).[32] Moreover, Baraldi et al. (2022b) have shown that the change of officeholders is driven by a change in voters' behaviour rather than by a change in the candidate pool. Thus apparently the enforcement of Law 164

[32]The evidence of policies hostile to organised crime put in place by these new, better qualified politicians makes it unlikely that the reduction in violence after their election is due to collusive agreement with the local clans.

is effective in undercutting the popular belief in the inevitability of the mafia's influence on politics and thereby increasing the trust of local communities in the state's capacity to fight corruption (Kline and Moretti, 2014b).

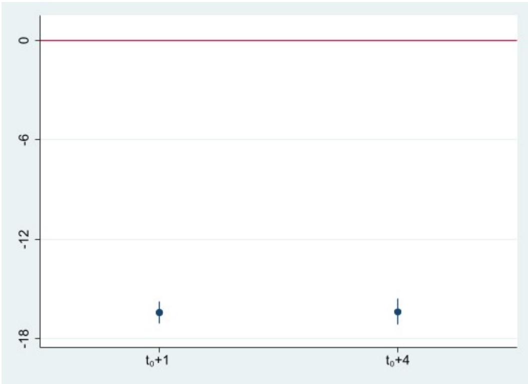
Since better educated individuals are less likely to engage in criminal activities (see, Lochner and Moretti, 2004; Lochner, 2004), the negotiation costs of influencing politics should increase in the quality of officeholders proxied by their education (Dal Bó et al., 2006). Thus, the evidence reviewed above indicates that as a target for organised crime the new local government is likely to have substantially higher negotiation costs, and hence a lower expected payoff to corruption. In fact, our evidence shows that the persistence of the measure's effect on the number of mafia attacks after the second electoral round (at least up to $t_0 + 7$) is most likely driven by the improvement in the political environment thanks to the application of Law 164, which presumably affects the future political class as well as the municipal environment in general.

Moreover, the enforcement of Law 164 *per se* might increase the negotiation costs as it is likely to have a deterrence effect on the behaviour of better qualified politicians, who have more to loose from a city council dismissal. Indeed, after a city council dissolution due to mafia infiltration, newly elected politicians are more likely to be investigated for collusion with local clans; so, the enforcement of Law 164 might induce them to step away from organised crime. This has relevant implications for clans' violence against politicians. Indeed, attacks often take place when colluded local administrators do not fulfill their electoral promises to organised crime (Daniele and Dipoppa, 2017; Dell, 2015). Hence, if city council politicians are deterred from collusion, then they are less likely to be a target of attacks.

The renewal of the pool of elected politicians, and the consequent rise in the cost of bribery, could carry important implications for mafias' strategic use of violence around elections. The dynamic plotted in Graph 8a is intriguing: a significant negative coefficient at the first electoral round after compulsory administration (at approximately $t_0 + 1$), and an insignificant one at the second round (approximately $t_0 + 4$). Since in the period around an election mafias can target both candidates and the newly elected, in order to grasp the possible mechanism behind this dynamic, we compare the pattern depicted in Graph 8a with that in Figure 9, which, within the limits of the small sample, tries to shed light on the effect of the measure on the number of attacks against candidates.

Taken together, the Graph in 8a and Figure 9 indicate that organised crime uses violence differently in the two electoral rounds considered here. In the first ($t_0 + 1$), there is an appreciable change in the level of violence against both candidates and elected politicians in the treated compared to the untreated municipalities. Conversely, at the second electoral round ($t_0 + 4$), organised crime significantly reduces the number of attacks against candidates in treated compared with untreated municipalities (Figure 9), while not altering the number of attacks against elected politicians (Graph 8a) between the two groups of municipalities.

Figure 9: Dynamic of candidates



Notes. The graph reports coefficients and confidence intervals estimated according to eq. 1. Poisson FE model estimates, dependent variable is total number attacks against candidates at elections. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. All regressions include municipality FE, year FE, the log of resident population. Period: 2010-2019.

This change in the use of violence between the first and second electoral rounds after compulsory administration could reflect the higher cost imposed on organised crime owing to the renewal of the pool of politicians triggered by the dissolution. Specifically, at the first electoral round a criminal organization may refrain to attack candidates because violent intimidation can only be effective to the extent that organised crime has the power to oblige voters to cast their preferences for the mafia-backed candidate Gambetta (1996). The tendency of voters to elect more highly qualified individuals after the dissolution (see Baraldi et al., 2022b) indicates that organised crime is no longer able to guarantee strong support to its candidates. Hence the first electoral round after a dissolution could well result in a renewal of officeholders.

To the extent that newly elected politicians have been shown to be of better quality and less prone to corruption, threatening them by violent intimidation might no longer be a winning strategy. This may explain the decrease in the number of attacks against elected officials starting from the first electoral round, or in our timeline at about $t_0 + 1$ (Graph 8a). Moreover, these newly elected politicians are likely to implement policies hostile to the local interests of organised crime, in particular as regards the allocation of public resources and public procurement. This would further raise the cost of corruption, with financial losses for organised crime and weakened control of the local territory. This represents a plausible explanation for the durable decrease in the number of attacks against elected politicians after the first electoral round.

When the second electoral round approaches, at $t_0 + 4$, local clans, having lost their tight control of the territory and no longer able to guarantee electoral support, might try to prevent anti-mafia policies and recoup their power by directly attacking elected politicians rather than candidates. Indeed, as Dal Bó et al. (2006, p. 46) put it, "if politicians are being coerced by groups they will tend to sell their favors relatively cheaply". This might explain the insignificant difference between treated and untreated municipalities in the number of attacks against elected politicians at $t_0 + 4$ (Graph 8a) and the significant reduction in the number of attacks against candidates in treated municipalities at $t_0 + 4$ (Figure 9).

Nonetheless, the smaller number of attacks against elected politicians after elections between $t_0 + 5$ and $t_0 + 7$ (Graph 8a) strongly indicates that the improvement in the pool of elected politicians and in the municipal environment after the dissolution entails a substantial loss of deterrent power for mafia violence.

Finally, one could object that the dissolution might simply induce organised crime to turn to income streams other than public funds and procurement and substitute bribes for violence as the tool for influencing politics. This would entail an increase in corruption after compulsory administration, casting doubt upon the complementary relationship that our empirical analysis has found between bribes and violence. This concern is allayed by an examination of Tables A.8 to A.14, which regress the treatment variable *Policy* on crimes at province level. Specifically, crimes like exploitation and abetting of prostitution (C19),[33] theft of artworks and archaeological material, theft of trucks, motorcycles, scooters, and cars (C27-C31), extortion (C38) and usury (C45), can be deemed as a proxy for alternative sources of money for organised crime that might finance its corrupting influence on politics. The significant negative coefficients of *Policy* reported in the tables show that the city council dissolution also reduces these potential alternative sources of revenue. Thus, within the limits of the available data, we have additional suggestive evidence that the underlying mechanism, whereby city council dissolution decreases violence against city-council politicians by reducing the profitability of corruption, is a coherent reading of our results.

8 Spillover effects

In Section 3.1.2 we support the validity of the SUTVA by searching for spatial spillovers of city council dissolution on crimes against politicians in cities geographically closer to a dissolved municipalities (the cities in the neighbor of the dissolved municipalities) as well as in cities within a 20, 30 and 40 km radius. Finding evidence of spillover effects only in neighboring municipalities, following Kline and Moretti (2014a) we dropped them from the control group and we estimated the treatment effect on violence against politicians.

In this section, we offer further investigation of the spillover effects of the anti-mafia measure on violent intimidation against local politicians by following the new methodological approach proposed by Butts (2021b) that provides unbiased estimation of the *total effect* (the treatment effect on the treated) and the *spillover effects* (treatment effect on the untreated in the treated clusters, i.e., the units in the control group that receive spillover effects — partially treated units) over the entire sample of units. Following Butts (2021b), we estimate a linear dynamic model as in eq. 1 on the whole sample of municipalities. The Butts (2021b)'s model includes the dynamic effects of the treatment variable and a spillover variable. Because the effects of council dissolution may vary across groups (Sun and Abraham, 2021), Butts (2021b) proposes the application of the two-stage estimator by Gardner (2022) that identifies the average treatment effects of the event times dummies.[34]

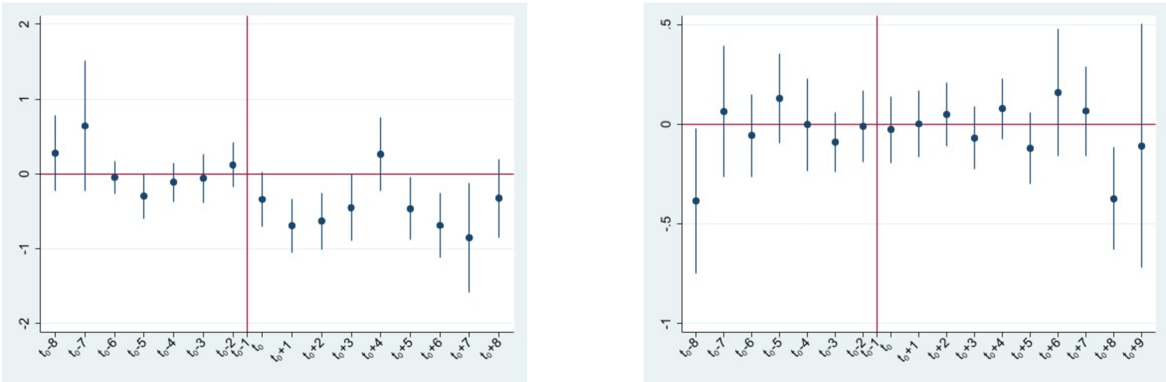
Figure 10 shows the plots of the event study estimated coefficients with treatment (*total effect*) and spillover average effects (*spillover effects*) when standard errors are clustered at

[33]The numbers in brackets refer to the categories of crimes as in Tables A.8-A.14.
[34]We use the unofficial Stata command *did2s* by Kyle Butts (Butts, 2021a).

city level. In our model, the geographic spillovers (the spillover variable) are captured by a dummy variable taking value 1 if in year t, municipality i is located no farther than a given distance from the nearest city with dissolved council, and 0 otherwise. As in Section 3.1.2, we consider possible spillovers in neighboring municipalities and in municipalities located at 20km/30km/40km to define the largest ring.

Figure 10: Total and Spillover Effects

(a) *Total effect-cluster city* (b) *Spillover effect-cluster city*



Note. The graphs report coefficients and confidence intervals estimated according to eq. 1 using the *did2s* Stata command. The dependent variable is the total number attacks against local politicians. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 95% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). We include event-time dummy variables for 8 years before and 9 years after the dissolution; in Graph 10a the event dummy at $t_0 + 9$ has been dropped because of collinearity. In all regressions we control for municipality FE and year FE and the resident population. Period: 2010-2019.

The four graphs in Figure 10 refer to contiguous cities. Although Poisson estimates in Section 3.1.2 showed statistically significant spillovers in neighboring municipalities to the dissolved ones, the Butts (2021b)'s procedure provides slightly different results. Indeed, Graph 10b does not provide evidence of spillover effects in neighboring municipalities. The same result is obtained when we adopt the other three values of distance[35]. Furthermore, the estimates of the *total effect* of the council dissolution on political violence as in Graph 10a confirms the main findings (Graphs in Figure 5), showing that spillovers are not a serious concern in our analysis.

9 Conclusions

This paper offers an empirical measure of the efficacy of Law 164/1991 mandating the dissolution of city councils in cases of mafia infiltration in preserving public safety by deterring organised crime from resorting to acts of violence to intimidate politicians and influence local politics.

We referred to Dal Bó et al. (2006)'s model. In this framework, law enforcement that undercuts the profitability of bribery (the payoff) without expanding the police presence could in theory induce criminal organizations to shift from corruption to violent intimidation,

[35] Regression results are not shown but are available upon request

thereby raising the level of violence; or, on the other hand, it could have an overall negative effect on violence against politicians if it induces enough criminal groups to go inactive. In substance, empirical analysis of the impact of Law 164/1991 on organised criminal violence against local politicians is essential to assessing its effectiveness in raising entry barriers to the mafias' "business" of influencing politics.

Our diff-in-diff analysis provides evidence that the enforcement of Law 164/1991 reduces the number of attacks against politicians substantially, with an effect that persists for at least the first two elections after compulsory administration. We validate the exogeneity of the treatment to the outcome by controlling for reverse causality and omitted variable bias.

Having investigated alternative mechanisms, such as increased deployment of law enforcement bodies and the perceived deterrence implicit in the enforcement of Law 164, we found evidence suggesting that the most likely driver of our results is the renewal and improvement of the pool of politicians, together with a change in voters' behaviour resulting in the election better qualified politicians after compulsory administration. To the extent that the cost to a criminal organization of influencing politics increases as it loses control of the electorate and as the quality of officeholders improves (Dal Bó et al., 2006), our evidence indicates that the newly elected local governments represent a target for organised crime with substantially higher negotiation costs, implying lower expected payoffs to corruption, thereby inducing criminal clans to lower the level of violence against politicians.

This paper makes two key contributions to the literature. First, it addresses the possibly ambivalent effect of a shock to the profitability of corruption as in Dal Bó et al. (2006) by showing that the enforcement of Law 164/1991 is effective in lowering mafia organizations' expected payoff from influencing politics, and that this appears to induce criminal clans to reduce violence. Second, it adds to the substantial body of work on the effects of Law 164/1991, with novel empirical evidence that the Law's application diminishes mafia violence against politicians. Our results expand on recent studies documenting the effectiveness of city council dissolution in improving long-run economic performance (Fenizia and Saggio, 2022), female political empowerment (Baraldi and Ronza, 2022), the quality of elected officials (Daniele and Geys, 2015), and the allocation of public resources and tax collection (Di Cataldo and Mastrorocco, 2022). Finally, given that various studies have shown that repressive measures tend to provoke violent reprisals by criminal organizations (e.g. Calderón et al., 2015; Castillo and Kronick, 2020), our analysis contributes to the empirical analysis of the efficacy of non-repressive government measures in fighting organised criminal violence (Daniele and Dipoppa, 2022).

From the normative perspective, while city council dismissal is meant to be an *ad hoc* measure responding to specific circumstances within the local government, the persistence of the damping effect on violence against local politicians up to at least the second electoral round after compulsory administration constitutes powerful evidence of the medium-run efficacy of Law 164/1991 in restoring the autonomy of the local government and public safety.

The evidence presented here is in line with Daniele and Dipoppa (2017) and Alesina et al. (2019). The sine curve of the post-treatment coefficients between the first two elections after compulsory administration is consistent with the thesis that the electoral pressure exerted by criminal clans is a consequence of violent intimidation against politicians as a mechanism of reinforcement of corruption. Our findings document the efficacy of the city council dissolution in deterring violence by organised crime precisely when it would be of the greatest strategic value in wielding political influence. This helps clarify the way in which criminal organizations redirect public resources to their own advantage.

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A *Tables and Conceptual framework*

Conceptual framework In this paragraph we derive the empirical hypothesis to be tested, summarizing the relevant aspects of the model of Dal Bó et al. (2006). In this framework, politicians have discretionary power over public resources that can be re-directed to the pressure group as a lump-sum transfer (π). To acquire these resources, pressure groups decide whether or not to influence politicians at a cost, through bribery (b) and credible threats of punishment (p).

In the absence of pressure groups, politicians' income is equal to their salary w, but where pressure groups are active and the politician accepts bribery, this will be supplemented by bribes (b) and reduced by the costs of corruption c (moral costs, say, or the risk of detection). If instead the politician refutes the bribe offer, their salary will be reduced by the cost of punishment (p). Thus, the politician will accept the bribe offer if $w + b - c \geq w - p$. Accordingly, active pressure groups will set the optimal bribe offer equal to the difference between the cost of being corrupted for the politician and the cost of punishment ($b^* = c - p^*$).

To choose the optimal levels of bribes and threats of violent punishment, pressure groups maximize the following payoff function: $Max_{b,p}\,\Pi(b,p) = \gamma[\pi - \beta\Phi(b)] - (1-\gamma)\rho\Psi(p)$, subject to the constraint $b^* = c - p^*$, where γ and $(1-\gamma)$ are respectively the probability of the politician's accepting and rejecting the bribe; π is the fraction of public resources that politicians can redirect to the pressure group; $\beta\Phi(b)$ and $\rho\Psi(p)$ respectively are the costs of delivering a bribe offer and carrying out a punishment[36] The parameters β and ρ capture institutional features (i.e. law enforcement) that affect the costs of bribery and punishment respectively. The implementation of non-repressive measures that reduce the economic sources of organised crime are an instance of a change in the parameters β and π (i.e. the amount of public resources that complicit politicians can redirect to the pressure group). The expansion of police forces, instead, represents a change in the parameter ρ.

When the politician accepts the bribe, the pressure group obtains $\pi - \beta\Phi(b)$, the fraction of public resources managed by the politician net of the cost of the bribe. Otherwise, the pressure group bears the cost $\rho\Psi(p)$ of punishing the politician who rejects the offer. Whenever $\Pi(b,p) \geq 0$, the pressure group will be active; otherwise it remains inactive and makes no profit. Hence, setting $\Pi(b,p) = 0$ allows calculation of the threshold amount of public resources to be redirected to the pressure group ($\bar{\pi}$) below which the business of influencing politics is no longer profitable.

On this account, if the amount of public resources that can be redirected (π) is lower than $\bar{\pi}$, the pressure group's expected payoff would be negative. Hence, $\bar{\pi}$ can be interpreted as an inverse measure of "state capture", i.e. the degree of the pressure group's influence on politics: the greater $\bar{\pi}$, the stiffer the entry barriers to the business of influencing politics and the lower the degree of "state capture". Any change in law enforcement that affects the

[36] $\Phi(.)$ and $\Psi(.)$ are the cost functions respectively for delivering a bribe and carrying out a punishment. They are assumed to be twice continuously differentiable; also, $\Phi(0) = \Psi(0) = 0$, $\Phi'(0) = \Psi'(0) = 0$, $\Phi' > 0$, $\Phi'' > 0$ $\Psi' > 0$ and $\Psi'' > 0$.

costs of "bribery and threats of punishment" (i.e., β and ρ) will alter the entry barriers and induce an active pressure group to modify its optimal mix of bribes and threats.

Intriguingly, for this study an increase in the cost of delivering a bribe — i.e, an increase in the β parameter — has a theoretically ambivalent effect on the level of criminal violence. On the one hand, if a pressure group is active both before and after the increase in β, it will substitute punishments for bribes, since the relative cost of the former diminishes: that is, the active mafia-style organization will step up its violent intimidation as a form of retaliation for the higher costs of bribery. On the other hand, an increase in the cost of bribes stiffens the barriers to entry into the business of influencing politics as such, as measured by the increase in $\bar{\pi}$. Some pressure groups within the range of variation of $\bar{\pi}$ would earn negative profits and will accordingly refrain from seeking influence either through bribery or through threats. If enough groups lie within this range, overall the rise in β will decrease the resort to threats of violent punishment. This is implied by Proposition 6 in Dal Bó et al. (2006). However, the model does not allow any straightforward prediction of what happens when the costs of bribery increase. Thus, which of the foregoing effects prevails is ultimately an empirical question; and this is what our analysis investigates.

City council dissolution by enforcement of Law 164/1991 imparts an exogenous shock to the pressure group's cost of making a bribe (i.e. an exogenous shock to the β parameter) and to the amount of public resources that politicians can redirect to organised crime (i.e. to the π parameter). Compulsory administration by external commissioners will presumably bring a sudden cut in funding for public projects, especially in the sectors targeted by organised crime such as manufacturing, waste management and construction (Acconcia et al., 2014). The Law, that is, is intended to lower the level of corruption by imposing an economic cost on organised crime's exercise of political influence, while it does not entail any stiffening of formal deterrence by such measures as expansion of police forces or increases in funds allocated to public safety (that is, it does not entail any change in the ρ parameter).

In the logic of Dal Bó et al. (2006), to the extent that city council dissolution increases the cost of corruption, it can curb overall violent intimidation only if it substantially cuts the amount of public resources to be redirected (π), thereby reducing the expected payoffs from influencing politics and inducing some criminal groups to go inactive. So if we are to assess the efficacy of Law 164/1991 in strengthening the barriers to influencing politics, empirical analysis of the effect on violent intimidation by organised crime is essential.

Table A.1: t-test

Group	Attacks to all politicians/Pop	Attacks to city council politicians/Pop	Attacks to city council politicians/Local politicians
1	0.0053	0.0038	0.0989
2	0.0033	0.0025	0.0858
Difference (p-value)	0.0019 (0.61)	0.0012 (0.52)	0.0130 (0.36)

Note. The table displays the mean difference test (t-test) between regions in group 1 and 2 of the mean of per capita attacks on politicians. Group 1 comprises Calabria, Campania, Apulia and Sicily, group 2 the rest of the Italian regions. P-value is in brackets. The mean is calculated over regions and time (2010-2019) within each group.

Table A.2: Distribution of attacks

No. Attacks	Frequency	Percentage	Cumulative
0	10,363	94.64	94.64
1	243	2.22	96.86
2	178	1.63	98.48
3	76	0.69	99.18
4	27	0.25	99.42
5	26	0.24	99.66
6	10	0.09	99.75
7	7	0.06	99.82
8	8	0.07	99.89
9	5	0.05	99.94
10	2	0.02	99.95
11	1	0.01	99.96
14	2	0.02	99.98
15	1	0.01	99.99
17	1	0.01	100
Total	10,950	100	

Notes. Distribution of number of attacks against politicians in each municipality. Period: 2010-2019.

Table A.3: Descriptive statistics

	Obs	Mean	Std.Dev.	Min	Max
Attacks	10,950	0.125	0.702	0	17
Pop	10,950	6.894	15.61	0.158	243.97
Mayor degree	10,950	0.576	0.494	0	1
Councilors degree	10,950	0.004	0.065	0	1
Aldermen degree	10,950	0.084	0.277	0	1

Notes. Descriptive statistics of variables. Population in thousands/1000. Period: 2010-2019.

Table A.4: Descriptive statistics for treatment and control group - Estimation sample

	Treatment	Control	Diff
Pop	22.29	12.83	0.46***
Mayor degree	0.456	0.599	-0.143***
Councilors degree	0.000	0.005	-0.005
Aldermen degree	0.112	0.091	0.021

Notes. Descriptive statistics of variables for municipalities in the treatment and control group on the sample of Poisson estimates. Population in thousands/1000. Period: 2010-2019.

Table A.5: Types of attacks

	(1)	(2)
	Threats	Violence
Policy	-0.734**	-0.844***
	(0.363)	(0.303)
Observations	2,044	2,397
No. Municipalities	206	241
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to eq. 2 by Poisson FE model. *Violence* comprises set the car on fire, set City Hall on fire, set the house on fire, physical assault, homicide and physical assault in public places; *Threats* comprises all the other attacks. *Policy* is a dummy taking the value of 1 for all the years from the first after compulsory administration to the end of the period and 0 for previous years. We control for the log of resident population, *Mayor degree*, *Councilors degree* and *Aldermen degree*. The coefficients of municipality FE and year FE are not reported. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.6: Granger causality

	(1)	(2)	(3)	(4)
Dep. Var.:	Policy	Policy	Policy	Policy
Attacks	-0.00143		0.00243	
	(0.00356)		(0.00305)	
$Attacks_{-1}$	-0.00213	-0.00202	-0.000781	-0.000984
	(0.00295)	(0.00272)	(0.00222)	(0.00222)
$Attacks_{-2}$	-0.00222	-0.00211	0.00128	0.00109
	(0.00314)	(0.00303)	(0.00326)	(0.00330)
Observations	8,703	8,703	8,377	8,377
R-squared	0.045	0.045	0.027	0.027
No. Municipalities	1,094	1,094	1,088	1,088
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note. The table reports coefficients of panel FE estimations. For estimations in Columns 1 and 2 the dependent variable, *Policy*, is a dummy taking the value of 1 for all the years from the first year after compulsory administration to the end of the period and 0 for previous years. In Columns 3 and 4 *Policy* is a dummy taking the value of 1 in treated municipalities for the years of dissolution only and 0 previously, and 0 for untreated municipalities. *Attacks* is the total number attacks in municipality i. All regressions include municipality FE, year FE, population, *Mayor degree*, *Councilors degree* and *Aldermen degree* whose coefficients are not reported. Robust standard errors are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.7: Propensity score matching

	(1)	(2)
Dep. Var.:	No. attacks	No. attacks
$t_0 + 1$	-1.440**	
	(0.564)	
$t_0 + 2$	-1.271***	
	(0.473)	
$t_0 + 3$	-0.914*	
	(0.505)	
$t_0 + 5$	-1.113***	
	(0.372)	
$t_0 + 6$	-1.184***	
	(0.419)	
$t_0 + 7$	-1.154**	
	(0.562)	
Policy		-0.639**
		(0.322)
Ln(pop)	0.285	0.317
	(3.119)	(3.120)
Observations	1,534	1,534
No. Municipalities	154	154
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to Poisson FE model in eq. 1 (in Column 1) and in eq. 2 (in Column 2). The dependent variable is total number of attacks against politicians. In estimating eq. 1 in Column 1 we include event-time dummy variables for 6 years before and 7 years after the dissolution; the omitted category is the year before the dissolution ($t_0 - 1$). We report only the event study dummies that are significantly different from 0. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 for previous years. The coefficients of municipality FE and year FE are not reported. We control for *Mayor degree*, *Councilors degree* and *Aldermen degree*. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.8: Estimations of anti-mafia measure on crimes - 1

Dep. Var.:	C1	C2	C3	C4	C5	C6	C7	C8
Policy	-0.00320	-2.357***	-0.0987	-0.507	0	-2.529**	0.0195	-0.0505
	(0.0727)	(0.721)	(0.0861)	(0.407)	(0)	(1.022)	(0.0283)	(0.102)
Observations	1,160	1,160	1,160	1,160	1,160	1,160	1,160	1,160
R-squared	0.007	0.121	0.044	0.028		0.114	0.005	0.015
No. provinces	106	106	106	106	106	106	106	106
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Panel FE estimations. *Policy* takes the value of 1 if at least a municipality has been dissolved for mafia infiltration, from the year of dissolution onward, and 0 for all the other Italian provinces. *C1* is mass murderers; *C2* is homicides; *C3* is homicides, with intent of theft, robbery; *C4* homicides, mafia type; *C5* is homicides, terrorist; *C6* is attempted homicides; *C7* is infanticides; *C8* is unintentional homicides. Crimes are at province level in 2010-2016. The coefficients of province FE, year FE and the province population are not reported. Standard errors adjusted for clustering at the province level are in brackets. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.9: Estimations of anti-mafia measure on crimes - 2

Dep. Var.:	C9	C10	C11	C12	C13	C14	C15	C16
Policy	1.218	-1.302**	2.652	-55.47	-33.82	-3.462**	-114.7	-3.450
	(1.060)	(0.641)	(5.781)	(36.92)	(40.95)	(1.346)	(85.19)	(2.819)
Observations	1,160	1,160	1,160	1,160	1,160	1,160	948	1,160
R-squared	0.017	0.077	0.083	0.085	0.175	0.299	0.615	0.109
No. province	106	106	106	106	106	106	106	106
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Panel FE estimations. *Policy* takes the value of 1 if at least a municipality has been dissolved for mafia infiltration, from the year of dissolution onward, and 0 for all the other Italian provinces. *C9* is culpable homicides; *C10* is culpable homicides, traffic; *C11* is assault and battery; *C12* is malicious injuries; *C13* is threats; *C14* is kidnapping; *C15* is insults; *C16* is sexual assaults. Crimes are at province level in 2010-2016. The coefficients of province FE, year FE and the province population are not reported. Standard errors adjusted for clustering at the province level are in brackets. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.10: Estimations of anti-mafia measure on crimes - 3

Dep. Var.:	C17	C18	C19	C20	C21	C22	C23	C24
Policy	-0.223	0.512	-2.858*	1.389	-2,179**	-19.50	47.14	-143.5
	(0.631)	(0.339)	(1.681)	(1.472)	(945.0)	(33.62)	(162.8)	(123.2)
Observations	1,160	1,160	1,160	1,160	1,160	1,160	1,160	1,160
R-squared	0.023	0.035	0.351	0.097	0.291	0.189	0.345	0.305
No. provinces	106	106	106	106	106	106	106	106
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Panel FE estimations. *Policy* takes the value of 1 if at least a municipality has been dissolved for mafia infiltration, from the year of dissolution onward, and 0 for all the other Italian provinces. *C17* is sexual abuse of minors; *C18* is corruption of minor; *C19* is exploitation and abetting of prostitution; *C20* is prostitution of minors, possession of child pornography materials; *C21* is theft; *C22* is snatch thefts; *C23* is pickpocketing; *C24* is thefts in dwelling. Crimes are at province level in 2010-2016. The coefficients of province FE, year FE and the province population are not reported. Standard errors adjusted for clustering at the province level are in brackets. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.11: Estimations of anti-mafia measure on crimes - 4

Dep. Var.:	C25	C26	C27	C28	C29	C30	C31	C32
Policy	-18.89	-569.9	-1.345*	-9.951**	-123.2***	-178.3*	-463.2**	-97.71*
	(34.16)	(350.0)	(0.687)	(4.347)	(34.85)	(91.45)	(194.4)	(49.48)
Observations	1,160	1,160	1,160	1,160	1,160	1,160	1,160	1,160
R-squared	0.213	0.230	0.235	0.395	0.684	0.566	0.525	0.112
No. provinces	106	106	106	106	106	106	106	106
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Panel FE estimations. *Policy* takes the value of 1 if at least a municipality has been dissolved for mafia infiltration, from the year of dissolution onward, and 0 for all the other Italian provinces. *C25* is shoplifting; *C26* is thefts in parked car; *C27* is thefts of artworks, archaeological material; *C28* is thefts of goods transport truck; *C29* is scooter thefts; *C30* is motorcycle thefts; *C31* is car thefts; *C32* is robberies. Crimes are at province level in 2010-2016. The coefficients of province FE, year FE and the province population are not reported. Standard errors adjusted for clustering at the province level are in brackets. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.12: Estimations of anti-mafia measure on crimes - 5

Dep. Var.:	C33	C34	C35	C36	C37	C38	C39	C40
Policy	-3.756	-8.129**	-0.380	-34.98**	-18.28	15.90**	488.2**	15.42
	(3.846)	(3.426)	(0.937)	(14.01)	(22.23)	(7.661)	(208.9)	(15.30)
Observations	1,160	1,160	1,160	1,160	1,160	1,160	1,160	1,160
R-squared	0.214	0.603	0.134	0.213	0.054	0.540	0.617	0.304
No. provinces	106	106	106	106	106	106	106	106
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Panel FE estimations. *Policy* takes the value of 1 if at least a municipality has been dissolved for mafia infiltration, from the year of dissolution onward, and 0 for all the other Italian provinces. *C33* is robberies in dwelling; *C34* is bank robberies; *C35* is robberies in P.O.; *C36* is robberies in shops; *C37* is street robberies; *C38* is extortion; *C39* is computer frauds; *C40* is IT crimes. Crimes are at province level in 2010-2016. The coefficients of province FE, year FE and the province population are not reported. Standard errors adjusted for clustering at the province level are in brackets. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.13: Estimations of anti-mafia measure on crimes - 6

Dep. Var.:	C41	C42	C43	C44	C45	C46	C47	C48
Policy	-5.370	-11.63	-23.70	-4.126	-1.587**	-1,475**	-44.81***	-5.447
	(13.50)	(8.993)	(21.89)	(4.238)	(0.620)	(712.9)	(13.78)	(8.472)
Observations	1,160	1,160	1,160	1,160	1,160	1,160	1,160	1,160
R-squared	0.158	0.237	0.184	0.052	0.110	0.584	0.291	0.180
No. provinces	106	106	106	106	106	106	106	106
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Panel FE estimations. *Policy* takes the value of 1 if at least a municipality has been dissolved for mafia infiltration, from the year of dissolution onward, and 0 for all the other Italian provinces. *C41* is falsification of brands or products; *C42* is violation intellectual property rights; *C43* is receipt of stolen property; *C44* laundering of illicit money, goods or valuables; *C45* is usury; *C46* is property damage; *C47* is arson; *C48* is arson, forest. Crimes are at province level in 2010-2016. The coefficients of province FE, year FE and the province population are not reported. Standard errors adjusted for clustering at the province level are in brackets. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.14: Estimations of anti-mafia measure on crimes - 7

Dep. Var.:	C49	C50	C51	C52	C53	C54	C55
Policy	-21.25**	31.66	-2.491	-3.089	0.782***	-2.377	45.08
	(9.164)	(33.84)	(1.544)	(2.091)	(0.298)	(3.994)	(181.4)
Observations	1,160	1,160	1,160	1,160	1,160	1,160	1,160
R-squared	0.219	0.336	0.111	0.070	0.028	0.044	0.150
No. provinces	106	106	106	106	106	106	106
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Panel FE estimations. *Policy* takes the value of 1 if at least a municipality has been dissolved for mafia infiltration, from the year of dissolution onward, and 0 for all the other Italian provinces. *C49* is property damage and arson; *C50* is violations of drug law; *C51* is bombings, personal attacks; *C52* is criminal conspiracy, organization; *C53* is mafia-type criminal organization; *C54* is smuggling; *C55* is other crimes. Crimes are at province level in 2010-2016. The coefficients of province FE, year FE and the province population are not reported. Standard errors adjusted for clustering at the province level are in brackets. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.15: Controlling for crimes - 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dep. Var.:	Attacks	Attacks	Attacks	Attacks	Attacks	Attacks	Attacks	Attacks	Attacks	Attacks	Attacks
Policy	-0.607**	-0.817***	-0.758***	-0.800***	-0.820***	-0.647**	-0.735**	-0.714**	-0.711**	-0.690**	-0.711**
	(0.291)	(0.303)	(0.287)	(0.307)	(0.315)	(0.286)	(0.286)	(0.284)	(0.286)	(0.282)	(0.283)
C4	0.0849***										
	(0.0222)										
C11		0.00660***									
		(0.00181)									
C12			0.00202***								
			(0.000683)								
C13				0.00115**							
				(0.000478)							
C15					0.000516**						
					(0.000251)						
C18						0.0844**					
						(0.0390)					
C24							0.000635**				
							(0.000279)				
C25								0.00152***			
								(0.000555)			
C26									0.000362*		
									(0.000205)		
C33										0.00805*	
										(0.00429)	
C44											0.0146**
											(0.00654)
Observations	3,157	3,157	3,157	3,157	2,008	3,157	3,157	3,157	3,157	3,157	3,157
No. Municipalities	319	319	319	319	253	319	319	319	319	319	319
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table reports coefficients estimated according to Poisson FE model in eq. 2. The dependent variable is the total number of attacks against politicians. In each equation we control, one-by-one for the specified crime. *C4* is homicides, mafia type; *C7* is infanticides; *C11* is assault and battery; *C12* is malicious injuries; *C13* is threats; *C15* is insults; *C18* is corruption of minors; *C24* is thefts in dwelling; *C25* is shoplifting; *C26* is thefts in parked car; *C33* is robberies in dwelling; *C44* is laundering of illicit money, goods or valuables. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 for previous years. We control for municipality FE, year FE, the log of resident municipal population, *Mayor degree*, *Councilors degree* and *Aldermen degree* whose coefficients are not reported. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.16: Controlling for crimes - 2

	(1)	(2)
Dep. Var.:	No. attacks	No. attacks
Policy	-0.813***	-0.896***
	(0.315)	(0.294)
C4	0.117***	
	(0.0336)	
C11	0.00602**	
	(0.00303)	
C12	0.00177	
	(0.00122)	
C13	-0.00210*	
	(0.00111)	
C15	0.000730**	
	(0.000298)	
C18	0.0869*	
	(0.0488)	
C24	0.000331	
	(0.000372)	
C25	0.000668	
	(0.000848)	
C26	0.000766**	
	(0.000330)	
C33	-8.43e-05	
	(0.00614)	
C44	0.00237	
	(0.0100)	
Sum crimes		0.000120
		(0.000101)
Observations	2,008	3,174
No. Municipalities	253	319
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to Poisson FE model in eq. 2. The dependent variable is the total number of attacks against politicians. In Column 1 all those crimes are together; in Column 2 we estimate the coefficient of their sum. Crimes are at province level in 2010-2016. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 for previous years. We control for municipality FE, year FE, the log of resident municipal population, *Mayor degree*, *Councilors degree* and *Aldermen degree* whose coefficients are not reported. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.17: Poisson RE

	(1)	(2)
Dep. Var.:	No. attacks	No. attacks
$t_0 + 1$	-1.257**	
	(0.553)	
$t_0 + 2$	-0.965*	
	(0.506)	
$t_0 + 3$	-0.464	
	(0.532)	
$t_0 + 5$	-0.653	
	(0.401)	
$t_0 + 6$	-0.768*	
	(0.439)	
$t_0 + 7$	-0.929	
	(0.568)	
Policy		-0.571**
		(0.279)
Ln(pop)	0.964***	0.964***
	(0.073)	(0.073)
Observations	10,876	10,876
No. Municipalities	1,091	1,091
Year FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to Poisson FE model in eq. 1 (in Column 1) and in eq. 2 (in Column 2). We drop the year 2012. The dependent variable is total number of attacks against politicians. In estimating eq. 1 in Column 1 we include event-time dummy variables for 6 years before and 7 years after the dissolution; the omitted category is the year before the dissolution ($t_0 - 1$). We report only the event study dummies that are significantly different from 0. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 for previous years. The coefficients of municipality FE and year FE are not reported. We control for *Mayor degree*, *Councilors degree* and *Aldermen degree*. We also control for the level of education and unemployment of the municipalities that proxy for fixed effect given that they are constant over 2010-2019 (census data). Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.18: Excluding 2012

	(1)	(2)
Dep. Var.:	No. attacks	No. attacks
$t_0 + 1$	-1.634***	
	(0.558)	
$t_0 + 2$	-1.388***	
	(0.469)	
$t_0 + 3$	-0.991**	
	(0.495)	
$t_0 + 5$	-1.151***	
	(0.356)	
$t_0 + 6$	-1.265***	
	(0.416)	
$t_0 + 7$	-1.458***	
	(0.551)	
Policy		-0.781***
		(0.277)
Ln(pop)	0.780	0.957
	(2.530)	(2.677)
Observations	2,829	2,829
No. Municipalities	316	316
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to Poisson FE model in eq. 1 (in Column 1) and in eq. 2 (in Column 2). We drop the year 2012. The dependent variable is total number of attacks against politicians. In estimating eq. 1 in Column 1 we include event-time dummy variables for 6 years before and 7 years after the dissolution; the omitted category is the year before the dissolution ($t_0 - 1$). We report only the event study dummies that are significantly different from 0. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 for previous years. The coefficients of municipality FE and year FE are not reported. We control for *Mayor degree*, *Councilors degree* and *Aldermen degree*. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

Table A.19: Multiple dissolutions

	(1)	(2)
Dep. Var.:	No. attacks	No. attacks
$t_0 + 1$	-1.591***	
	(0.546)	
$t_0 + 2$	-1.402***	
	(0.499)	
$t_0 + 3$	-0.921*	
	(0.497)	
$t_0 + 5$	-1.064***	
	(0.358)	
$t_0 + 6$	-1.264***	
	(0.402)	
$t_0 + 7$	-1.362**	
	(0.557)	
Policy		-0.825***
		(0.286)
Ln(pop)	0.844	1.119
	(2.555)	(2.716)
Observations	3,134	3,134
No. Municipalities	315	315
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to Poisson FE model in eq. 1 (in Column 1) and in eq. 2 (in Column 2). We drop municipalities dissolved for mafia infiltration more than once. The dependent variable is total number of attacks against politicians. In estimating eq. 1 in Column 1 we include event-time dummy variables for 6 years before and 7 years after the dissolution; the omitted category is the year before the dissolution ($t_0 - 1$). We report only the event study dummies that are significantly different from 0. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 for previous years. The coefficients of municipality FE and year FE are not reported. We control for *Mayor degree*, *Councilors degree* and *Aldermen degree*. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

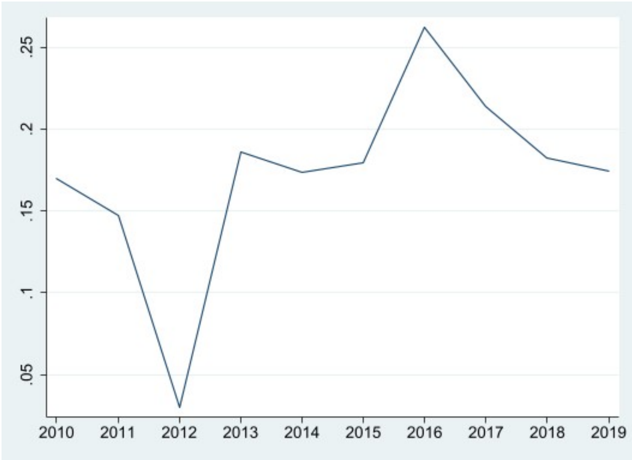
Table A.20: Political party of administration

	(1)	(2)
Dep. Var.:	No. attacks	No. attacks
$t_0 + 1$	-1.633***	
	(0.552)	
$t_0 + 2$	-1.401***	
	(0.473)	
$t_0 + 3$	-1.006**	
	(0.489)	
$t_0 + 5$	-1.163***	
	(0.349)	
$t_0 + 6$	-1.258***	
	(0.397)	
$t_0 + 7$	-1.440***	
	(0.547)	
Policy		-0.858***
		(0.301)
Ln(pop)	0.915	1.190
	(2.555)	(2.689)
Centre-right	-0.130	-0.159
	(0.216)	(0.222)
Centre-left	0.0635	0.0376
	(0.271)	(0.278)
Civic lists	-0.0631	-0.0957
	(0.179)	(0.185)
Observations	3,174	3,174
No. Municipalities	319	319
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Note. The table reports coefficients estimated according to Poisson FE model in eq. 1 (in Column 1) and in eq. 2 (in Column 2). The dependent variable is the total number of attacks against politicians. We control for dummies for mayor's party affiliation. In estimating eq. 1 in Column 1 we include event-time dummy variables for 6 years before and 7 years after the dissolution; the omitted category is the year before the dissolution ($t_0 - 1$). We report only the event study dummies that are significantly different from 0. *Policy* is a dummy taking the value of 1 for all the years from the dissolution onward and 0 for previous years. The coefficients of municipality FE and year FE are not reported. We control for *Mayor degree*, *Councilors degree* and *Aldermen degree*. Standard errors adjusted for clustering at the municipal level are in brackets. Period: 2010-2019. Significant coefficients are indicated by * (10% level), ** (5% level) and *** (1% level).

B *Figures*

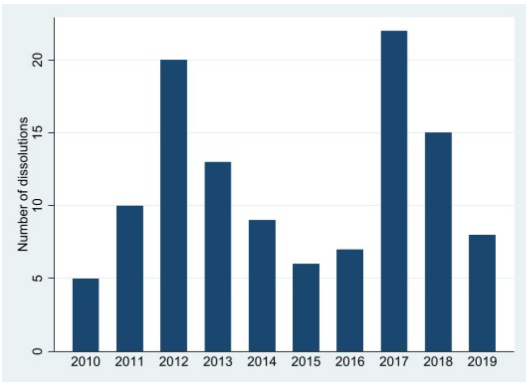
Figure B.1: Yearly distribution of attacks



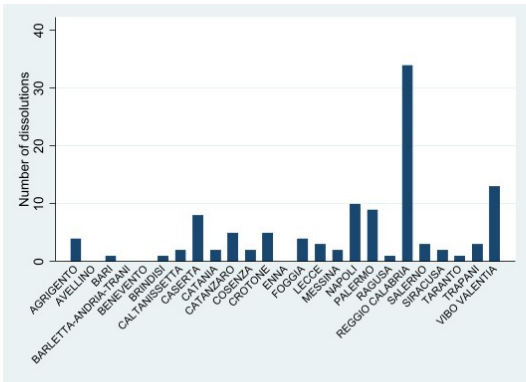
Notes. The Figure shows the trend in the mean, over municipalities, of attacks against politicians. 2010-2019.

Figure B.2: Dissolutions by year and province

(a) By year

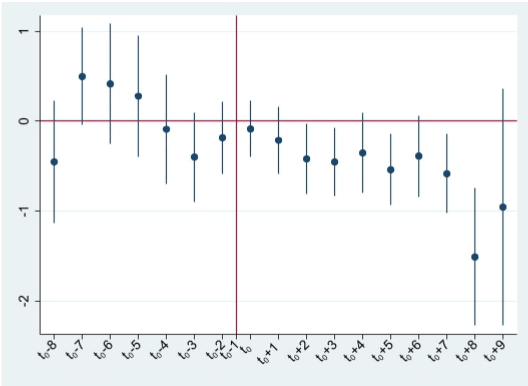


(b) By province



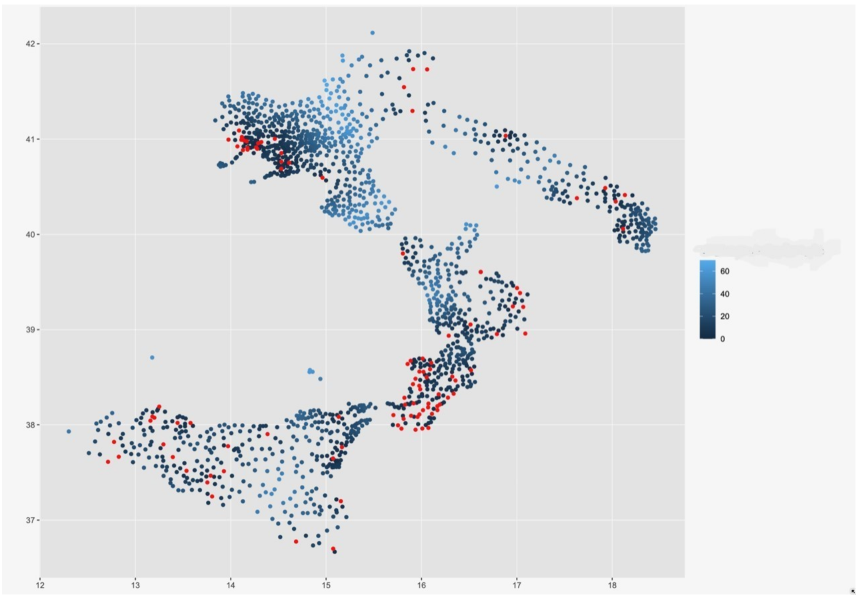
Note. Graphs B.2a and B.2b show the distribution of city council dissolutions for mafia infiltration, by year and by province, respectively, in Calabria, Campania, Apulia and Sicily.

Figure B.3: Spillovers - Event study



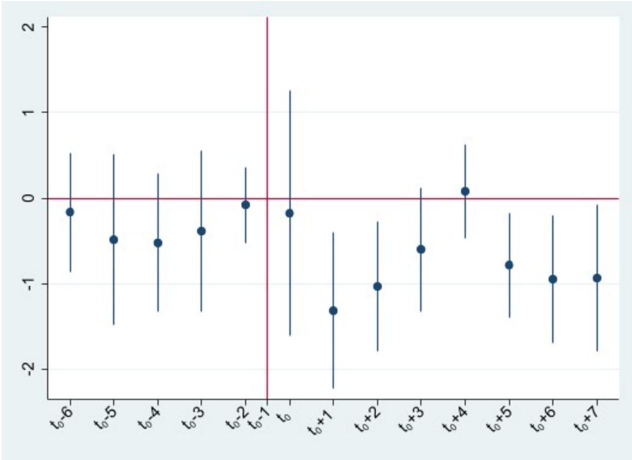
*Notes.*The graph reports coefficients and confidence intervals estimated according to eq. 1. Graphs show the Poisson FE model estimates where the dependent variable is the total number attacks in neighboring municipalities. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). We include event-time dummy variables for 8 years before and 9 years after the dissolution. All regressions include municipality FE, year FE, and the log of resident population. Period: 2010-2019.

Figure B.4: Distance to the dissolved municipalities



Notes. The figure shows the distance of the never dissolved municipalities in the control group from the dissolved municipalities (the red points) according to the distance expressed in scale of blue. The picture refers to year 2019.

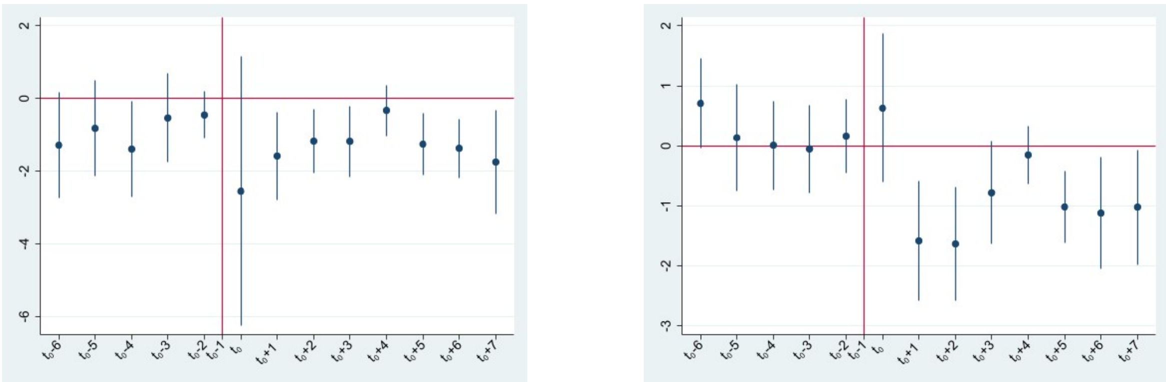
Figure B.5: Event study - Region x year FE



Notes. The graphs report coefficients and confidence intervals estimated according the Poisson model of eq. 1. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. The regression include municipality FE, year FE, Region x year FE, the log of resident population, *Mayor degree*, *Councilors degree* and *Aldermen degree*. Period: 2010-2019.

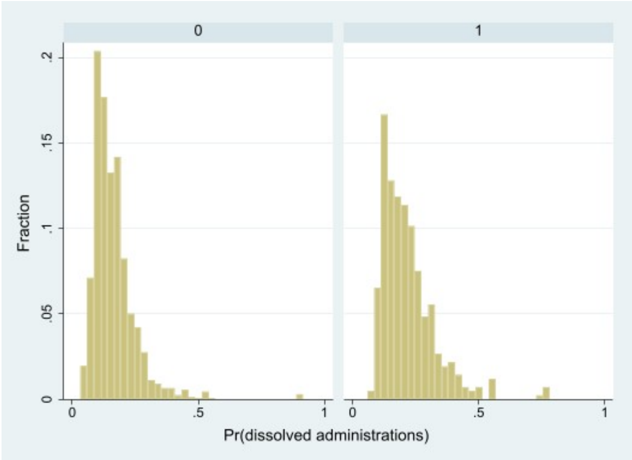
Figure B.6: Types of attacks

(a) Threats (b) Violence



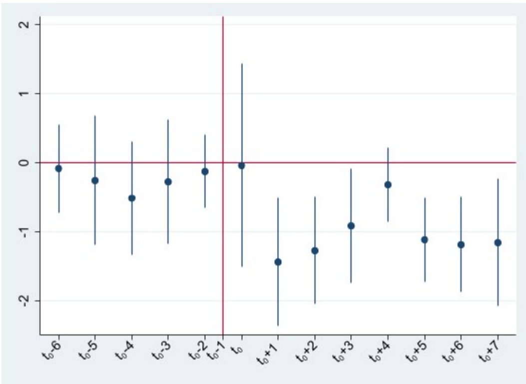
Note. The graphs report coefficients and confidence intervals estimated according to eq. 1. Graph B.6a shows the Poisson FE model estimates where the dependent variable is the total number of *Threats* against local politicians; Graph B.6b shows the Poisson FE model estimates where the dependent variable is the total number of *Violence* against local politicians. Standard errors are clustered at municipal level. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. All regressions include municipality FE, year FE, the log of resident population, *Mayor degree*, *Councilors degree* and *Aldermen degree*. Period: 2010-2019.

Figure B.7: Overlap in propensity scores in treated and matched samples



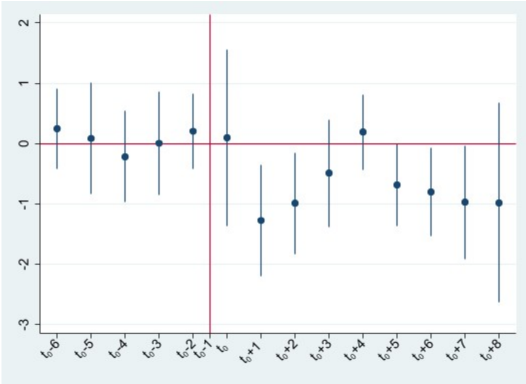
Notes. Distributions of the estimated propensity scores of dissolved municipalities for the treatment group (i.e. all municipalities put under compulsory administration; right-hand side) and the control group (i.e. the "nearest neighbor" of treated municipalities as derived from the matching procedure; left-hand side). 2010-2019.

Figure B.8: Propensity score matching - Event study



Notes. The graph reports coefficients and confidence intervals estimated according to eq. 1 by Poisson FE model. The dependent variable is the total number of attacks against politicians. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. We include event-time dummy variables for 6 years before and 7 years after the dissolution. We control for municipality FE, year FE, the log of resident population, *Mayor degree*, *Councilors degree* and *Aldermen degree*. Period: 2010-2019.

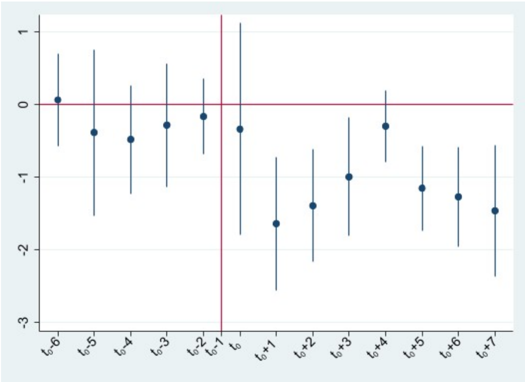
Figure B.9: Poisson RE - Event study



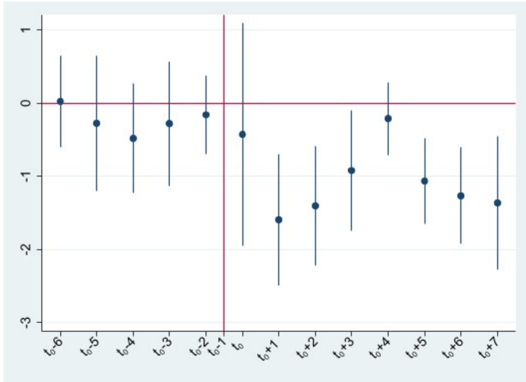
Notes. The graph reports coefficients and confidence intervals estimated according to eq. 1 by Poisson FE model. The dependent variable is the total number of attacks against politicians. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. We include event-time dummy variables for 6 years before and 7 years after the dissolution. We control for municipality FE, year FE, the log of resident population, *Mayor degree*, *Councilors degree* and *Aldermen degree*. Period: 2010-2019.

Figure B.10: Robustness - Event study

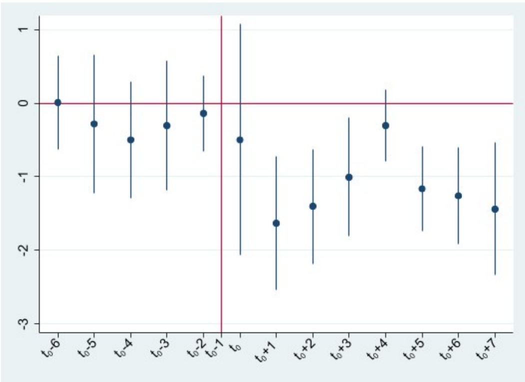
(a) *Excluding 2012*



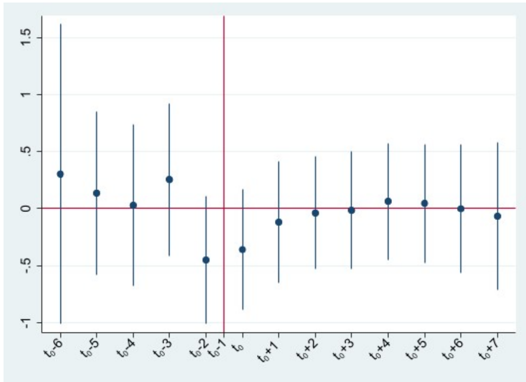
(b) *Multiple dissolution*



(c) *Political parties in power*



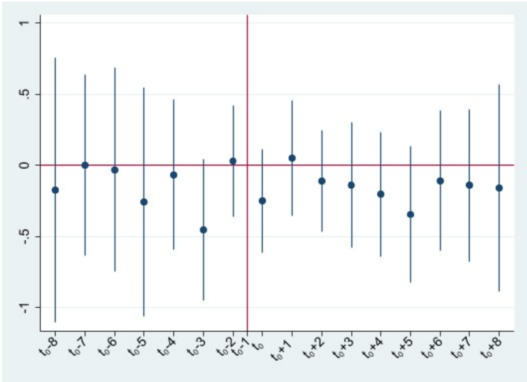
(d) *Placebo test*



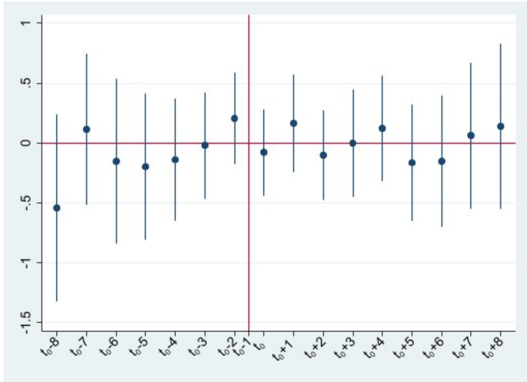
Note. The graphs report coefficients and confidence intervals estimated according to eq. 1. Poisson FE model estimates, dependent variable is total number attacks against local politicians. Dots refer to point estimates, spikes to 90% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). The event dummy t_0 is the fraction of the year that is treated. We include event-time dummy variables for 6 years before and 7 years after the dissolution. We control for municipality FE, year FE, the log of resident population, *Mayor degree*, *Councilors degree* and *Aldermen degree*. Standard errors are clustered at municipal level. Period: 2010-2019. In Graph B.10a we exclude 2012. In Graph A.19 we drop municipalities dissolved for mafia infiltration more than once. In Graph **??** we drop municipalities already dissolved for mafia infiltration before 2010. In Graph B.10c we control for dummies for mayor's party affiliation. In Graph B.10d we drop all the municipalities dissolved because of mafia infiltration.

Figure B.11: Spillovers - 20/30/40 km radius

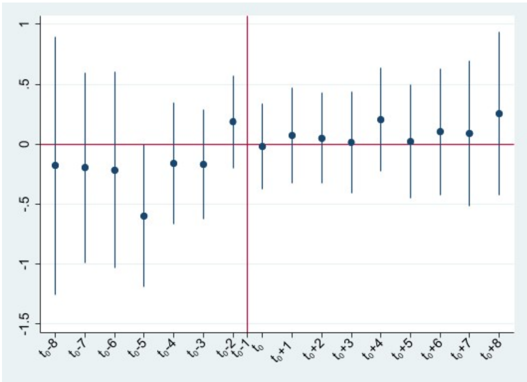
(a) *20 km - municipality cluster*



(b) *30 km - municipality cluster*



(c) *40 km - municipality cluster*



Note. The graphs report coefficients and confidence intervals estimated according to eq. 1. Poisson FE model estimates, dependent variable is total number attacks against local politicians. Dots refer to point estimates, spikes to 95% confidence intervals. The omitted category is the year before the dissolution ($t_0 - 1$). Standard errors are clustered at municipal level. We include event-time dummy variables for 8 years before and 8 years after the dissolution (the ninth year dummy is dropped because of collinearity). We control for municipality FE, year FE, the log of resident population. Standard errors are clustered at municipal level. Period: 2010-2019.

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