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Attacking Women or their Policies? Understanding Violence against Women in Politics

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Abstract

Surveys across countries indicate that female politicians are more often targets of violence compared to males. Why are women attacked more? Is this due to their gender, or to correlated factors? We provide the first causal evidence that violence is driven by gender: leveraging 12 years of data on attacks against Italian politicians, we show that marginally elected female mayors, similar in all respects to their male colleagues, are attacked three times more. We argue that violence can stem from two distinct sources: identity-based motives and divergent policymaking. Attacks concentrate where female empowerment in politics is highest, consistent with a misogynistic backlash hypothesis. Instead, there are no gender differences in expenditures and corruption, indicating that women's policies do not motivate

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attacks. Violence can have pernicious consequences: female mayors are less likely to rerun for office after an attack, underscoring how violence may foster the persistence of the political gender gap.

1 Introduction

Across countries, women continue being underrepresented in political office. As of 2023, women hold 26% of parliamentary seats worldwide – a slow and uneven increase from 11.3% in 1995 – and 31 executive positions as heads of state or government across 195 countries. The barriers to female access to political office are multifaceted and often intertwined: Studies have shown that gaps in representation are a product of external factors, such as parties' strategies (Lawless and Pearson, 2008; Folke, Rickne et al., 2016; Huidobro and Falcó-Gimeno, 2021), voters' perceptions (Teele, Kalla and Rosenbluth, 2018; Cruz and Tolentino, 2019) and cultural norms (Brulé and Gaikwad, 2021; Robinson and Gottlieb, 2021), medium level factors, such as within-household bargaining and constraints (Iversen and Rosenbluth, 2006; Prillaman, 2023; Bernhard, Shames and Teele, 2021), as well as individual factors, such as resources (Schlozman, Burns and Verba, 1994) and self-perception (Fox and Lawless, 2004).

In this paper, we focus on a major obstacle to women participation into politics: violence against female politicians. This phenomenon is likely to have wide-ranging consequences on female representation: Victims of attacks might withdraw from politics, impoverishing the pool of women with political experience and reducing the number of role models for younger generations. A visible attack can discourage other women considering to run for office, with potentially larger effects for those with children, exasperating extant levels of underrepresentation of women. When interacting with conservative cultural and familial norms, an attack might have broader repercussions on society, by validating the narratives of those suggesting that politics is not an appropriate profession for women.

Despite the potentially serious ramifications of this phenomenon, we still know little about its prevalence and motives. First, while recent studies indicate that political violence targets women more often than men (Håkansson, 2021; Krook, 2020; Bardall, Bjarnegård and Piscopo, 2020), we do not know whether this phenomenon is causal: Women might be attacked more because they are women or due to other factors correlated with being a woman, such as where they are elected or personal traits other than their gender – e.g., age, time in politics, ideology. Second, while seminal research based on interviews and case studies has considered how institutional factors affect violence against women in politics (Sanín, 2022; Collier and Raney, 2018), we lack a comprehensive understanding of the set of reasons leading to higher violence against female politicians, as well as quantitative evidence on the conditions under which the gender gap in political violence emerges. Our study tackles these questions by combining detailed, third-party data on attacks against politicians with information on the victims, their policy choices, and the characteristics of the cities they run.

Our setting is Italy, a country at the bottom of the European distribution of female labor force participation (World Bank Data, 2021) and with high rates of intimate partner violence (UNDOC, 2020). This setting is more representative of the average levels of gender inequality across countries than Northern Europe, on which extant large-sample studies have focused. Italy is also a place where criminal organizations routinely use threats and violence to influence politics (Daniele and Dipoppa, 2017; Alesina, Piccolo and Pinotti, 2019), providing us with the opportunity to consider attacks driven by both independent individuals and organized groups with political objectives.

Data on attacks against local politicians come from the annual reports compiled by the NGO Avviso Pubblico, a reputable source which works in close collaboration with the Italian government. The data comprises both online and offline attacks, including verbal threats and violent attacks on both property and individuals. Unlike all other data on violence against female politicians in previous studies, this information is generally validated by the police and indicates when attacks are self-reported. Also, it spans a longer time period than most extant data sets on this topic.

We start by testing whether female mayors are more likely to be targets of violence than their male colleagues, using a close-election regression discontinuity design (RDD) in mixed-gender local elections. We find that marginally elected women – who are comparable to men along sixteen observable characteristics other than gender – are approximately three times more likely to be the victims of an attack. This differential is not driven by the possibility of unequal reporting of attacks across genders, as the findings are robust to removing all the attacks reported to the police by the victim. The results also hold under alternative bandwidths and polynomial forms, and are validated by placebo tests using irrelevant cutoffs. One might wonder whether competitive elections – the sample considered in RDDs – might be the only settings in which women are attacked more. This is unlikely to be the case: Replicating the analyses using a two-way fixed effects model on the entire sample of elections and controlling for observable characteristics of candidates and locations, we find effects similar in sign and significance.

After demonstrating the existence of a gender gap in violence against Italian mayors, we proceed to systematically unpacking the theoretical reasons behind this gap. Combining insights from previous work, we propose two sets of explanations for why women suffer more attacks. First, women might be targeted for reasons related to structural factors, particularly their gender *identity*: Female politicians may be particularly vulnerable to violence due to their higher visibility and their embodiment of ideas related to female empowerment and independence. If violence is driven by misogyny, places where women are more empowered might be those in which backlash against female politicians take place. Second, women might be targeted for reasons related to their *policymaking*. Previous studies have indicated that women tend to adopt different policies, have different priorities, and different likelihoods of being corrupted than their male colleagues (Gottlieb, Grossman and Robinson, 2018; Brollo and Troiano, 2016). If women diverge from men in their behavior while in power, this might explain why they are attacked at higher rates.

Our evidence overwhelmingly points to the prominence of identity-based explanations for attacks. The gender gap in violence is driven by contexts in which the election of a female mayor coincides with relatively high levels of female representation across political institutions: *(i)* Municipalities with an exogenously high share of female politicians because of gender quotas; *(ii)* Municipalities with a high share of female councillors; *(iii)* Municipalities with a growing share of female politicians over time; and *(iv)* Municipalities within regions governed by a female president.

On the other hand, differences in policymaking are unlikely to explain the gender gap in attacks. Similar to Casarico, Lattanzio and Profeta (2022) and Baltrunaite et al.

(2019), we find no significant differences in spending choices between male and female Italian mayors, including on categories like healthcare, social welfare, and education. Additionally, using both official data on corruption charges and three proxies for transparency in public procurement, we find little evidence that female politicians are less prone to corruption in the context of our study. These results suggest that women are targeted regardless of their policy choices and their propensity to cater to interest groups. Consistent with this, removing from the data all the attacks that Avviso Pubblico explicitly links to policy choices does not change our results. Differences in attacks are also not explained by a higher prevalence of attacks from organized crime, which typically strikes with the aim of influencing the allocation of public resources (Pulejo and Querubín, 2022). Finally, we find that differences in gender norms do not explain the gap in violence, consistent with attacks being driven by individuals' backlash against female politicians rather than a generalized culture of misogyny. Overall, these results indicate that the gender gap in violence can be interpreted as a backlash to high levels of women political empowerment. Indeed, attacks take place where women have a higher say in politics and where their representation has been growing, both over time and across political offices.

Finally, we offer suggestive evidence about the consequences that violence against female mayors may have for their persistence in politics. We find that, in general, female mayors are equally likely to re-run for political office. However, when focusing on the subset of mayors who have been attacked, attacked women are significantly less likely to remain in politics with respect to attacked men. This effect is driven by a lower likelihood of attacked women to rerun for mayor, suggesting that women may withdraw from local politics in fear of retaliation and hostility from members of their own community. This is consistent with attacks being a form of local backlash against female empowerment, aimed at contrasting the growth in female representation by pushing women to select out of politics.

Our study makes three unique contributions. It provides the first causal evidence that women politicians suffer more attacks because of their gender, rather than other factors correlated to it. Unlike previous observational studies (Håkansson, 2021), we compare politicians who marginally win or lose, finding no other individual characteristics that distinguishes male and female candidates aside from their gender. To the best of our knowledge, such a condition had thus far only been obtained in the context of a vignette experiment featuring fictitious public officials (Håkansson, 2023).

Second, this is the first study comprehensively and quantitatively investigating the motives behind the higher levels of violence experienced by female politicians. In doing so, we contribute to the literature studying the logic of attacks against public institutional actors, such as politicians and journalists (Dal Bó, Dal Bó and Di Tella, 2006; Holland and Rios, 2017). Unlike previous studies, our results show that strategic incentives to obtain concessions by organized groups are not the main reason for differentially targeting women. Rather, violence is largely driven by identity motives, and it is increasing in women's power and influence in the political arena. This finding challenges the notion that growing female representation will naturally lead to higher acceptance of women in politics.

Our paper also speaks to the vast literature on the determinants of women's under-representation in politics, presenting a worrying new explanation for the persistence of the gender gap: Female politicians are not only attacked more, but are also less likely to run for office after being attacked. This finding contributes to explaining why generations of women in politics and gender-affirming policies have been insufficient in fully closing the gender gap: The problem is not only filling the gap in who selects into politics (Gulzar, 2021), but also filling the gap in who selects *out* of it. Findings from this paper have direct implications for policy, indicating a necessity to differentially protect disproportionately affected politicians, and have broader implications for the functioning of democratic institutions.

2 Theoretical Framework

2.1 Prevalence of Violence Against Women in Politics

The existing evidence suggests that female politicians are more likely to be targets of attacks than their male colleagues. This evidence is mostly drawn from surveys of incumbents, with varying degrees of representativeness and estimated gender gaps in violence that differ substantively across contexts. For instance, a survey by the International Parliamentary Union (IPU, 2016) found that 82% of 55 female Members of Parliament across 39 countries reported experiencing psychological violence during their parliamentary work. In Mexico, in-depth interviews with 150 female politicians showed that 60% experience gender-based violence regularly (Serrano Oswald, 2023), similarly to a survey of 270 US mayors finding that women are twice more likely to suffer psychological abuse (Herrick et al., 2019). Instead, interviews with 197 politicians in Sri Lanka revealed no difference in the levels of violence experienced by men and women (Bjarnegård, Håkansson and Zetterberg, 2022). The most comprehensive survey, which was conducted in Sweden and included 8,000 female mayors, found that women were only 1% more likely than men to report exposure to violence (Håkansson, 2021). Researchers have also tackled the conceptual and methodological challenges embedded in understanding gendered political violence (Bardall, Bjarnegård and Piscopo, 2020; Krook and Sanín, 2020).

While this evidence has been fundamental to uncover a pattern of systematic attacks against women in politics, it is still insufficient to draw conclusions on its prevalence and on whether attacks are causally linked to gender. Extant studies are based on self-reported measures of violence and, with the exception of Håkansson (2021), they rely on small and unrepresentative samples. Importantly, while women receive more attacks on average, we cannot establish whether this is due to their gender or to other factors correlated to it. For example, places that elect women might differ from those that do not in ways that affect the prevalence of attacks: If women are elected in more liberal areas, we might be systematically underestimating the prevalence of violence in the average location. Similarly, women who run for office might be different from their male counterparts in ways correlated with the probability of being targets of violence. They might be younger, less corrupt, less dependent on interest groups, all factors potentially conducive to becoming targets of political violence. Addressing both data quality and endogeneity issues is essential to establishing whether violence targets certain politicians precisely because they are women.

If women are indeed attacked more because of their gender, the next question is why. We propose that motives for gender-specific attacks can be grouped into two categories, reflecting the distinction between structure and agency. Women might be attacked due to agency – the policies they adopt, their spending behavior, the choice to yield or not to corruption and clientelism – or due to structural factors, such as their gender identity and the political and institutional environment they face. In the context of violence against politicians, the broader categories of agency and structure translate into motivations for attacks related to *policy* and motivations related to *identity*.

2.2 Explaining the Gender Gap in Violence: Policy Motives

Studies of violence against politicians have identified political influence as the main reason why public officials across countries fall victims of attacks. The use of threats and violence as tools of political influence has been theorized by Dal Bó, Dal Bó and Di Tella (2006) and demonstrated empirically in the context of Italy, Mexico, and Brazil. Politicians are victims of strategic attacks aimed at discouraging hard-to-corrupt candidates from running (Alesina, Piccolo and Pinotti, 2019), and punishing politicians who reject bribes (Pulejo and Querubín, 2022). Politicians are strategically attacked more after elections to capture their governments and influence their policymaking (Daniele and Dipoppa, 2017; Trejo and Ley, 2021). Violence is also used strategically against other political actors, including journalists, who are attacked to affect the content of their reporting (Holland and Rios, 2017).

There are reasons to think that strategic motives might explain the increased prevalence of attacks against female politicians. Women are often different policymakers and different institutional actors than men. Female politicians tend to improve institutional quality by reducing corruption (Brollo and Troiano, 2016; Bauhr and Charron, 2021) and increasing government responsiveness (Thomsen and Sanders, 2020). In terms of policies, female legislators invest more in health and sanitation (Chattopadhyay and Duflo, 2004; Pande and Ford, 2009; Baskaran and Hessami, 2019), and favor women welfare by reducing women's victimization (Bochenkova, Buonanno and Galletta, 2023). They are more likely to favor redistribution, social security, and taxation (Iversen and Rosenbluth, 2006), and tend to prefer higher provision of public goods (Alesina and La Ferrara, 2005; Funk and Gathmann, 2015), particularly when they come from disadvantaged socioeconomic backgrounds (Clots-Figueras, 2011; Gottlieb, Grossman and Robinson, 2018).[1] Hence, differences in governing styles and political choices might explain why women are targeted more than men.

2.3 Explaining the Gender Gap in Violence: Identity Motives

Women in all professions and settings are victims of various forms of discrimination (World Bank, 2023) which can translate into verbal (e.g., Weaving et al., 2023) and physical violence, ranging from intimate partner violence (González and Rodríguez-Planas, 2020), to rape (Wood, 2018) and homicides by misogynistic extremist groups (Speckhard et al., 2021). These forms of gendered violence are often perpetrated as anaffirmation of

[1] Although other papers find no effect of electing women on total spending, including in Italy (Baltrunaite et al., 2019; Accettura and Profeta, 2021).

male supremacy through the degradation of women (Heise, 1998).

The increased visibility of female politicians as women's representatives could make them particularly likely targets of such violence. However, the literature offers contrasting predictions on which contexts should be conducive to the manifestation of hostilities. On the one hand, evidence indicates that violence against women is most widespread where gender equality is lowest (González and Rodríguez-Planas, 2020), and more generally in low-income countries (WHO, 2021). Accordingly, one could expect attacks against female politicians to be most prevalent where gender norms are most conservative.

On the other hand, places where gender equality is highest might be those with more attacks, if violence arises as a form of backlash against female empowerment. This alternative hypothesis is supported by psychological theories explaining attacks against other minorities, such as immigrants and minority ethnic groups. Majority groups can backlash against marginalized groups when the demographic, economic, or political importance of the out-group increases, threatening the dominant status of the in-group (Dugan and Chenoweth, 2020; Cikara, Fouka and Tabellini, 2022; Zonszein and Grossman, 2022). In line with these studies, it might be exactly in locations were women have more political influence that violent male perpetrators might feel threatened, and respond with verbal and physical violence against female officials.

An important difference between these two bodies of literature, however, is that gender-norms mechanisms are geared towards explaining structural discrimination against women. On the other hand, backlash theories are meant to rationalize sporadic, violent attacks perpetrated by a few extremists against an out-group. As the action of even one radicalized individual is a sufficient condition for political violence to take place, attacks against women may thus happen even in the absence of widespread, conservative gender norms. After having estimated the gender differential in attacks in our context, we will thus test for the relative role of each of these two factors in explaining the prevalence of violence against women in politics.

3 Background and Data

3.1 Municipal Governments in Italy

Municipal governments in Italy represent the lowest tier of administration. Each of the 7,901 municipalities (as of 2023) is governed by a mayor, an executive committee, and a municipal council. The municipal government has responsibility on a variety of policy areas, from the management of basic services (e.g., waste management, transportation, public facilities) to local policing and social welfare. Municipal institutions are elected every five years: Mayors are directly elected and can be in office for a maximum of two consecutive terms.[2] Municipal councils are also elected, but the majority is tied to the elected mayor through a majority bonus system. The mayor also selects the executive committee, making this institution the most important and most identifiable municipal policymaker.

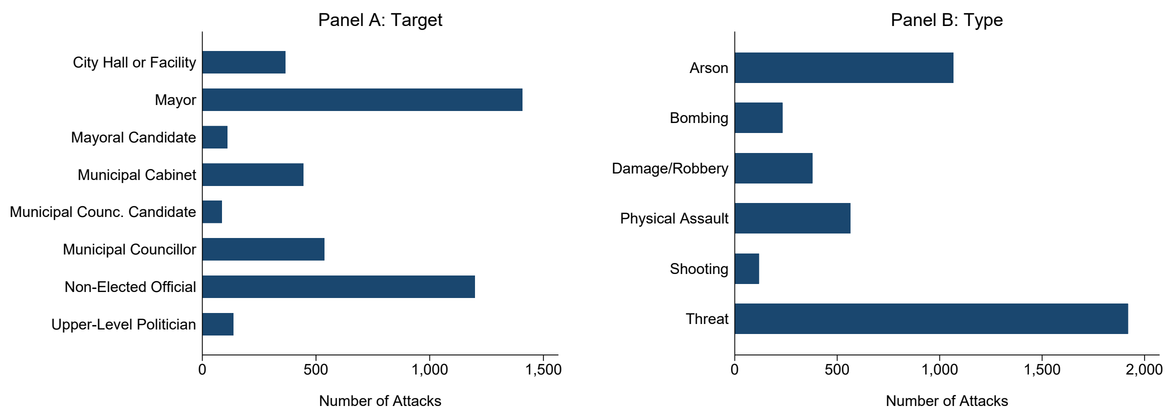
[2]Since 2014, mayors can complete up to three terms in municipalities below 3,000 inhabitants.

3.2 Data on Violence against Politicians

We gather information on attacks and threats against municipal politicians from the yearly reports published by the NGO Avviso Pubblico. *Avviso Pubblico* is an independent organization, aimed at preserving the safety and integrity of Italian public administrators. The association daily tracks online and offline information about attacks against public officials, leveraging both primary and secondary sources. The resulting yearly reports are considered a reliable source of information by institutional actors – they were used as a basis for legislation in Parliament (Avviso Pubblico, 2017) – and by academics: The data have been used in Daniele and Dipoppa (2017) and Pulejo and Querubín (2022).

On top of the exact date and location, they specify the type of attack, as well as the victim(s). For the purposes of this study, we digitize the universe of *Avviso Pubblico*'s reports, covering the period 2010–2021. This provides us with extensive information on 4,285 attacks against Italian politicians and administrators, 2,584 of which have one or more municipal politician(s) as their target, and the remaining targeted to non-elected officials, facilities, or politicians at higher levels of government (Panel A, Figure 1). Among elected municipal officials, mayors constitute the modal victim of attacks (1,407 episodes), followed by municipal councillors (536) and members of the municipal cabinet (443). As shown in Panel B of Figure 1, the episodes are equally distributed between threats (1,920, or 45%) and actual attacks (2,365, 55%) against properties (76%) or individuals (24%).

Figure 1: Number of Attacks, by Target and Type



Notes: In Panel A, *Municipal Cabinet* includes attacks to members of the executive committee and vice mayors. Non-elected officials are mostly police officers and clerks of the municipal bureaucracy. Upper-level politicians include provincial, regional, and national politicians. All categories in Panel A also include attacks on family members of each type of public official.

This source of data has four advantages over previous measures used in the literature studying attacks against female politicians. First, rather than being mostly self-reported, attacks in this database are validated by a reputable independent organization which classifies when the information is purely based on self-reports, allowing us to test for reporting bias. Second, while previous studies largely rely on data on psychological abuse (Håkansson, 2021; Herrick et al., 2019; Gorrell et al., 2018), descriptive evidence indicates that women in politics may be subject to physical violence, too (Krook, 2018; Bardall, Bjarnegård and Piscopo, 2020; Krook and Sanín, 2020; Krook, 2020; Piscopo, 2016). Our data includes both verbal and physical attacks, allowing us to study a wider range of strategies employed against female politicians. Third, our data reports attacks from a variety of perpetrators, spanning criminal groups, political opponents, and ordinary citizens. For 639 episodes, it also mentions the policy choice or in-office behavior that may have led to the attack, which we will use as a way to uncover the underlying reasons behind attacks against female politicians. Indeed, Italy has been historically characterized by violent political confrontation and by an endemic presence of organized criminal groups seeking to influence policy making (Pinotti, 2015; Daniele and Geys, 2015). Therefore, we are in an ideal position to analyze gendered differentials by type of perpetrators, and especially to test for heterogeneous effects between criminal and non-criminal perpetrators. Finally, our data span twelve years, longer than most extant studies, allowing us to study the timing of gendered differentials in attacks.

4 Empirical Strategy

We adopt two empirical strategies to assess whether women politicians receive more attacks. First, we use a panel-data, two-way fixed effects approach on the full sample of municipal elections held since 2006:

$$Attacked_{i,t} = \tau_t + \phi_i + \alpha FemaleMayor_{i,t} + \theta X'_{i,t-1} + \epsilon_{i,t}, \tag{1}$$

where i indexes municipalities and t elections. Vectors of election-year and municipality fixed effects (τ_t and ϕ_i) capture, respectively, year-specific shocks common to all municipalities – such as changes in national governments, or overall trends in violence – and time-invariant, municipality-specific characteristics – such as whether a city is smaller, less urban, more conservative. The specification also includes a large vector of pre-election, time-varying municipal characteristics ($X'_{i,t-1}$). These covariates capture political and socioeconomic features of a municipality that may affect both the probability of electing a female mayor and the probability that the winning candidate will be targeted by an attack. The parameter of interest is α, which aims to gauge the change in the probability of observing at least one attack during terms in which municipality i is governed by a woman. While useful to offer evidence on the full sample of municipalities, this specification suffers a major sources of bias: even if using a comprehensive battery of dynamic covariates, it will not be able to account for a potentially large range of unobservable, time-varying factors that may influence both the explanatory variable and the outcome of interest.

We address endogeneity using a Politician-Characteristic Regression Discontinuity (PCRD) design. PCRD is a close-election Regression Discontinuity Design (Imbens and Lemieux, 2008; Lee and Lemieux, 2010), aimed at isolating the effects of a characteristic of the winning candidate – here, gender. Our regression equations have the form:

$$\begin{aligned} Attacked_{i,t} = \tau_t + \phi_r + \beta FemaleMayor_{i,t} + \gamma f(FemaleMargin)_{i,t} + \\ + \lambda (FemaleMayor \times FemaleMargin)_{i,t} + \theta X'_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

The parameter of interest is β, which measures the effect of electing a female mayor at the cutoff of 0 margin of victory of the most voted female candidate ($FemaleMargin_{i,t}$). Hence, Equation (2) gauges the effect of electing a female mayor on attacks by comparing towns where a female candidate narrowly won with those where a female candidate narrowly lost and a male candidate was elected. Equation (2) also has region fixed effects (ϕ_r) and election-year fixed effects (τ_t), so it compares municipalities close to the cutoff within the same region, holding elections in the same year. Finally, for efficiency, it features a long vector of pre-election municipal characteristics, $X'_{i,t-1}$.[3] As in all PCRD designs, elections opposing only candidates of the same sex are excluded from the analysis. However, in this setting, there are only 88 elections featuring only women (1.1% of the sample), such that we are effectively considering the quasi-universe of elections involving female candidates.

An important institutional feature in our setting is the presence of a threshold at 5,000 inhabitants which determines a variety of relevant changes. First, municipalities above this threshold mandate a double electoral preference for the municipal council with a woman among the two candidates (Law n.215, 2012), as well as imposing a gender quota on candidates lists, which must include at least one-third of candidates of each gender. Baltrunaite et al. (2019) shows that this discontinuity increases female representation in municipal councils by 18%. Second, all mayors at this threshold receive 29% larger salaries, a dimension which has been shown to affect political selection, including of women (Gagliarducci and Nannicini, 2013), and the likelihood of observing violence against politicians (Pulejo and Querubín, 2022). Third, municipalities below this threshold were subject to budget constraints until 2013 which limited their autonomy in spending, with consequences on corruption and criminal interests (Daniele and Giommoni, 2021). Finally, starting in 2014, municipalities with less than 5,000 residents

[3] Log surface, log longitude, log latitude, log elevation, log distance from regional capital, log population, log population density, log foreign residents per 100 inhabitants, indicator for provincial capital, average age, % high-school educated, unemployment rate, % employed in agriculture, mafia-presence as of 2006, vote share in women-related referenda, turnout and vote share of the right-wing coalition in the last national election.

lost competence on a number of public services, with effects on citizens' satisfaction and voting behavior (Cremaschi et al., 2022). The difference in municipalities across this threshold is reflected in unbalanced pre-treatment municipal characteristics at the cutoff. To account for this set of differences, which cannot be disentangled one from the other, all our analyses refer to the sample of municipalities above 5,000 residents.[4]

Our design fits the standard identifying assumptions of the RDD: We show that, in our sample of municipalities above 5,000 inhabitants, the McCrary (2008) and Cattaneo, Jansson and Ma (2018) tests indicate that the forcing variable is smooth (Figure B.1), and that pre-treatment municipal characteristics are balanced at the cutoff (Table A.1).

Importantly, this study meets the assumptions under which PCRD can effectively identify the effect of politicians characteristics (Sekhon and Titiunik, 2012; Marshall, 2022): Figure B.2 shows that narrowly elected female mayors do not differ from narrowly elected male mayors on any of the sixteen observable characteristics on which we have data, including education, profession, incumbency status, and political affiliation. This assuages concerns that estimates from Equation (2) may identify a compound treatment effect or conflate the influence of compensating differentials. Third, observable, pre-treatment municipal characteristics are balanced at the cutoff (Table A.1).

5 Estimating the Gender Differential in Attacks

Two-way fixed effects estimates of $\hat{\alpha}$ from Equation (1) are in Table 1. Across all models, we find that Italian municipalities are more likely to have their mayor attacked when

[4]The main results replicate on the full sample and are available upon requests.

she is a woman. The size of the effect ranges from 0.12 to 0.13 standard deviations on the extensive margin (columns 1 and 2) and from 0.10 to 0.11 standard deviations on the intensive margin (columns 3 to 6). These magnitudes are larger than those found for Swedish mayors in Håkansson (2021). Yet, as noted in Section 4, these estimates are far from conclusive, as they might suffer from both omitted variable bias and heterogeneity issues. We thus move in the direction of causality by considering a RDD design comparing municipalities in which the most voted female candidate narrowly won to municipalities in which the most voted female candidate narrowly lost.

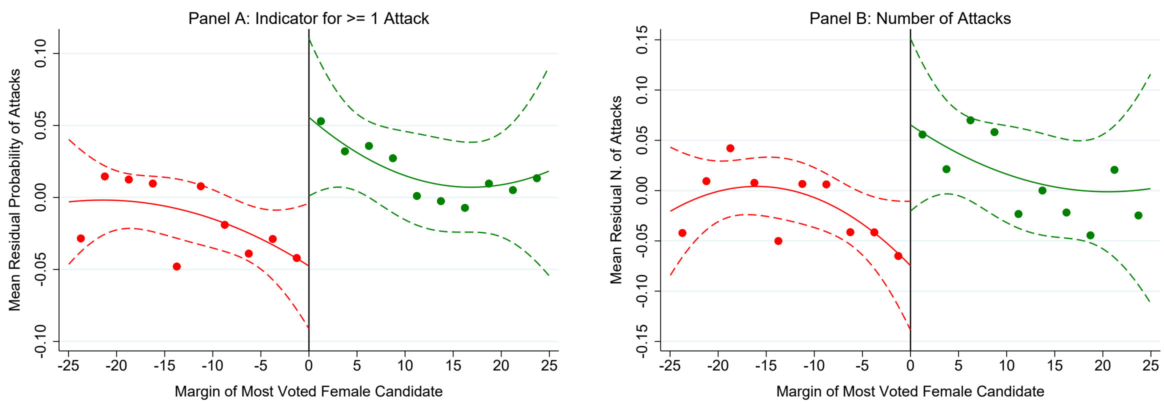
Table 1: Gender Differential in Attacks to Mayor, TWFE Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	$\geq$ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.035***	.037***	.026***	.028***	.033**	.035***
	(.011)	(.011)	(.010)	(.010)	(.013)	(.013)
SD Depvar	.284	.285	.252	.254	.326	.328
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	8,026	7,903	8,026	7,903	8,026	7,903

Notes: Controls: Log population, log population density, log foreign residents per 100 inhabitants, average age, % high-school educated, unemployment rate, % employed in agriculture, turnout and vote share of the right-wing coalition in the most recent parliamentary election. Robust standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Before illustrating the results from estimating Equation (2), we provide graphical evidence of the existence of a gender differential in attacks, by means of RDD plots. Figure 2 shows the change on both the extensive (Panel A) and the intensive margin of attacks on the mayor (Panel B) at the cutoff of 0 margin of victory, which determines the election of a female candidate. In both cases, there is a clear jump in the polynomial fit at the cutoff, suggesting that the victory of a female candidate increases the likelihood that the mayor will be attacked during her term in office.

Figure 2: Gender Differential in Attacks to Mayor, RDD Plots



Notes: Panel A plots the average probability of observing at least one attack on the mayor of municipality i during term t, for a given binned level of margin of victory of the most voted female candidate. Panel B plots the average number of attacks on the mayor of municipality i during term t, for a given binned level of margin of victory of the most voted female candidate.

Table 2 displays estimates of $\hat{\beta}$ from Equation (2). All the specifications yield positive and significant coefficients, confirming that narrowly elected female mayors are more likely to suffer attacks than their narrowly elected male colleagues. The effect ranges from 0.43 to 0.46 standard deviations on the extensive margin (columns 1 and 2) and from 0.40 to 0.42 standard deviations on the intensive margin (columns 3 to 6). To understand the magnitudes of these effects, consider that 5.7% of narrowly elected male mayors receive any attack during their term in office: Electing a female almost triples the probability of an attack, bringing the average likelihood of violence towards the mayor to 15.7%. These magnitudes are larger than those in Table 1, suggesting that the gender differential in attacks is amplified when women win by narrow margins, or when we consider more comparable politicians.

Table 2: Gender Differential in Attacks to Mayor, RDD Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	≥ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.100***	.106***	.079***	.087***	.102***	.111***
	(.036)	(.034)	(.030)	(.027)	(.038)	(.034)
Mean Depvar	.057	.057	.045	.049	.058	.065
SD Depvar	.233	.232	.198	.209	.255	.274
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	18.62	18.72	17.56	19.00	17.55	19.47
Effective N	1,304	1,272	1,234	1,293	1,233	1,312
N Left	767	748	722	763	722	776
N Right	537	524	512	530	511	536

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Robustness: We begin by showing that the coefficients are robust to fitting a quadratic polynomial (Table A.2) and to using a wide range of symmetric bandwidths (Figure B.3), both smaller and larger than those yielding the results of Table 2. Next, Table A.3 shows that using lagged dependent variables as placebo outcomes yields a null effect, in line with the absence of anticipation effects from the election of a female mayor. Third, we verify that while the election cutoff determines a jump in treatment effects, there are no significant jumps detected around irrelevant cutoffs of the forcing variable (Figure B.4). Results are also robust to transformations of the dependent variable and count models, such as Poisson and Negative Binomial regressions (Table A.4). Finally, as attacks on mayors are rare events, we make sure that the coefficients are not driven by a handful of observations. As shown in Figure B.5, the estimate of the treatment effect remains positive and strongly significant regardless of which region (Panel A) or which election year (Panel B) is excluded from the sample.

Alternative interpretations: We consider two possible alternative explanations for the results of Table 2. First, we test whether municipalities that narrowly elect a female mayor also witness an increase in the frequency of attacks towards other local officials. If this was the case, the coefficients in Table 2 may reflect a generalized increase in political violence, rather than an attempt at targeting the mayor. However, Figure B.6 shows that this is not the case. Second, rather than experiencing more attacks, female mayors may simply be more likely to denounce these episodes. Under this scenario, the coefficients in Table 2 would reflect differential reporting rather than an actual increase in attacks. Three different tests suggest that this is unlikely to be the case: First, *Avviso Pubblico* flags when an attack was reported by the victim(s). If we repeat our analysis excluding the 368 self-reported episodes,[5] our findings are virtually unchanged (Table A.5). Second, we differentiate between attacks in a private and public space, as

[5] 11.69% of attacks are reported when the target is a woman, 9.36% when it is a man.

the former might be underreported. Our findings are similar across the two samples (Figure B.7). Third, we exclude online attacks from the sample, to account for the possibility that findings are fully driven by differential sensitivity to attacks by online communities. Findings are again robust to this exclusion (Table A.6). This set of tests suggest that reporting bias is unlikely to explain the increase in attacks experienced by female politicians. Overall, these analyses provide robust causal evidence that female mayors are more likely to be subject to political violence. Importantly – given our RDD setting – this holds true even after accounting for both cross-sectional and time-varying differences in the characteristics of municipalities electing a woman, another potential issue that had not fully been addressed by extant studies on the topic.

Characterizing gendered violence: The literature studying violence against women in politics has emphasized that attacks targeting women can be qualitatively different, encompassing symbolic forms of violence such as sexist comments and objectification of women (Krook, 2022; Bardall, Bjarnegård and Piscopo, 2020). While the limited description of the attacks in our database does not allow us to conduct a categorization of all attacks, we code all the attacks – mostly threats – containing explicitly sexist references. Only about 1% of attacks contain explicit sexist references.[6] We check whether the gender gap in violence is fully driven by this kind of attacks: Excluding attacks with sexist content, we still obtain positive and significant results with comparable magnitude (Table A.7). This finding helps us characterizing violence against women in politics, by

[6] For example, the mayor of Carbonera, Federica Ortolan, received messages asking her to "stay at home and knit stockings" and to "dress sexy" for meetings. The mayor of Augusta received a Facebook message saying "Kill this unattractive mayor".

underscoring that women are attacked more even independently of the higher rate at which they receive sexist attacks.

6 Explaining the Gender Differential in Attacks

In this Section, we aim at unpacking the gender differential in attacks. Following the discussion in Section 2, we organize our empirical exploration along two questions: *(i)* Are attacks triggered by policy or identity motives? *(ii)* What are the consequences of attacks against women for the gender gap in political representation?

6.1 Motivations for Attacks Against Women

6.1.1 Policy Motives

Policies as explicit motive: We start by considering cases in which policies have been ascertained to be the reason for violence. Indeed, for 639 events, *Avviso Pubblico* reports that a particular policy is likely to have led to the attack.[7] While this is likely a lower bound of the number of policy-motivated episodes, repeating our analyses after excluding these attacks from the sample is a way of testing whether the gender differential is driven by the in-office behavior of female mayors. Table A.8 shows that policy choices are unlikely to be the main motivation behind higher attacks towards women: Coefficients remain positive and significant across all the specifications, and akin in magnitude to those in Table 2.

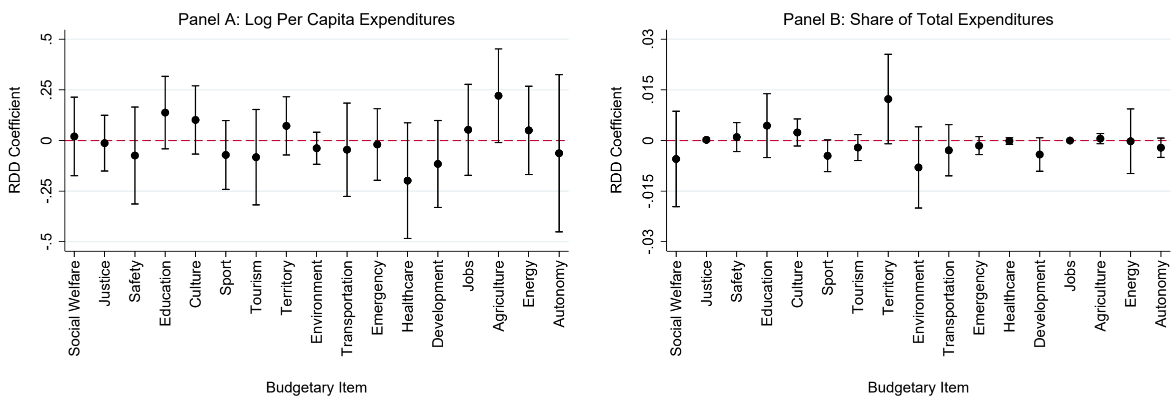
[7] 20.4% of the attacks targeting a woman have an explicit policy motivation, 14.7% of the attacks targeting a man have a policy motivation.

Municipal Expenditures: To assess the extent to which female mayors adopt different policy choices, we gather yearly data on all chapters of municipal expenditures from AidaPA. We fit the RDD model of Equation (2) using as outcomes expenditures on seventeen different budgetary items. The results are reported in Figure 3, for both log total expenditures per capita (Panel A) and share of total expenditures (Panel B). For all the spending categories analyzed and for both dependent variables, the models reject any significant difference in budget allocation across narrowly elected female and male mayors. This is true also for spending categories in which women have been found to invest more, such as healthcare, education, and social welfare. These results are in line with those of Casarico, Lattanzio and Profeta (2022), who do not find significant gender differences in the size and composition of Italian municipal expenditures for the period 2000-2015.[8]

Perpetrators: A complementary way to investigate whether attacks are driven by different policies is to look at perpetrators: In Italy, organized crime routinely uses attacks against politicians for strategic, policy-related motives (Daniele and Dipoppa, 2017; Pulejo and Querubín, 2022). To inquire the extent to which the actions of mafia groups may determine the observed gender differential in attacks, we perform two complementary exercises, reported in Figure B.9. First, we re-estimate Equation (2) separately for municipalities with and without a proven presence of organized crime in the years before

[8]Figure B.8 in the Appendix shows that the results are similar when replicating these analyses considering only the first year of the term (to limit the possible influence of attacks on spending decisions).

Figure 3: Gender Differential in Municipal Expenditures, by Item



Notes: Each coefficient represents one RDD estimate from Equation (2). All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on bias-corrected standard errors clustered at the municipality level.

2006.[9] The coefficients in Panel A indicate that female mayors are more likely to be attacked in both types of municipalities. These patterns are confirmed when separating attacks that, according to our coding of the descriptions in *Avviso Pubblico*'s reports, are likely perpetrated by criminal organizations or by other perpetrators (Figure B.9, Panel B). Similar results are obtained when testing for these heterogeneities on the intensive margin of attacks (Figure B.10). We thus conclude that the gender differential in violence is not driven by attacks perpetrated by criminal groups.

Political Orientation: If women were attacked more due to their political platform, we might expect to see a role for political ideology in explaining attacks. In Table A.9, we split our sample by partisan and non-partisan affiliation of the winning mayoral

[9]To gauge mafia presence at the municipal level, we follow Dipoppa (2022) and combine three indicators: *(i) Mafia Victims*, which is equal to 1 if municipality i experienced at least one mafia-related homicide according to Vittimemafia.it; *(ii) Mafia Seizures*, equal to 1 if municipality i experienced at least one seizure of goods, properties, or firms belonging to mafias, from cases of application of Law 646/1982; *(iii) Mafia Infiltrated*, which is equal to 1 if municipality i experienced at least one dissolution of its city council due to mafia infiltration, from cases of application of Law 221/1991.

candidate. The results do not reveal clear heterogeneities between left- and right-wing mayors, nor between partisan and non-partisan mayors.[10] Thus, female mayors are attacked more irrespective of their ideological leaning, suggesting that their political positions are not the main reasons why they are targets of violence.

Corruption: Across countries, there is evidence that female politicians (Brollo and Troiano, 2016; Bauhr and Charron, 2021) and female bureaucrats (Decarolis et al., 2023) are less corrupt than males. If this holds true among the mayors in our sample, it may be driving the observed gender differential in attacks. To test for this channel, we combine two complementary sets of measures for corruption at the municipal level, and use them as outcomes in Equation (2). The first is an official count of corruption-related crime charges at the municipal level, recorded by the Ministry of Internal Affairs and covering the period 2006-2014.[11] As shown in Table A.10, we find no evidence of changes in corruption at the cutoff for three different transformations of this variable: *(i)* Count of corruption charges (columns 1 and 2); *(ii)* Corruption charges per 1,000 inhabitants (columns 3 and 4), and *(iii)* Corruption charges per 1 million EUR of municipal expenditures (columns 5 and 6).

While coming from official governmental records, corruption charges have two important limitations. First, they are only available up to 2014, halfway through our sample period. Second, they only include prosecuted cases of corruption, which are likely to be a small fraction of all the malfeasance episodes (ANAC, 2019). We address both limitations using official data on more than 1.5 million municipal procurement contracts for

[10] Most Italian mayors run with civic list without a discernible political orientation.
[11] These data are not available after 2015 (see Daniele and Giommoni, 2021).

the period 2007-2022, provided by the Italian Anti-Corruption Authority (ANAC, henceforth). With this information at hand, we follow Pulejo and Querubín (2022) and build three proxies for corruption in the management of public resources. First, we consider municipalities designing contracts that bunch at thresholds at which there are additional regulatory requirements, such that one can suspect the municipal government is trying to avoid additional scrutiny. Second, we consider the number of firms invited to bid in negotiated procedures, where a higher number signals more transparent procurement (Decarolis et al., 2021). Finally, we consider the frequency of subcontracting, which has been associated to criminal infiltration (Decarolis et al., 2021).[12]

The only outcome suggesting that female-led administrations may be less prone to favoring criminal interests in procurement is subcontracting: Municipalities that narrowly elect a female mayor are less likely to have their contracts subcontracted by about a fifth of a standard deviation (columns 5 and 6, Table A.11). However, the other two outcomes do not follow a similar pattern. If anything, results on bunching (columns 1 and 2) suggest that female-led administrations are slightly *more* likely to sort their contracts' values below regulatory thresholds.

6.1.2 Identity Motives

We now turn to investigating whether the gender gap in attacks can be attributed to identity motives. We seek to determine whether identity, and particularly, gender-related characteristics of the municipalities we consider, have any leverage in explaining attacks.

[12] Additional details on these measures are in Pulejo and Querubín (2022), Section 6.

If they do, as we discuss in Section 2, we could expect opposing factors to explain attacks: on the one hand, violence could emerge where gender equality is *lowest*, in line with studies finding that violence against women arises where gender norms are most restrictive. On the other hand, violence might emerge where women's political empowerment is *highest*, in line with the literature on backlash against emerging minority groups. We test each hypothesis in turn.

Gender norms: We consider the two measures of gender norms available in Italy at the municipal level: how municipalities voted in two important referenda on women rights and the rates of female labor force participation.[13] The two referenda are the 1974 vote to decide whether to abolish the right to divorce – we code voting against abolishing as being pro-women – and the 1981 referendum on abortion. The latter involved two questions, one expanding and one restricting the conditions allowing abortion, which we code as pro and against women rights, respectively. The RDD coefficients presented in Figure B.11 indicate no differences between the two groups of municipalities, with coefficients of almost identical size. We obtain a similar result considering female labor force participation (Figure B.12). These results suggest that restrictive gender norms are unlikely to explain the gender differential in attacks.

Women empowerment in politics: Having excluded agency motives, as well as gender norms, we now ask whether the higher violence that women experience is the result of backlash against a minority group that is gaining power. We present four

[13] Other extant measures, such as attitudes in the World Value Survey or ITANES, are either available only at higher levels or for a small subset of municipalities, and are thus not suitable to our empirical approach.

different tests examining this possibility.

First, we consider the effect of gender quotas. Since 2013, municipalities with more than 5,000 residents use gender quotas for the election of their municipal council, which exogenously increases the share of women in this institution. Figure 4, Panel A, shows support for the backlash hypothesis: The gender differential in attacks is driven by places that – on top of electing a female mayor – have more women in office as a result of gender quotas. Instead, municipalities electing a female mayor but lacking gender quotas display no differences in attacks between female and male politicians.

Second, within places subject to gender quotas, we consider municipalities which have elected a higher and lower share of women in the municipal council. Also in this case (Panel B of Figure 4), the differential in violence across gender comes from municipalities with an above median share of women elected in the municipal council, while places electing fewer women do not display a gender gap in violence.

This pattern might be relevant within the legislature electing more women, or it might also matter dynamically: Perhaps electing an *increasingly* higher share of women over time triggers more attacks. As a third test, we thus consider the difference in effects for municipalities across quintiles of growth in women's election in the municipal council.[14] Figure 4, Panel C shows that the gender differential in violence is concentrated in the 4th and 5th quintile, where the growth in female representation has been the largest.

Finally, Panel D of Figure 4 shows that the gender differential in attacks is stronger in municipalities within regions governed my a woman, again in line with violence being

[14] We analyze the change from 1993 onwards, the year in which direct mayoral elections were introduced.

triggered by the presence of several women in positions of power. All these heterogeneities also obtain when using the log numbr of attacks as dependent variable (Figure B.13).

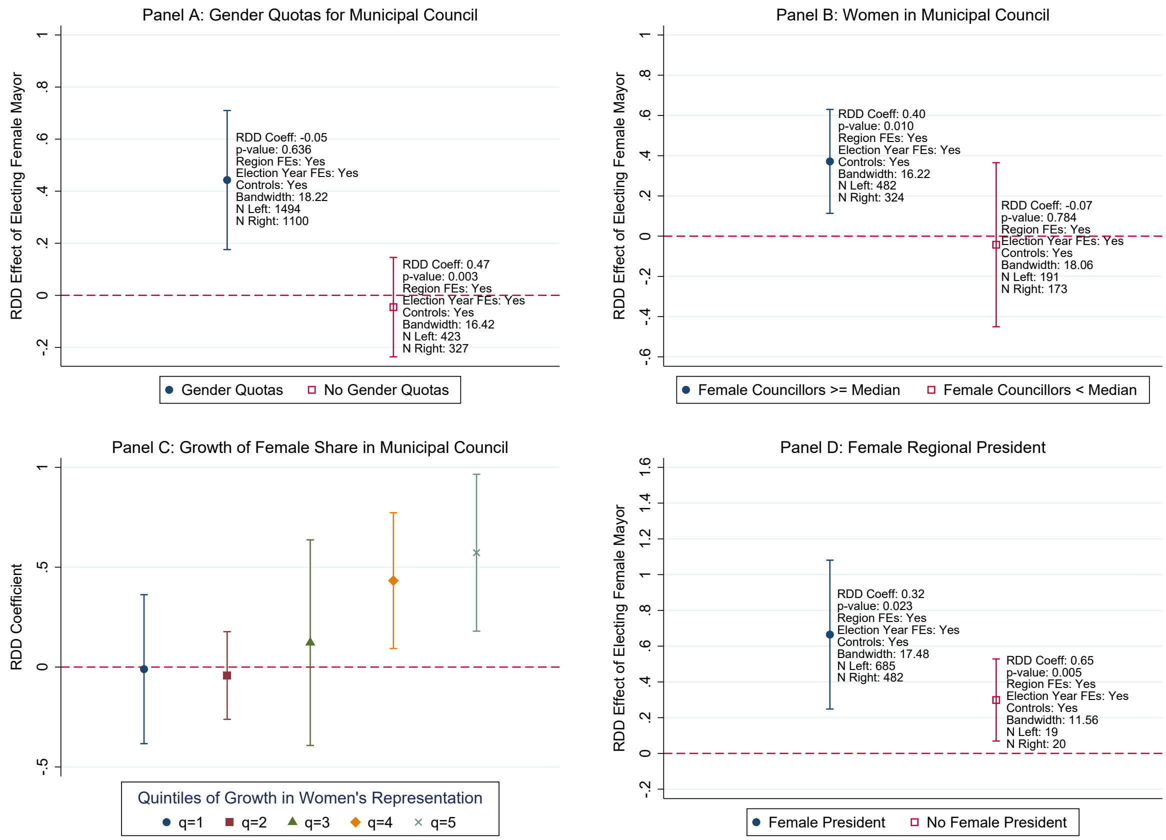
One might contend that a higher prevalence of women in power might itself affect policymaking and if this – rather than women participation into politics – causes more attacks. However, when we re-run the same analysis on policymaking as in Section 6.1.1 considering only municipalities-periods with above-median share of women in office, we find again no differences in policymaking.[15]

Taken together, our findings indicate that women are not targeted due to the choices they make while governing. Violence is also not explained by restrictive gender norms. Instead, the gender gap in violence is explained by backlash against a large and increasing female presence in positions of power. Thus, growing female empowerment appears as the catalyst for violence against female politicians.

In light of this result, an important question is whether this backlash attenuates over time, as female representation in politics becomes more common. We test for this by comparing cities which had previously elected female mayors to those electing a woman for the first time. Figure B.14 in the Appendix shows no evidence that repeatedly electing women attenuates this backlash in our context: The gender gap in attacks is identical in municipalities that did and did not elect female mayors in the past.

[15]These results are available upon request.

Figure 4: Female Representation and Gender Differential in Probability of Attacks on Mayor



Notes: RDD estimates from Equation (2). In all panels, the dependent variable is an indicator for the mayor of municipality i being attacked during term t. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on bias-corrected standard errors clustered at the municipality level.

6.2 Consequences of Attacks against Women

We conclude our empirical exploration by investigating whether attacks on female mayors have different consequences than those on male mayors. The importance of this question is twofold. First, finding differential consequences by gender could speak to the efficacy of attacks towards women: Attacks might be used at higher rates against women if are more effective at pushing them out of politics. Second, differential effects of attacks on political persistence might explain part of the gender gap in representation observed across countries (Fulton et al., 2006; Peveri and Sangnier, 2021; Wasserman, 2023).

First, if attacks aim at pushing women out of politics, they should target mayors who can re-run for office. In Italy, mayors cannot be elected for a third consecutive term, so that mayors in their second term face a binding term limit. In line with attacks being a means to curb women's representation, we find that the gender gap in violence is fully concentrated on mayors in the first term, who can be re-elected (Figure B.15).[16]

Second, we consider the effect of attacks on the probability of running again for office. We estimate a variant of Equation (2), in which the outcome is an indicator for whether the mayor of municipality i is running for any election (municipal, regional, national, or European) at the end of the term in office. We then subset results by whether mayors were attacked during their first term. This restriction considerably shrinks our sample, on top of creating endogenous subsets. As such, we recommend to interpret our results with caution, taking them as descriptive evidence of what we can infer from the data.

We start by showing that, on average, female mayors re-run at the same rate as men (Table 3, column 1). In column 2, we restrict the sample to mayors that did *not* incur an attack during their term in office. Once again, we find no gender differentials in re-running probabilities. Yet, it is interesting to note how the point estimate increases in magnitude compared to column 1. This suggests that, in the absence of attacks, female mayors – if anything – would be *more* likely than male mayors to seek re-election.

Then, in column 3, we consider the gender differentials in the probability of re-

[16] Within the first term, the gender differential in attacks is driven by the first two years (Figure B.16 and B.17). This might be consistent with the the gap in violence not being motivated by policy: If attacks were a reaction to a certain policy, we would expect perpetrators to strike relatively late, after having observed the policies implemented.

running among mayors who incurred at least one attack Conditional on being attacked – female mayors are 89% – or one standard deviation – less likely to re-run for election. This is a large drop in the likelihood of remaining in politics, which we interpret with caution, as these results come from a small sample selected based on an endogenous event. In Table A.12, we decompose these results by the type of office mayors run for, distinguishing between rerunning for mayor or running for higher office (regional, national, European). We find that the decrease in political persistence is entirely driven by a lower probability of attacked female mayors to re-run for mayor. No significant differences are instead detected in the decision to run for higher-level offices. This is consistent with female mayors fearing further retaliation at the local level. Together with the gender gap in violence being concentrated in the first term, this indicates that attacks may be more effective at discouraging women to stand for re-election, and thus ultimately more efficient under the point of view of their perpetrators.

Table 3: Attacks on Mayor and Persistence in Politics

	(1)	(2)	(3)
	All Mayors	*Non-Attacked Mayors*	*Attacked Mayors*
Female Mayor	.000	.039	-.487***
	(.043)	(.051)	(.124)
Mean Depvar	.431	.440	.552
SD Depvar	.495	.497	.506
Region FEs	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes
Controls	No	No	No
Bandwidth	22.67	16.95	12.95
Effective N	1,536	1,093	74
N Left	934	653	29
N Right	602	450	45

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The dependent variable is a dummy for whether the mayor seeks election in the same or another office at the end of the term. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

7 Conclusion

Taking Italian local politics as a case study, this article finds a strong gender differential in violence against politicians: Narrowly elected female mayors, similar to men on a large set of observables, are three times more likely to be targets of attacks during their tenure in office. These findings constitute an important complement to extant studies on violence against women in politics, by causally demonstrating the existence of a gender gap based on independent records of attacks and leveraging as-if random variation in the gender of elected officials.

We also provide new insights on the logic behind violence against women in politics. We argue that motives for attacks can be categorized into factors pertaining to the agency of politicians – the policies they adopt, their choices with respect to corruption and clientelism – , and to structural factors – politicians' gender identity and the political environment they face. We observe no differences in policymaking and corruption across genders, suggesting that the decisions women make while in office are not the reason for the gender gap in attacks. We also find no differential violence in places with more restrictive gender norms, consistent with violence against politicians being a rare event perpetrated by a few individuals, rather than a mass phenomenon.

Instead, our findings concur in indicating that the gap in violence is the result of a backlash against women's political empowerment: Attacks concentrate where more women obtain political power and where female representation is growing fastest. Violence can be thus conceptualized as an attempt to preserve the status of the dominant group by suppressing an outgroup that is becoming more powerful and threatening. This finding resonates with the literature studying violent backlash against the demographic, economic, social, and political advancement of other minorities, such as immigrants and minority ethnic groups (Dugan and Chenoweth, 2020; Zonszein and Grossman, 2022). Indeed, consistent with violence being used a tool to preserve men's hegemony over political power, we find that it has perverse consequences on political selection: *(i)* Attacks are directed at mayors who can run for re-election, and *(ii)* Although women re-run at the same rate as men, female mayors are significantly less likely to run for office again after an attack.

From a policy perspective, these findings point to the importance of offering effective public safety measures to newly elected women. From an institutional perspective, our findings highlight how – on top of promoting women's entry into politics – efforts should be made to prevent their selection out of it. Although other papers have focused on women's persistence in politics after an electoral defeat (Peveri and Sangnier, 2021; Wasserman, 2023), our results indicate that higher levels of exit may be a concern even following the victory of a female candidate. This result can contribute to explaining the persistence of the gender gap in political representation.

While our setting allows to examine violence against women in politics from a number of different angles, several aspects remain to be explored. For instance, when studying the relationship between in-office behavior and attacks, the data at our disposal has allowed us to focus on two dimensions: the allocation of the budget across policy domains and the management of public procurement contracts. Yet, while distributing public resources is probably their most important endeavor, politicians perform several additional tasks. Examining the relationship between political violence and other features of women's policymaking style represents an important target for future scholarship.

Furthermore, on top of what they do, elected politicians are often defined by what they say. Indeed, public discourse has been shown to have a strong impact on citizens' attitudes and beliefs, and studies have demonstrated that female politicians tend to adopt a distinctive rhetoric with respect to their male colleagues, both on the campaign trail and after assuming office (Hayes and Lawless, 2016). While the scant presence of Italian mayors on social media prevents us from assessing gender differences in political speech within our context, future research should analyze whether women's public discourse triggers attacks against them, contributing to explaining gender differentials in political violence.

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SUPPLEMENTARY INFORMATION

— For Online Publication —

A Additional Tables

Table A.1: Balance Checks for Relevant Covariates at Cutoff

Dependent Variable	$\hat{\beta}$	(SE)	Dependent Variable	$\hat{\beta}$	(SE)
Log Surface	-.191	(.224)	Anti-Women VS Referenda	-.017*	(.009)
Log Longitude	.003	(.007)	Anti-Abortion VS	-.001	(.005)
Log Latitude	-.001	(.001)	Abortion Restriction VS	-.025**	(.012)
Log Elevation	-.070	(.146)	Anti-Divorce VS	-.025	(.016)
Provincial Capital	-.019	(.022)	Mafia Dissolutions (Pre 2006)	-.003	(.013)
Log Km from Reg. Capital	-.030	(.099)	Mafia Seizures (Pre 2006)	.070	(.053)
Log Population	-.009	(.093)	Mafia Killings (Pre 2006)	.001	(.028)
Pop. Above 10,000	.015	(.072)	Log Transcrime Index	-.004	(.013)
Pop. Above 15,000	.006	(.060)	Mayor Independent (t-1)	-.016	(.088)
Log Population Density	.127	(.134)	Mayor Far Left (t-1)	.058	(.060)
Log Foreigners x 100 Inhab.	.016	(.080)	Mayor Far Right (t-1)	.019	(.034)
Had SPRAR	-.026	(.031)	Mayor Left (t-1)	-.043	(.040)
Average Age	.424	(.321)	Mayor Right (t-1)	.024	(.044)
% High School	-.004	(.006)	Mayor Aligned Nat. (t-1)	-.033	(.033)
% Unemployed	-.001	(.003)	Mayor Aligned Reg. (t-1)	-.063	(.057)
% Youth Unemployed	-.001	(.009)	Mayor Nat. Party (t-1)	-.058	(.058)
% Agriculture	-.003	(.007)	Mayor College (t-1)	-.094	(.060)
% Industry	.001	(.011)	Mayor Local (t-1)	.083	(.070)
N. of Candidates	-.020	(.231)	Mayor's Age (t-1)	-.604	(1.291)
N. of Councillors	-.067	(.720)	Mayor's Education (t-1)	-0.252	(.005)
Turnout National Election[a]	.006	(.004)	Mayor High Skilled (t-1)	-.026	(.446)
VS Center Right[a]	.001	(.010)	Mayor Male (t-1)	.005	(.065)

Notes: The coefficients displayed are bias-corrected RD estimates of $\hat{\beta}$ from Equation (2), using a first-order polynomial, with robust variance estimator (Calonico, Cattaneo and Titiunik, 2014). The outcome variable of each model is listed in each column's title. All regressions include election-year and region fixed effects. Robust standard errors clustered at the municipal level in parentheses. [a]These outcomes are referred to the most recent parliamentary election prior to municipal election t. *** p<.01, ** p<.05, * p<.1.

Table A.2: Gender Differential in Attacks to Mayor, Quadratic Polynomial

	(1)	(2)	(3)	(4)	(5)	(6)
	$\geq$ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.083*	.094**	.060	.071**	.077	.091**
	(.043)	(.041)	(.037)	(.036)	(.048)	(.046)
Mean Depvar	.062	.060	.051	.051	.066	.065
SD Depvar	.241	.238	.210	.209	.271	.269
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	25.32	26.39	23.33	23.67	23.40	23.76
Effective N	1,685	1,686	1,565	1,539	1,568	1,551
N Left	1,034	1,038	953	938	956	949
N Right	651	648	612	601	612	602

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Placebo with Lagged Outcome, Attacks to Mayor

	(1)	(2)	(3)	(4)	(5)	(6)
	≥ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.000	-.006	-.012	-.018	-.016	-.024
	(.032)	(.030)	(.027)	(.025)	(.035)	(.033)
Mean Depvar	.076	.076	.063	.063	.082	.080
SD Depvar	.265	.265	.236	.237	.306	.306
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	22.73	23.00	19.60	18.70	19.47	18.55
Effective N	1,479	1,456	1,303	1,231	1,297	1,225
N Left	899	889	771	725	765	719
N Right	580	567	532	506	532	506

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Gender Differential in Attacks to Mayor, Robustness to MLE

	(1)	(2)	(3)	(4)
	Poisson	*Poisson*	*Negative Binomial*	*Negative Binomial*
Female Mayor	1.502***	1.314***	1.521***	1.402***
	(.441)	(.379)	(.413)	(.379)
Mean Depvar	.100	.098	.100	.098
SD Depvar	.441	.423	.441	.423
Election FEs	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Polynomial	1st	1st	1st	1st
Bandwidth	18.62	18.72	18.62	18.72
Effective N	1,163	1,328	1,163	1,328

Notes: In all models, the dependent variable is the count of the number of attacks against the mayor of municipality i during term t. Columns 1 and 2 present estimates of the effect of electing a female mayor from Poisson regression models. Columns 3 and 4 present estimates of the effect of electing a female mayor from Negative Binomial regression models. In all columns, the sample is restricted to municipality-election observations within the optimal RDD bandwidth selected by the algorithm in Table 2. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Gender Differential in Attacks to Mayor, Excluding Attacks Denounced

	(1)	(2)	(3)	(4)	(5)	(6)
	≥ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.114***	.122***	.090***	.098***	.116***	.126***
	(.034)	(.032)	(.028)	(.026)	(.036)	(.034)
Mean Depvar	.048	.047	.037	.039	.048	.048
SD Depvar	.214	.212	.178	.181	.230	.230
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	17.31	17.50	17.11	17.36	17.12	17.10
Effective N	1,219	1,197	1,205	1,187	1,206	1,172
N Left	711	699	702	692	703	682
N Right	508	498	503	495	503	490

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Gender Differential in Attacks to Mayor, Excluding Attacks Online

	(1)	(2)	(3)	(4)	(5)	(6)
	≥ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.080***	.085***	.062**	.069***	.080**	.089***
	(.031)	(.030)	(.025)	(.024)	(.033)	(.031)
Mean Depvar	.040	.041	.033	.032	.042	.042
SD Depvar	.196	.197	.164	.162	.211	.210
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	18.14	18.26	17.67	18.06	17.68	18.31
Effective N	1,296	1,271	1,207	1,210	1,206	1,210
N Left	760	748	704	709	703	709
N Right	536	523	503	501	503	501

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Gender Differential in Attacks to Mayor, Excluding Attacks with Sexist Content

	(1)	(2)	(3)	(4)	(5)	(6)
	≥ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.082**	.088***	.062**	.068***	.080**	.088***
	(.034)	(.033)	(.027)	(.026)	(.034)	(.033)
Mean Depvar	.047	.047	.037	.040	.047	.052
SD Depvar	.211	.212	.180	.191	.232	.247
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	18.51	18.68	17.16	17.69	17.13	17.69
Effective N	1,296	1,271	1,207	1,210	1,206	1,210
N Left	760	748	704	709	703	709
N Right	536	523	503	501	503	501

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Gender Differential in Attacks to Mayor, Excluding Policy-Motivated Attacks

	(1)	(2)	(3)	(4)	(5)	(6)
	≥ 1 Attack		*Ln(Attacks +1)*		*InvHSin(Attacks)*	
Female Mayor	.099***	.109***	.078***	.088***	.100***	.112***
	(.034)	(.033)	(.029)	(.027)	(.037)	(.035)
Mean Depvar	.054	.054	.045	.045	.058	.057
SD Depvar	.226	.226	.199	.199	.257	.255
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	17.19	16.82	16.77	16.78	16.74	16.91
Effective N	1,209	1,151	1,181	1,148	1,180	1,155
N Left	705	665	683	663	682	668
N Right	504	486	498	485	498	487

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The dependent variable is an indicator for the mayor of municipality i being attacked during term t. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Gender Differential in Attacks to Mayor, RDD Estimates by Party

	(1)	(2)	(3)	(4)
	Independent	*Partisan*	*Left-Wing*	*Right-Wing*
Female Mayor	.059*	.233***	.201***	.140**
	(.036)	(.062)	(.076)	(.060)
Mean Depvar	.051	.059	.111	.040
SD Depvar	.220	.235	.318	.197
Region FEs	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Bandwidth	18.67	15.51	11.70	12.94
Effective N	838	359	105	187
N Left	495	203	45	124
N Right	343	156	60	63

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The dependent variable is an indicator for the mayor of municipality i being attacked during term t. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. In column 1, the sample is restricted to mayors running as independents. In column 2, the sample is restricted to mayors running with a partisan affiliation. In column 3, the sample is restricted to partisan mayors running in left-wing coalitions. In column 4, the sample is restricted to partisan mayors running in right-wing coalitions. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: Gender Differential in Corruption Charges, 2006-2014

	(1)	(2)	(3)	(4)	(5)	(6)
	Count of Corruption Charges		*Charges per 1,000 Inhabitants*		*Charges per 1Mil EUR Spent*	
Female Mayor	1.353*	1.130	-.014	-.007	-.003	-.002
	(.763)	(1.005)	(.019)	(.018)	(.003)	(.003)
Mean Depvar	1.34	.924	.056	.055	.009	.057
SD Depvar	7.51	2.26	.139	.139	.023	.009
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	13.83	8.95	19.08	18.86	21.73	18.35
Effective N	492	310	644	627	711	609
N Left	274	154	382	373	430	362
N Right	218	156	262	254	281	247

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.11: Gender Differential in Procurement Outcomes, 2007-2022

	(1)	(2)	(3)	(4)	(5)	(6)
	Bunching of Contract Values		*Log N. of Firms Invited*		*Probability of Subcontracting*	
Female Mayor	.024*	.022	-.013	-.010	-.032*	-.036**
	(.013)	(.014)	(.097)	(.093)	(.018)	(.018)
Mean Depvar	-.020	-.020	1.68	1.68	.103	.104
SD Depvar	.109	.111	.823	.818	.154	.152
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election-Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Bandwidth	20.77	19.16	20.95	22.19	17.65	16.61
Effective N	1,416	1,293	1,206	1,239	1,192	1,096
N Left	848	763	721	746	695	626
N Right	568	530	485	493	497	470

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

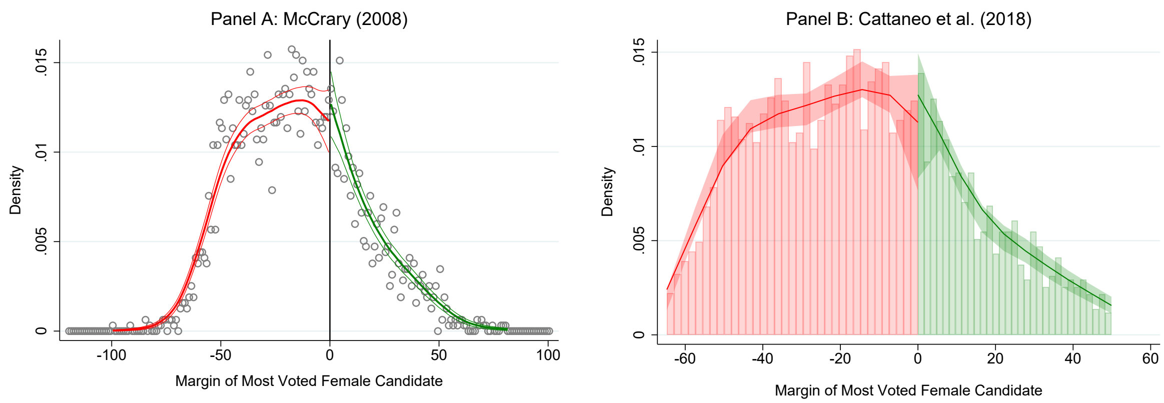
Table A.12: Attacks on Mayor and Persistence in Politics, by Type of Office

	(1)	(2)	(3)	(4)	(5)	(6)
	DV: Re-Running for Mayor			DV: Running for Higher Office		
	All Mayors	*Non-Attacked Mayors*	*Attacked Mayors*	*All Mayors*	*Non-Attacked Mayors*	*Attacked Mayors*
Female Mayor	.057 (.074)	.097 (.077)	-.660*** (.175)	.024 (.032)	.007 (.032)	.020 (.049)
Mean Depvar	.539	.532	.520	.100	.100	.085
SD Depvar	.499	.499	.510	.300	.300	.280
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No
Bandwidth	16.80	15.91	13.20	14.61	14.62	8.97
Effective N	785	686	64	1,044	968	49
N Left	463	409	25	581	552	14
N Right	322	277	39	463	416	35

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

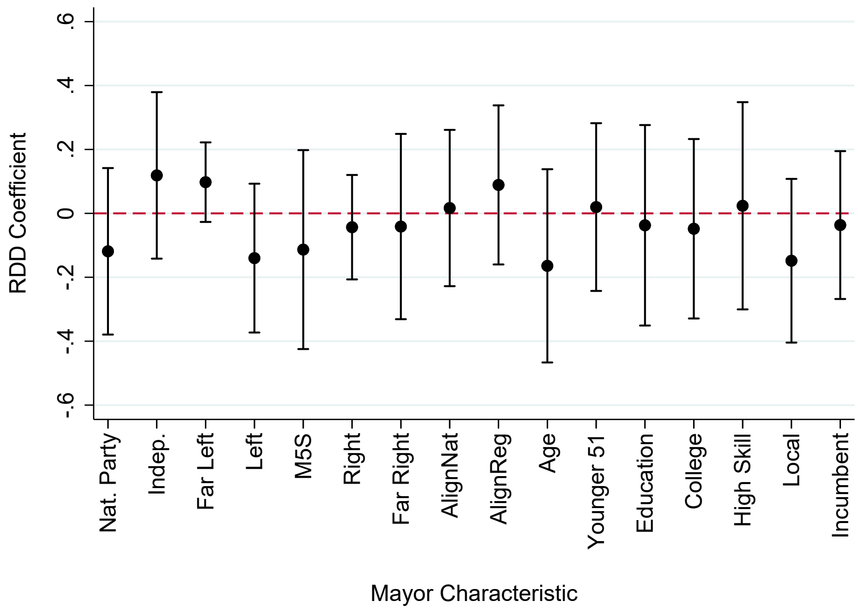
B Additional Figures

Figure B.1: Tests of No-Sorting Assumption



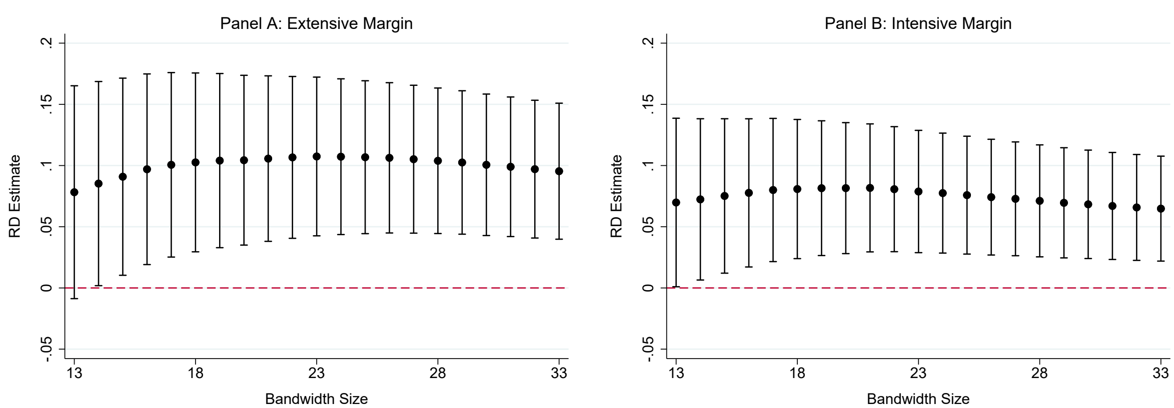
Notes: Left: McCrary (2008). Right: Cattaneo et al. (2018).

Figure B.2: Threats to PCRD - Other Characteristics of Female Mayors



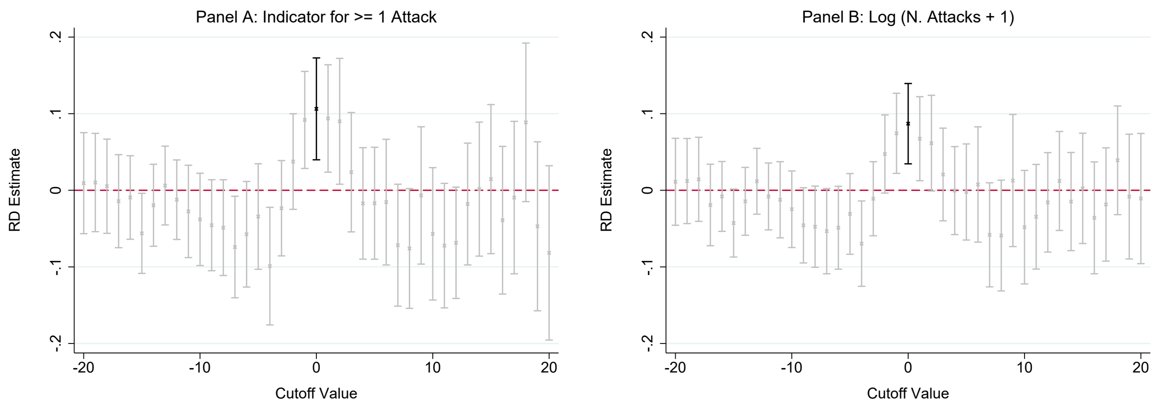
Notes: Each dot represents one RDD estimate from Equation (2). The dependent variables are standardized to enhance the comparability of coefficients' magnitudes. *Education* is the number of years of schooling of the mayor. *Local* is an indicator for the mayor being born in the municipality. *AlignNat* and *AlignReg* are indicators for the mayor sharing partisanship with the Prime Minister and the President of the Regional Executive, respectively. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.3: Robustness Test, Choice of Bandwidth Value



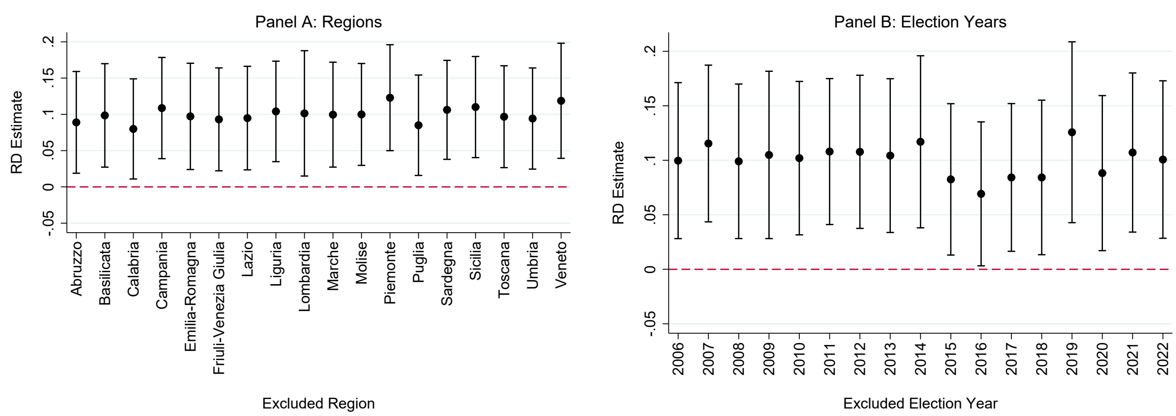
Notes: Each dot represents one RDD estimate from Equation (2), using the bandwidth of the size indicated on the horizontal axis on each side of the cutoff. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipal level.

Figure B.4: Placebo Test, Alternative Cutoffs of Running Variable



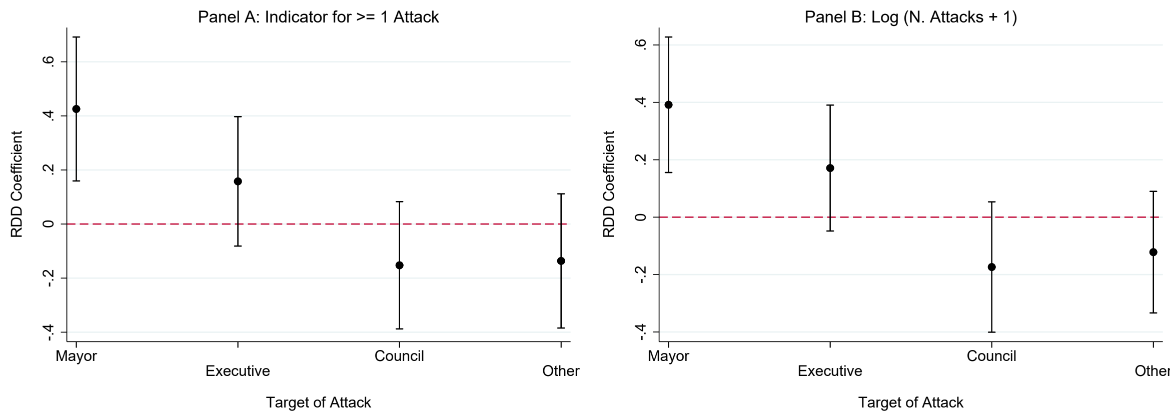
Notes: Each cross represents one RDD estimate from Equation (2), using the cutoffs for $(FemaleMargin)_{i,t}$ indicated on the horizontal axis. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level. The black estimate in the middle refers to the real cutoff of 0 margin of victory.

Figure B.5: Jackknife Tests, by Region and Election Year



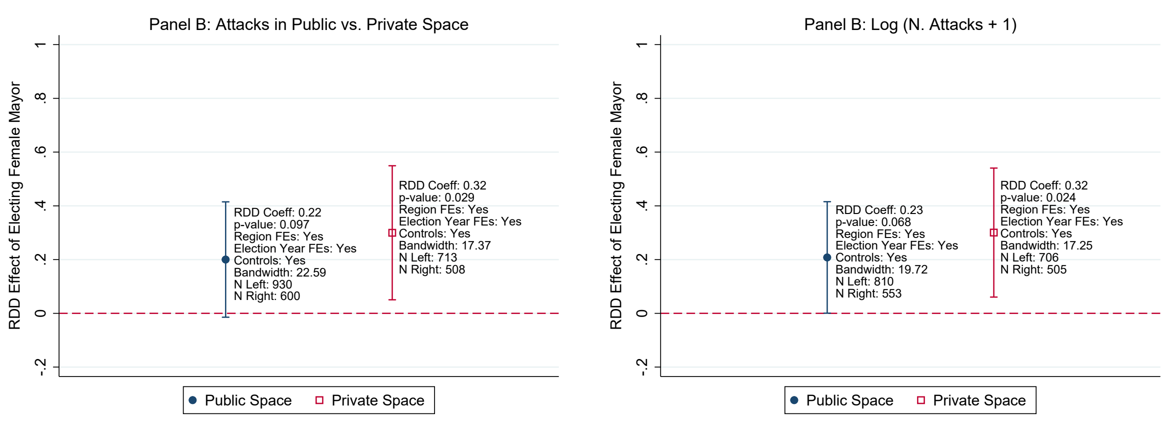
Notes: In both panels, the dependent variable is an indicator for the mayor of municipality i being attacked during term t. In Panel A, each dot represents one RDD estimate from Equation (2), excluding all municipalities within the region indicated on the horizontal axis. In Panel B, each dot represents one RDD estimate from Equation (2), excluding all municipalities holding elections during the year indicated on the horizontal axis. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.6: Placebo Test, Attacks on Other Municipal Officials



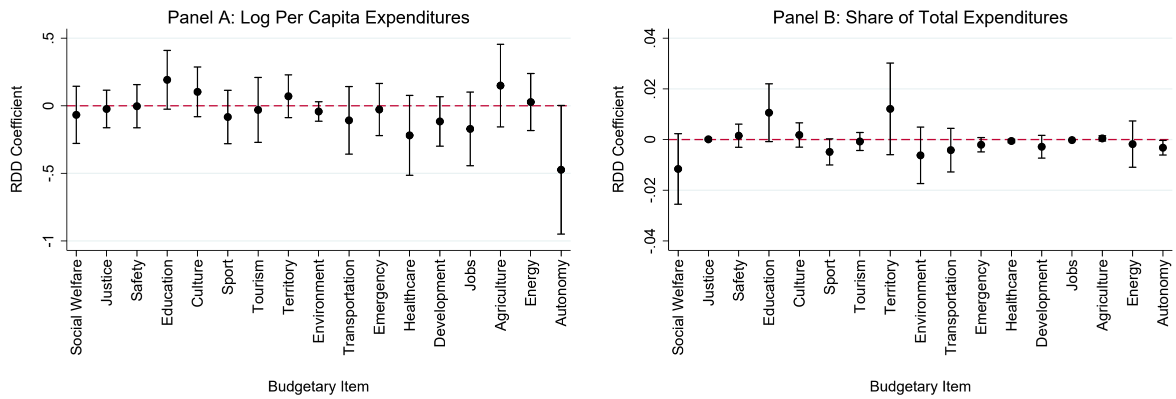
Notes: Each dot represents one RDD estimate from Equation (2), using as outcome the attacks on the type of municipal official indicated on the horizontal axis. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.7: Gender Differential in Attacks in Public and Private Spaces



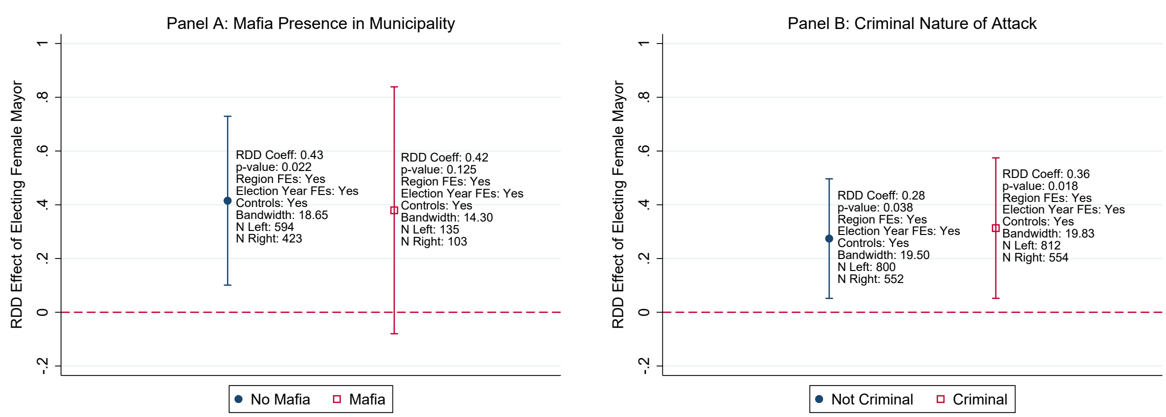
Notes: RDD estimates from Equation (2). All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.8: Gender Differential in Municipal Expenditures in First Year of Term, by Item



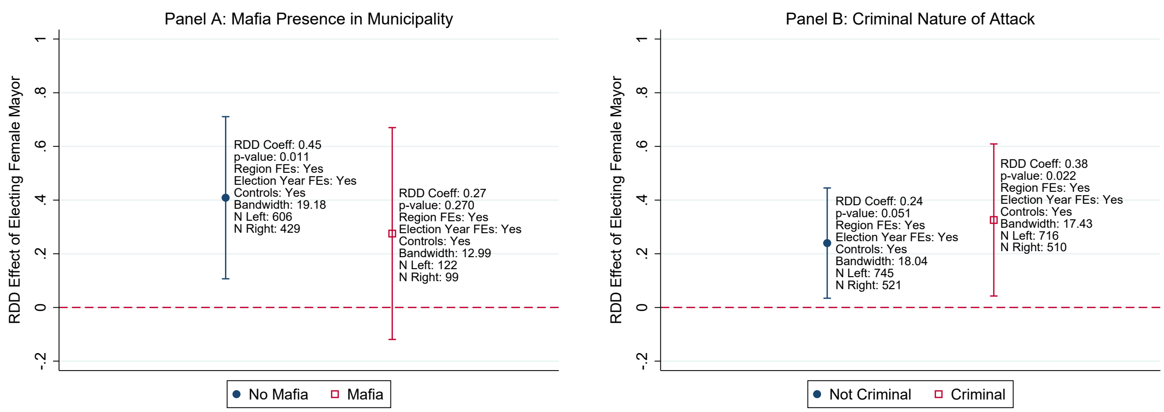
Notes: Each coefficient represents one RDD estimate from Equation (2). All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on bias-corrected standard errors clustered at the municipality level.

Figure B.9: Gender Differential in Probability of Being Attacked and Criminal Groups



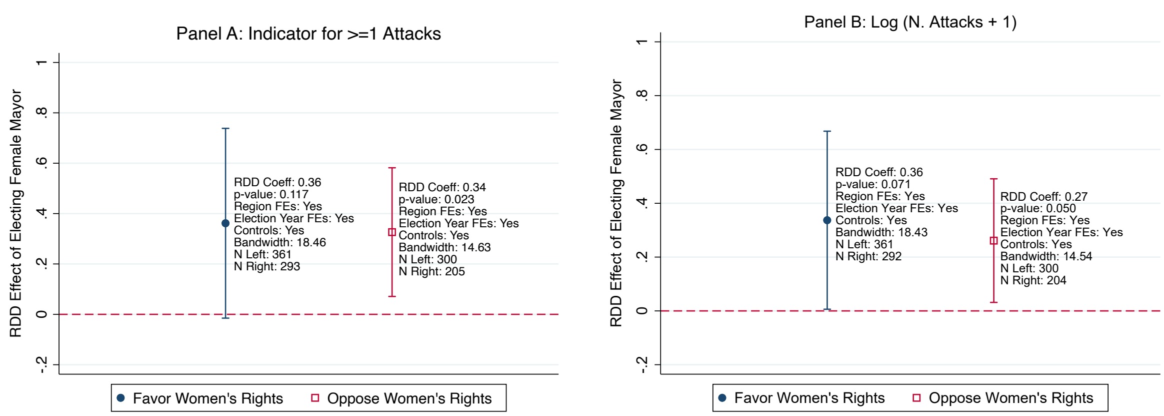
Notes: Each coefficient represents one RDD estimate from Equation (2). In Panel A, the dependent variable is an indicator for the mayor of municipality i being attacked during term t. In Panel B, the dependent variable is an indicator for the mayor of municipality i being attacked by an organized criminal group during term t. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on bias-corrected standard errors clustered at the municipality level.

Figure B.10: Gender Differential in Log Number of Attacks and Criminal Groups



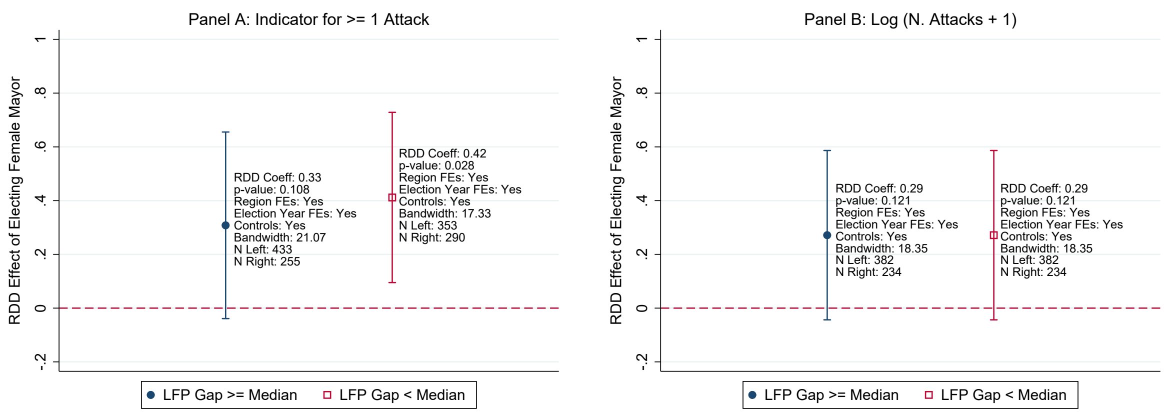
Notes: Each coefficient represents one RDD estimate from Equation (2), using as outcome the log number of attacks on the mayor of municipality i during term t, augmented by 1. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.11: Gender Differential in Attacks and Support for Women Rights in Referenda



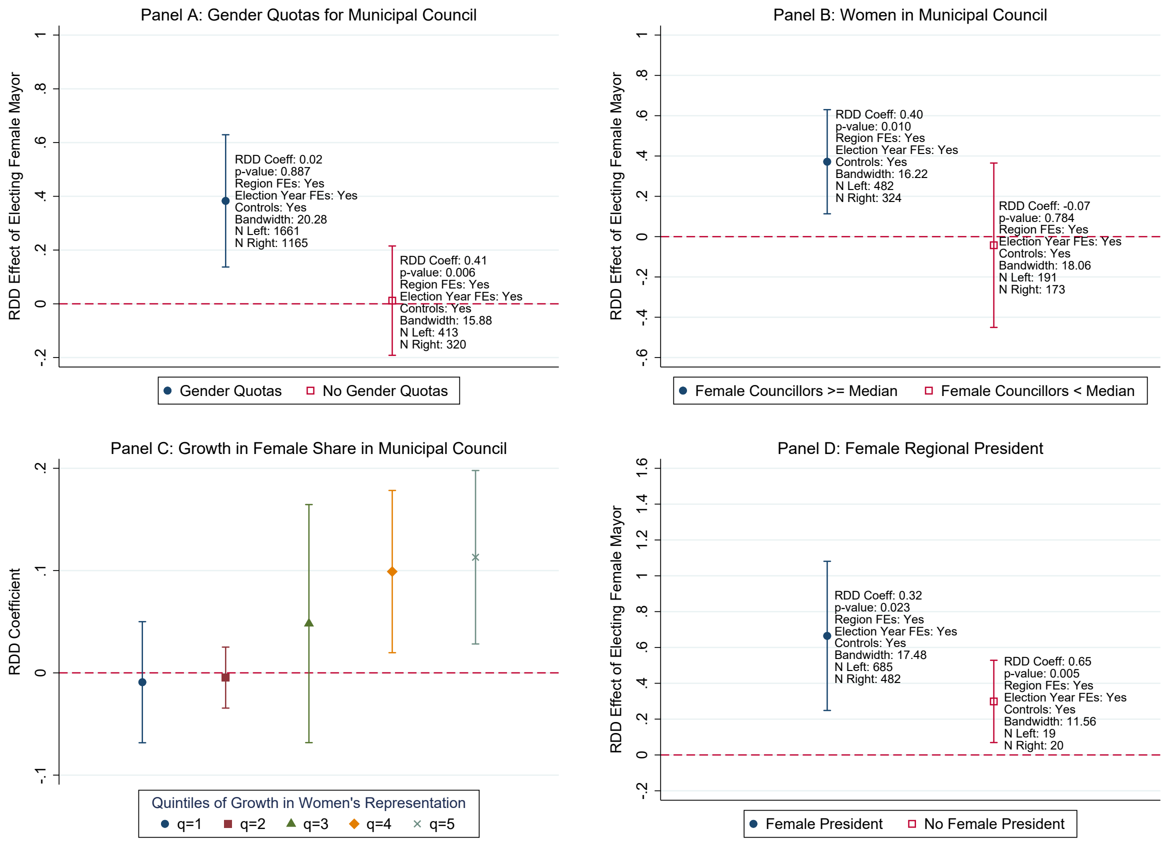
Notes: RDD estimates from Equation (2). Here we split results by whether a municipality voted in support of women rights in two referenda on divorce and abortion – we consider vote for women rights above median as cutoff. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.12: Gender Differential in Attacks and Female Labor Force Participation



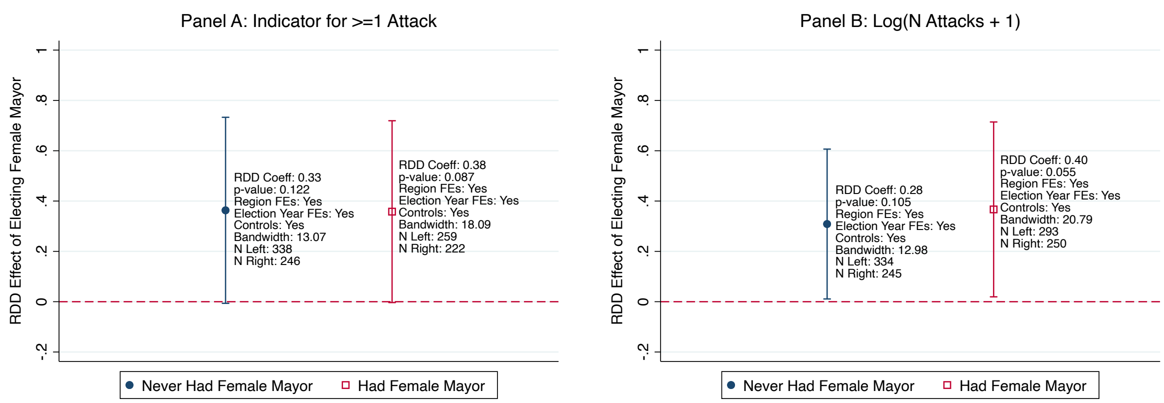
Notes: RDD estimates from Equation (2). Here we split results by female labor force participation in municipality i is above the median of all municipalities. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.13: Female Representation and Gender Differential in Log Attacks on Mayor



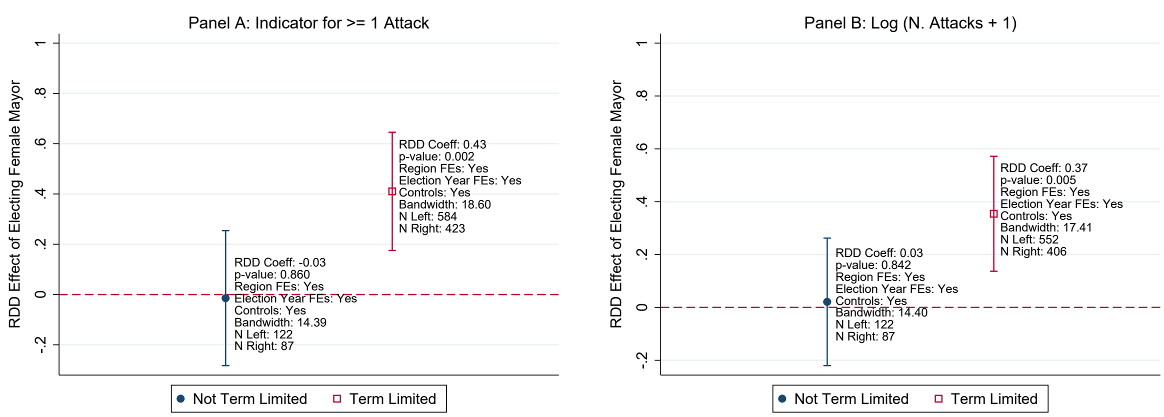
Notes: RDD estimates from Equation (2), using as outcome the log number of attacks on the mayor of municipality i during term t, augmented by 1. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.14: Gender Differential in Attacks, by Previous Election of Female Mayor



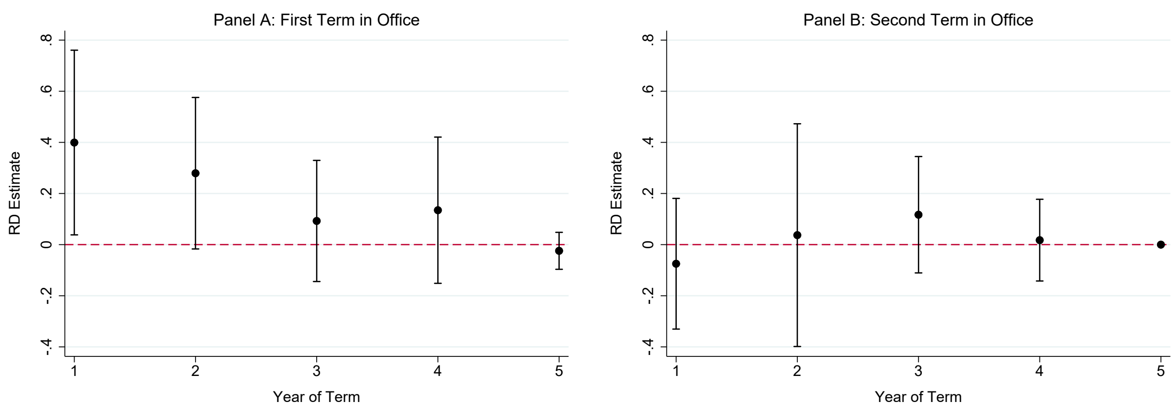
Notes: RDD estimates from Equation (2). All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.15: Gender Differential in Attacks, Mayors with versus without Term Limit



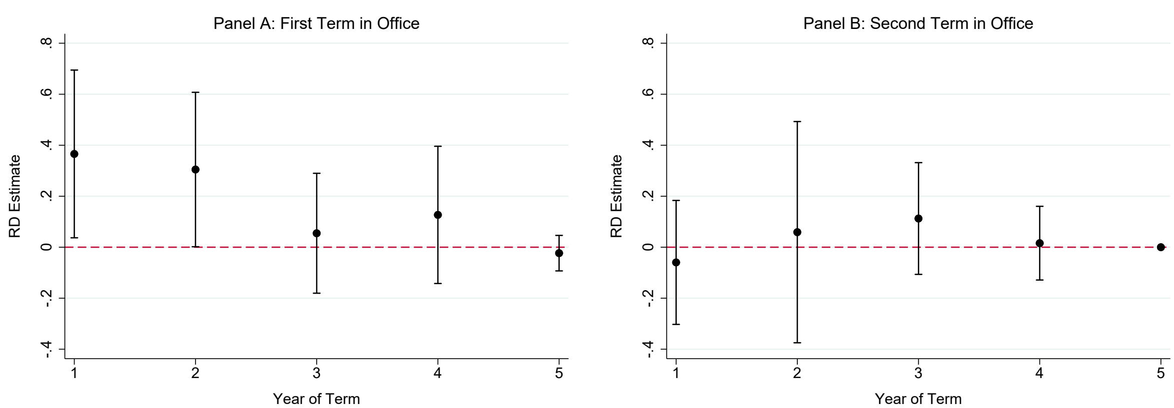
Notes: Each coefficient represents one RDD estimate from Equation (2). All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.16: Gender Differential in Probability of Being Attacked, by Year of Term



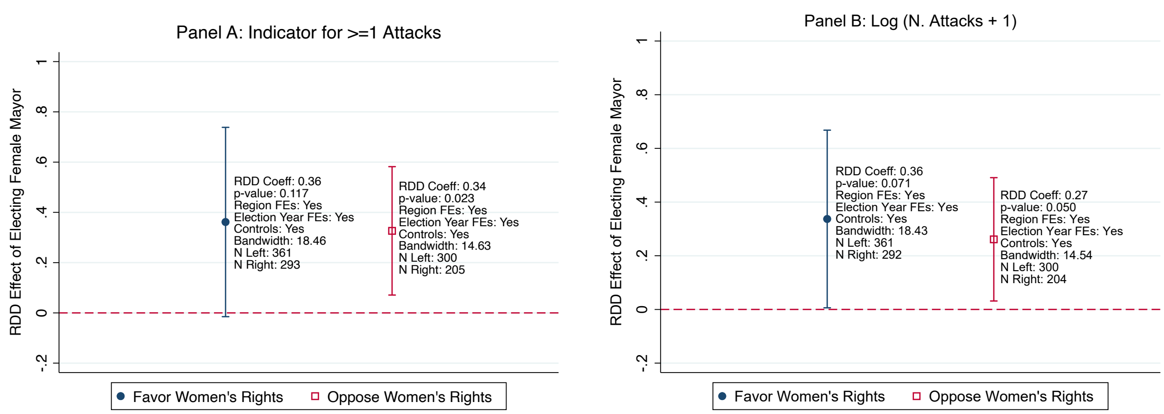
Notes: Each dot represents one RDD estimate from Equation (2). In both panels, the dependent variable is an indicator for the mayor of municipality i being attacked during term t. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on bias-corrected standard errors clustered at the municipality level.

Figure B.17: Gender Differential in Log Number of Attacks, by Year of Term



Notes: Each dot represents one RDD estimate from Equation (2), using as outcome the log number of attacks on the mayor of municipality i during each year of her term in office, augmented by 1. All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on robust, bias-corrected standard errors clustered at the municipality level.

Figure B.18: Gender Differential in Probability of Being Attacked, by Municipal Gender Norms



Notes: Each coefficient represents one RDD estimate from Equation (2). All the dependent variables are standardized, to enhance the comparability of effects' magnitudes. Vertical bars are 95% confidence intervals, based on bias-corrected standard errors clustered at the municipality level.

C Table Versions of Figures (Not for Publication)

Table C.1: Table Version of Figure 4, Panel C

	(1)	(2)	(3)	(4)	(5)
	1st Quintile	*2nd Quintile*	*3rd Quintile*	*4th Quintile*	*5th Quintile*
Female Mayor	-.081 (.084)	-.046 (.143)	.201*** (.076)	.140** (.060)	.140** (.060)
Region FEs	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Bandwidth	6.92	10.49	17.50	11.28	13.71
Effective N	36	92	280	209	265
N Left	21	52	160	102	150
N Right	15	40	120	107	115

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The dependent variable is an indicator for the mayor of municipality i being attacked during term t, standardized by each quintile of growth in female representation in the municipal council. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Table Version of Figure 3, Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Social Welfare	Justice	Safety	Education	Culture	Sport	Tourism	Territory
Female Mayor	.017 (.121)	.006 (.081)	-.105 (.048)	.199 (.315)	-.012 (.053)	-.083 (.058)	-.051 (.036)	-.001 (.036)
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	23.33	14.51	16.30	25.65	20.92	21.86	11.84	19.91
Effective N	1,304	867	954	1,418	1,190	1,245	719	1,148
N Left	795	476	541	869	717	755	387	686
N Right	509	391	413	549	473	490	332	462
	Environment	Transport	Emergency	Health	Development	Jobs	Agriculture	Energy
Female Mayor	-.047 (.047)	-.063 (.140)	-.017 (.105)	-.181 (.131)	-.098 (.028)	.046 (.133)	.235* (.137)	.089 (.128)
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	15.26	22.78	22.61	16.72	20.69	21.01	24.55	20.08
Effective N	902	1,282	1,274	983	1,182	1,196	1,372	1,154
N Left	502	781	775	566	710	722	839	691
N Right	400	501	499	417	472	474	532	463

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.3: Table Version of Figure 3, Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Social Welfare	Justice	Safety	Education	Culture	Sport	Tourism	Territory
Female Mayor	-.004 (.008)	.000 (.000)	.000 (.002)	.005 (.005)	.003 (.002)	-.005* (.003)	-.003 (.002)	.013* (.008)
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	18.47	11.08	19.11	20.86	19.76	17.33	11.26	16.01
Effective N	1,074	669	1,098	1,177	1,131	1,009	678	937
N Left	626	351	644	708	671	584	359	529
N Right	448	318	454	469	460	425	319	408
	Environment	Transport	Emergency	Health	Development	Jobs	Agriculture	Energy
Female Mayor	-.010 (.007)	-.003 (.004)	-.002 (.002)	-.000 (.001)	-.004 (.003)	.000 (.000)	.001 (.001)	.001 (.006)
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	17.33	24.14	10.58	17.08	16.20	11.71	15.12	17.44
Effective N	1,009	1,336	638	992	939	703	790	1,016
N Left	584	815	334	574	530	375	494	588
N Right	425	521	304	418	409	328	396	428

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.4: Table Version of Figure B.2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	National Party	Indep. Party	Far Left	Left	M5S	Right	Far Right	Aligned National
Female Mayor	-.119 (.133)	.119 (.133)	.098 (.064)	-.140 (.119)	-.113 (.159)	-.043 (.083)	-.041 (.148)	.017 (.125)
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	15.72	15.72	12.71	15.21	17.94	19.24	14.25	16.28
Effective N	1,110	1,110	919	1,073	1,255	1,331	1,021	1,139
N Left	631	631	508	604	737	785	566	652
N Right	479	479	411	469	518	546	455	487
	Aligned Regional	Age	Younger Than 51	Years Education	College Degree	Skilled Job	Local	Incumbent
Female Mayor	.089 (.127)	-.164 (.154)	.020 (.134)	-.037 (.160)	-.048 (.143)	.024 (.165)	-.148 (.131)	-.037 (.118)
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No	No
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	15.84	15.30	16.29	16.72	19.36	14.89	18.37	17.43
Effective N	1,120	964	1,144	818	1,125	857	1,139	1,227
N Left	639	542	655	452	666	480	668	716
N Right	481	422	489	366	459	377	471	511

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.5: Table Version of Figure B.2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DepVar: Indicator for ≥ 1*Attack*				*DepVar: Log(Number of Attacks +1)*			
	Mayor	Executive	Council	Other	Mayor	Executive	Council	Other
Female Mayor	.426***	.158	-.152	-.136	.392***	.171	-.174	-.122
	(.136)	(.122)	(.120)	(.127)	(.120)	(.112)	(.116)	(.108)
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	18.72	24.76	23.31	14.25	18.87	22.22	20.63	11.82
Effective N	1,272	1,608	1,521	997	1,382	1,464	1,378	835
N Left	748	983	926	553	754	887	825	456
N Right	524	625	595	444	528	577	553	379

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.6: Table Version of Figure B.8, Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Social Welfare	Justice	Safety	Education	Culture	Sport	Tourism	Territory
Female Mayor	-.082	-.011	-.018	.213	.118	-.100	-.077	.070
	(.130)	(.082)	(.095)	(.133)	(.112)	(.120)	(.139)	(.097)
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	20.19	17.21	17.20	20.10	20.40	19.36	12.06	18.76
Effective N	1,158	1,019	1,019	1,055	1,172	1,119	725	1,094
N Left	694	586	586	691	703	660	390	641
N Right	464	423	423	464	469	459	335	453
	Environment	Transport	Emergency	Health	Development	Jobs	Agriculture	Energy
Female Mayor	-.051	-.129	-.037	-.247	-.096	-.211	.144	.061
	(.043)	(.150)	(.112)	(.175)	(.111)	(.162)	(.184)	(.125)
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	13.41	21.94	18.65	15.89	20.52	17.50	19.30	20.96
Effective N	805	1,247	1,092	941	1,176	1,027	1,148	1,193
N Left	440	756	640	532	706	597	686	719
N Right	365	491	452	409	470	430	462	474

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.7: Table Version of Figure B.8, Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Social Welfare	Justice	Safety	Education	Culture	Sport	Tourism	Territory
Female Mayor	-.012 (.008)	.000 (.000)	.001 (.003)	.012* (.007)	.002 (.003)	-.006* (.003)	-.001 (.002)	.013 (.011)
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	19.01	12.79	17.91	16.51	19.50	17.23	15.05	15.22
Effective N	1,099	1,038	1,098	958	1,117	998	884	891
N Left	645	417	605	545	660	578	489	494
N Right	454	375	433	413	457	420	395	397
	Environment	Transport	Emergency	Health	Development	Jobs	Agriculture	Energy
Female Mayor	-.008 (.007)	-.005 (.005)	-.002 (.002)	-.001 (.000)	-.003 (.003)	.000 (.000)	.001 (.001)	-.001 (.006)
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st
Bandwidth	18.04	19.17	10.03	11.88	17.44	13.99	22.65	20.87
Effective N	1,046	1,102	600	711	1,013	833	1,265	1,175
N Left	612	648	312	382	586	456	769	707
N Right	434	454	288	329	427	377	496	468

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.8: Table Version of Figure B.14, Panel C

	(1)	(2)	(3)	(4)	(5)
	1st Quintile	*2nd Quintile*	*3rd Quintile*	*4th Quintile*	*5th Quintile*
Female Mayor	.070 (.032)	-.006 (.143)	.028 (.075)	.001 (.044)	.140** (.060)
Region FEs	Yes	Yes	Yes	Yes	Yes
Election FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Bandwidth	5.92	10.71	15.22	11.28	15.42
Effective N	29	92	244	207	293
N Left	17	52	134	101	172
N Right	12	40	110	106	121

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. The dependent variable is an indicator for the mayor of municipality i being attacked during term t, standardized by each quintile of growth in female representation in the municipal council. The mean and standard deviation of the dependent variable are measured within the left half of the optimal bandwidth selected by the algorithm for each model. Controls: See footnote 3. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.9: Table Version of Figure B.16

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Mayor's First Term in Office					*Panel B: Mayor's Second Term in Office*				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Female Mayor	.399***	.279*	.093	.135	-.024	-.075	.037	.117	.018	–
	(.130)	(.151)	(.121)	(.146)	(.037)	(.112)	(.222)	(.116)	(.082)	–
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st	1st	–
Bandwidth	15.52	15.05	17.79	19.00	8.09	12.40	16.16	10.26	17.29	–
Effective N	867	836	978	1,025	481	176	232	149	249	–
N Left	485	459	567	594	240	101	139	86	151	–
N Right	382	377	411	431	75	577	93	63	98	–

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.10: Table Version of Figure B.17

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Mayor's First Term in Office					*Panel B: Mayor's Second Term in Office*				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
Female Mayor	.366**	.305**	.055	.127	-.023	-.060	.059	.113	.016	–
	(.168)	(.154)	(.120)	(.137)	(.035)	(.124)	(.221)	(.112)	(.074)	–
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–
Election FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–
Polynomial	1st	1st	1st	1st	1st	1st	1st	1st	1st	–
Bandwidth	15.21	16.69	14.56	17.88	18.87	12.30	16.19	10.26	17.29	–
Effective N	843	919	814	980	481	175	232	149	249	–
N Left	465	521	443	568	240	98	139	86	151	–
N Right	378	398	371	412	241	75	93	63	98	–

Notes: RDD estimates with triangular weighting kernel and data-driven optimal bandwidth selection (Calonico, Cattaneo and Titiunik, 2014). The running variable is the margin of victory of the most voted female candidate, computed as the difference between her vote share and the one of the most voted male candidate. Robust bias-corrected standard errors clustered at the municipality level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.