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ABSTRACT

Female Political Representation and Violence against Women: Evidence from Brazil*

This paper studies the effect of female political representation on violence against women. Using a Regression Discontinuity design for close mayoral elections between female and male candidates in Brazil, we find that electing female mayors leads to a reduction in episodes of gender violence. The effect is particularly strong when focusing on incidents of domestic violence, when the aggressor is the ex-husband/boyfriend, and when victims experienced sexual violence. The evidence suggests that female mayors might implement different policies from male mayors and therefore contribute to reduce gender violence.

JEL Classification: D72, J16, P16, I18, H75, K42
Keywords: gender, political economy, elections, violence

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1 Introduction

Despite significant progress in the last decades, violence against women remains a relevant problem worldwide. According to the World Health Organization, 1 in 3 women have experienced sexual or physical violence worldwide (World Health Organization, 2013). Victims of sexual violence are more likely to suffer anxiety, depression, insomnia, reproductive and gastrointestinal problems (Martin, Macy, and Young, 2011). Violence against women also produces a significant economic burden, since governments need to expend in health, justice and security. UN Women (2016) estimates that only domestic violence generates a productivity loss of 1.2% of the GDP in Brazil. It is therefore relevant to understand the mechanisms that can help reduce gender violence.

This article provides new evidence on the role of elected female mayors on violence against women. Our study focuses on Brazil, where gender violence is widespread. In 2017 there were 606 cases of domestic violence reported each day and 1,133 femicides occurred during that year (Fórum Brasilero de Segurança Pública, 2018). This rate is 48 times larger than the rate in the United Kingdom (Waiselfisz, 2015). Female politicians have also suffered from this wave of violence. Marielle Franco, a city councilwoman for Rio de Janeiro, was assassinated on March 14, 2018. She was a gay black activist who rallied against police brutality. Her death sparked protests in Rio and in other cities in Brazil, and has motivated other female politicians to run for office.[1]

We use administrative data on gender violence from the Brazilian Ministry of Health, taking advantage of a law promulgated in 2003 that established mandatory notification of all episodes regarding confirmed or suspected gender violence. These data, spanning through years 2005–2016, give not only information on the number of victims in each municipality, but also provides information on the type of violence, place of occurrence, or relationship with the aggressor. Combining this dataset with a database of mayoral electoral outcomes, we are able to estimate the effect of electing a female mayor on gender violence during her mandate.

Estimating this model by ordinary least squares might provide a biased estimate of the true effect. Municipalities less tolerant of the role of women in society might be prone to more violence against women and also less likely to elect a female mayor. To overcome this identification problem we use a regression discontinuity design (RD), restricting the analysis to races where the female candidate won by a narrow margin to races where the

[1] "A Year After Her Killing, Marielle Franco Has Become a Rallying Cry in a Polarized Brazil", The New York Times, March 14, 2019.

male candidate won by a narrow margin. This strategy has been used by Brollo and Troiano (2016) in the context of Brazilian elections to estimate the effect of a female mayor on corruption. To the best of our knowledge, we are the first to document the effect of electing a female mayor on violence against women.

The results show a large discrepancy between the raw correlations and the RD estimates: While on average female mayors do not have an effect on violence against women, when looking at contested elections we find that female mayors reduce overall violence against women by between 6 and 11 incidents per 10,000 women. The effect is sizeable, as it accounts for a reduction in violence of about 63 percent. The effect is particularly strong when focusing on incidents that occurred at home, when the aggressor is the ex-husband/boyfriend and when victims experienced sexual violence.

There are at least two possible mechanisms through which female mayors can have a negative effect on violence against women. First, female mayors might differ in their preferences regarding the role of police and prevention of violence against women. Second, these mayors can have a role model effect on other women, changing their attitudes and self-confidence and empowering them to act (Iyer, Mani, Mishra, and Topalova, 2012). There is, however, a third mechanism, in which the increase in political power of women alienates men, who feel that their position in society is diminished, and that it turn could lead to an escalation in violence against women. This phenomenon, known as male backlash, arises when women behave counterstereotypically (Rudman, 1998; Rudman and Phelan, 2008).[2] Despite notorious cases such as the one of Marielle Franco mentioned above, in none of our specifications we find an increase in violence against women after a female mayor is elected.

The evidence we find points towards the preferences hypothesis. First, we show that the effect of female mayors on violence against women is larger towards the end of their term, suggesting that policies take time to be implemented. Second, we find that the effect is larger when there are more women in the city council. This result is consistent with the findings of Gagliarducci and Paserman (2012), who show that female mayors in Italy are less likely to be voted out by the council when there are more female councilors. Consistent with the preferences hypothesis, more women in the council make policies to

[2] Evidence from male backlash can be found in experimental settings, such as in Gangadharan, Jain, Maitra, and Vecci (2016), who show that men contribute less to a public good when women are group leaders, instead of men. A decrease in female unemployment is associated with an increase in intimate partner violence due to backlash (Bhalotra, Kambhampati, Rawlings, and Siddique, 2021; Tur-Prats, 2021). Backlash might also reduce the likelihood of women running for office (Bhalotra, Figueras, and Iyer, 2018).

tackle violence against women more likely to be implemented. Finally, we do not find an effect on accidents or suicides for women, and no effect on homicides or overall violence against men.

Our paper contributes to various strands of the literature. First, it contributes to the literature analyzing the effect of selecting women leaders on various outcomes. The seminal work of Chattopadhyay and Duflo (2004) shows that women heads of village councils invest more money on public goods relevant to women. Evidence indicates that women politicians have an effect in reducing neonatal deaths (Bhalotra and Clots-Figueras, 2014) and increasing child immunization (Beaman, Duflo, Pande, and Topalova, 2007). In education, female representation leads to improvement on academic achievement in rural contexts (Clots-Figueras, 2012) and expands girls school attendance (Beaman et al., 2007). Brollo and Troiano (2016) find that female mayors are less corrupt than male mayors. To the best of our knowledge, we are the first to show that female mayors can have an effect in reducing violence against women.

Second, our paper contributes to the literature that analyzes the determinants of violence against women, as well as the policies to reduce it. Aizer (2010) shows that reductions in the gender wage gap increase female bargaining power, which is associated to higher domestic violence. Anderberg and Rainer (2013) show that the relationship between a woman's relative wage and domestic abuse follows an inverted U-shape, highlighting the non-monotonic relationship between female empowerment and domestic violence. Culture, in the form of more traditional gender norms, can influence the likelihood of reporting incidents of violence against women (Gonzalez and Rodriguez-Planas, 2020). Iyer et al. (2012) show that increased political power might raise reporting of crimes against women, but do not find an effect on the incidence of such crimes. In our setting this empowerment comes from electing female majors rather than through reserved seats, thus our paper highlights the importance of political leadership in reducing violence against women.

Regarding policies to reduce violence against women, the literature has analyzed the effect of women police stations (Perova and Reynolds, 2017; Kavanaugh, Sviatschi, and Trako, 2019; Jassal, 2020; Amaral, Bhalotra, and Prakash, 2021) and female police officers (Miller and Segal, 2019; Shoub, Stauffer, and Song, 2021), divorce laws (Stevenson and Wolfers, 2006; Brassiolo, 2016; García-Ramos, 2021), panic buttons (Tumen and Ulucan, 2020) and mass media campaigns (Cooper, Green, and Wilke, 2020). Since our results points to female majors enacting policies that reduce violence, we contribute to this literature by showing that electing female majors can offer a path to reducing gender-based violence.

The rest of the article is organized as follows: Section 2 presents the data and discusses the institutional context. In Section 3 we introduce the empirical strategy used in the paper. In Section 4 we explore the results, present robustness checks and analyze the possible mechanisms. Finally, Section 5 concludes.

2 Data and Institutional Context

2.1 Elections

Brazil is a presidential country and it is organized by a federal government, states and municipalities. Citizens vote for representation in every level through periodic elections.[3] In regard to the local administration, Brazil has 5,567 municipalities that are ruled by a mayor (*prefeito*) and a legislative body (*Câmara de vereadores*) elected directly by citizens. In municipalities with more than 200,000 voters, mayors are elected through a majority run-off rule. If the municipality has less than 200,000 voters, the election is solved through a plurality rule. This cases represent more than the 97% of the municipalities in Brazil.[4]

It is important to mention that Brazil has high political and economical decentralization (Souza, 2002). Local governments can collect taxes, promulgate laws and decide how to allocate the federal transfers they receive. Municipalities are in charge of the provision of several public goods and investment projects, such as health, education and infrastructure. Moreover, mayors have to propose, annually, a budget for the implementation of different programs and public policies. However, the local council can veto part of the proposal, so the mayor can only develop the programs and amounts approved. The legislative body can also create municipal laws and supervise the mayor's performance.

In this article, we focus on mayoral elections in 2008 and 2012 that were defined in the first round.[5] The elections' data and candidates' information come from the Superior Electoral Court (*Tribunal Superior Eleitoral*), the most important body in the brazilian electoral system.

[3] At a federal level, people vote for the president and for a federal parliament every four years. Moreover, each state has a legislative assembly voted periodically.

[4] See Fujiwara et al. (2011) to understand the effects of these rules in brazilian mayoral elections.

[5] The municipal mandates are: 2005-2008, 2009-2012 and 2013-2016.

2.2 Violence against women

The law 10,778 was promulgated during 2003 and establishes the compulsory notification of gender-based violence cases reported by either public or private health institutions. This same year the National Secretary of Politics for Women was created to improve legislation for women. In 2005, it introduced a phone line for gender violence victims (*Ligue 180*) available 24 hours a day. In 2006, the law *María da Penha* was promulgated to increase penalties, generate instruments for prevention and systematize the data on gender-based violence. In addition, the law 13,104 of 2015 establishes femicide as a crime.

The data on gender-based violence comes from the Ministry of Health's TABNET platform, where administrative data regarding morbidity, diseases and vitals statistics can be found. Within this platform, the Information System for Notification of Diseases, SINAN (*Sistema de Informação de Agravos de Notificação*) provides individual-level data on compulsory notification cases. We construct measures of violence against women such as physical and sexual violence, threats or harassment at the municipality level. The available data includes the municipality in which the case was notified and has information about the victim, like age, marital status and race. In addition, the database provides data on the suspected perpetrator, like relationship to the victim and alcohol use.

Figure A1 in the Appendix shows trends in violence against women for each of the five regions in Brazil. In all regions we see that the number of cases reported per 10,000 women has increased over time, particularly for the Southeast. It is possible that reporting incidents of violence improved over time because of the law *María da Penha* described above. However, because the law implemented mandatory notification of cases, the increase in cases should come from those relatively less severe.[6] Figure A2 shows the trends on female deaths caused by tumors. This allows us to conclude that the increase we see in the Southeast is probably not related to an increase on the inclusion of municipalities to the data. If the latter was the case, the deaths caused by tumors should have also increased more in the Southeast. Figure A3 in the Appendix shows trends over time by type of violence. We see that psychological violence experienced a threefold increase, which is consistent with an increase in the likelihood of reporting. Physical violence, the most common type of violence, also experienced a threefold increase. Sexual violence has remained below 2 cases per 10,000 women since 2009, and relatively stable over the period. Lastly, Figure A4 compares trends for our measure of violence against women and police reports for the city of Rio. This comparison has to be taken with caution, since

[6] Our results are robust to excluding the Southeast region from the analysis.

crimes against women are usually under-reported. However, we observe similar trends for both measures of violence.

Data on female homicides were obtained from SIM (*Sistema de Informações sobre Mortalidade*) for years 2005-2016. It includes all homicides, and not only femicides. However, we consider the deaths caused by assault that are included in the categories X85-Y09[7] of the International Statistical Classification of Diseases and Related Health Problems (ICD-10).

2.3 Covariates

For the covariates, we used two sources of data. On one hand, we used the 2010 Brazilian demographic census to have municipality characteristics, such as population, per-capita income and income ratio. On the other hand, we used the election data to assess the mayoral characteristics. Some of the variables we used are age, education and political affiliation of the mayors. The detail with the variables used as covariates and their definitions can be seen in Table A1.

3 Empirical Strategy

3.1 Identification

This paper studies the impact of female political representation on violence against women. So, we need to compare municipalities headed by women with municipalities headed by men and see if there are differences on violence outputs. However, the election is endogenous to local characteristics, thus comparing female mayors with male mayors will give bias estimations. For instance, voters can have attitudes towards women that benefit the triumph of a female mayor and, at the same time, that affect gender violence.

In order to find the effect of a female mayor on gender violence, we first estimate the following equation through Ordinary Least Squares (OLS):

$$Y_{it} = \alpha + \beta F_{it} + \mu_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the average violence outcome in municipality i and time t, F_{it} equals 1 if the mayor is female, μ are time fixed effects and ε_{it} is the standard error clustered

[7] This category includes deaths caused by injuries inflicted by another person with intent to injure or kill, by any means (World Health Organization, 2016).

by municipality. Y_{it} is measured as the rate of hospital attention for violence per 10,000 women. This specification will give us the correlation between the gender of the mayor and violence against women, but it does not represent a causal effect. This is because, as mention earlier, the mayor's gender is correlated with the error term, giving bias estimation caused by relevant variables omission.

To estimate the average treatment effect (ATE) we use a Regression Discontinuity Design (RDD) and estimate the following equation:

$$Y_{it} = \alpha + \beta F_{it} + f(MVF_{it}) + \mu_t + \varepsilon_{it}, \quad \forall \quad MVF_{it} \in (-h, h), \tag{2}$$

where $f(MVF_{it})$ is a continuous function in both sides of the threshold and h is the optimal bandwidth estimated using the methodology by Calonico, Cattaneo, and Titiunik (2014). The function $f(\bullet)$ is an order one polynomial, as high order polynomials are not recommended on RDD (Gelman and Imbens, 2018).

3.2 Sample Selection

To estimate using a RDD, we consider only mixed mayoral races, in other words, races where the two first places were filled with a female candidate and a male candidate.[8] We include elections with only two candidates and elections with more than two candidates. For the last case, we consider races in which the third-placed candidate had less than 15% of the vote share.[9] Finally, our main sample consists on 806 races, of which a woman is the winner in 334 of them. The number of races on the sample increases between 2008 and 2012, suggesting a growth on female political participation.[10]

RDD implementation requires certain assumptions to be met. Firstly, it is important to analyze the continuity of MVF_{it} around the threshold to prove that there is no cutoff manipulation. We employ McCrary's test to study MVF_{it} density around zero (McCrary, 2008). Panel (a) on Figure 2 shows, graphically, the result of McCrary's Density Test. We can see that the female margin of victory is continuous around zero, which implies that there is no manipulation of the threshold. When we replicate the test for each year

[8] We exclude supplementary elections, elections resolved in a second round and elections where the two first places were filled with same gender candidates. Table A2 in the Appendix compares mixed races with other races, showing significant differences in various municipality characteristics such as population or income.

[9] Mixed races with two candidates represent a 62.8% of our sample. In alternative specifications we vary the share of votes that the third candidate gets to select our sample of municipalities.

[10] On 2008, 9.12% of the winners where women, whereas 11.9% of female candidate won on 2012.

separately, we do not see manipulation on any election.

The histogram on panel (b) from Figure 2 presents the density of MVF_{it}. We can notice that there is lower density on the right side of zero, which means that there is less proportion of female winners compared to male winners. We can conclude that, around zero, the variable's density does not change, that is, MVF_{it} is continuous around the threshold. Both graphics allow us to deduce that there is no cutoff manipulation.

Secondly, we need to test the continuity of observable characteristics. If they are discontinuous, the treatment effect can be confound with the impact that these variables have on gender violence[11]. Table 1 shows descriptive statistics for municipal and mayoral characteristics according to the mayor's gender. Column (5) shows that pre-treatment municipal characteristics are statistically equal between both groups. Regarding mayoral characteristics, age and incumbency are statistically different between municipalities with female mayors and male mayors. These differences are analyzed with more detail below. We can conclude that treatment and control groups are comparable in most of the observable characteristics.

Table 2 shows municipal and mayoral characteristics' discontinuities around the cutoff. The corresponding RDD balance plots are presented in Figure A5 and Figure A6. Coefficients should be zero if these variables are continuous. We can observe that there is a statistically significant effect on three variables: population, urban and water access. These characteristics could confound the effect of a female mayor on gender violence, so they will be included as covariates in the estimation. Results interpretation should be more careful, since differences around the cutoff can bias the estimations. Regarding other variables, there are no discontinuities around the threshold. This implies that municipalities on each side of $MVF_{it} = 0$ are comparable after controlling by population, urban and water access. We thus provide estimates with and without these controls.

4 Results

4.1 Female mayors and gender violence

Table 3 shows the effect of electing a female major on reported cases of violence per 10,000 women. Columns 1 and 2 show OLS estimates of Equation 1. The results in column 1

[11] Recent evidence suggests that RDD assumptions do not hold on parliamentary elections in the United States (Grimmer, Hersh, Feinstein, and Carpenter, 2011; Caughey and Sekhon, 2011). However, Eggers, Fowler, Hainmueller, Hall, and Snyder Jr (2015) conclude that the assumptions hold on several elections, including mayor elections in Brazil.

show a coefficient close to 0 that is not statistically significant at conventional levels. Considering the estimates when covariates are included (column 2), the results show a negative (but not significant) coefficient. The effect of electing a female major reduces violence in 1.39 cases per 10,000, which translates in a reduction of 13 percent.

Columns 3 and 4 show the RDD estimates of Equation 2. Our results show a negative and significant effect of electing female mayors. The effect is sizeable: when a woman wins a close race to a male candidate, the average rate of reports decreases on 6.97 cases per 10,000 women, which translates to a reduction of 54 percent. Figure 3 shows the RDD plot where we show local linear estimates using the specification and optimal bandwidth of column 3. The figure confirms the results seen in Table 3, with a large and significant decrease in violence against women at the cutoff.

The rest of the columns in Table 3 show alternative specifications. In columns 5 and 6 we implement the RDD strategy using half (column 5) and double (column 6) the optimal bandwidth. The point estimate is larger and remains statistically significant when we reduce the bandwidth to half. This is reassuring since we observe an effect even for very close elections (elections decided by a margin of less than 6 percentage points). The results in column 6 are consistent with a smaller and statistically insignificant effect when Equation 2 is estimated using OLS. Columns 7 and 8 show the estimates of Equation 2 assuming that the control function is a second and third order polynomial, respectively. Coefficients increase in magnitude and statistical significance compared to results on column (3), so this effect is robust to different specifications.[12]

4.2 Robustness

In this section we present robustness checks recommended in the RDD literature (Imbens and Lemieux, 2008; Lee and Lemieux, 2010). We focus on outliers and sample restrictions.

Regarding outliers, we perform two separate excercises. First, as discussed previously, the number cases of violence in the Southeast region experienced a larger increase than any other region in Brazil. To make sure that our results are not driven by these changes, Table A3 in the Appendix shows results excluding this region. Looking at our preferred specifications (columns 3 and 4), the results are smaller in size to those in Table 3, with the effect ranging between 42 and 52 percent with and without controls, respectively. Second, we deal with outliers directly by either winsorizing or trimming the sample to the 99th,

[12] As mentioned before, Gelman and Imbens (2018) discourage the use of high-order polynomials in RDD.

95th or 90th percentile of the dependent variable.[13] The results, shown in Table A4 in the Appendix, are comparable to column 3 in Table 3. Overall, the results show similar effects to those found in our preferred specification. When trimming the sample to the 95th percentile (column 4), the effect of electing a female mayor on violence is 39 percent. When the sample is trimmed to the 90th percentile (column 6), the effect is no longer significant, but the point estimate is still of sizable magnitude (an effect of 28 percent).

Our sample includes elections with more that two candidates when the third place obtained 15% or less of the vote share. Table A5 in the Appendix shows estimates of Equation 2 for alternative thresholds for third-placed candidates, with column 6 replicating our preferred specification. Results are similar in significance and magnitude except in column 12, when we exclude all third-place candidates. However, the point estimate is quite similar to our benchmark estimate even though the sample is considerable smaller.

4.3 Heterogeneity

To better understand the effect of female mayors on curbing violence against women, Table 4 shows estimates for various types of violence, as well as other characteristics of the violent event, such as the place where it took place or the identity of the perpetrator. Odd columns show OLS estimates, while even columns present the corresponding RDD estimates. The definition of these variables can be found in Table A1 in the Appendix. Figures A7 and A8 show the corresponding RDD plots.

Panel A reports the results according to the type of violence reported by the victim. The most prevalent type is physical violence, followed by psychological and sexual violence (notice that these categories are not mutually exclusive). We find the largest effect on sexual violence (61 percent), followed by psychological (58 percent) and physical violence (37 percent).

In Panel B of Table 4 we analyze the effect of female mayors on violence by the place where the violent event took place. The results show a statistically significant effect when the episode occurred at home. We also find effects when the episode occurred on the street, but these results are not statistically significant. Neither they are when we consider other public places, such as schools, bars, shops, stadiums and others.

Panel C shows a significant effect when the perpetrator is the partner or ex-partner (this includes the husband or ex-husband and boyfriend or ex-boyfriend). The effect is of

[13] When trimming the sample, we keep the optimal bandwidth of the winsorized sample, to allow comparability between these two results.

similar magnitude but not significant when the perpetrator is a relative, which includes the father, stepfather, brother or son. We also find a significant effect when the perpetrator is in the other category, which includes a friend, boss, carer, policeman, person with an institutional relationship (doctor or priest) and other cases.

When we analyze the means used to exercise violence in panel D, we find large and significant effects for the cases of threat, followed by the categories of physical aggression and object aggression, which includes gun, knife and other objects. Finally, Panel E shows that electing female mayors significantly decreases cases in which alcohol use is suspected in the violent episode. For the case of recurrent violence, we find a negative effect that is not statistically significant.

Figures A7 and A8 in the Appendix show the corresponding RDD plots for these outcomes. Results in Table 4 are robust to including covariates and estimating through different specifications. The details can be seen in Tables A6 - A10 in the Appendix.

In addition to studying violence against women, we analyze the impact of mayors' gender on female homicides. Panel F in Table 4 presents the effect of a female mayor on homicides per 10,000 women (columns 1 and 2), as well as homicides occurring at home (columns 3 and 4). There is a negative effect on homicides (column 2), although not statistically significant. However, we do find a statistically significant effect for homicides at home. These results are reassuring, since data from homicides comes from a different source, and thus are not subject to improvements in reporting over time. Table A11 in the Appendix shows results when covariates are including as well as considering alternative specifications.

When analyzing the effect on violence against women by age group in Figure 4, we can see that it is negative for all age brackets. However, we only find significant effects for women 15-19 and 30-39 years old.

Summing up, our results show significant reductions in violence against women throughout types of violence, and more precisely estimated for cases of violence when the perpetrator is the partner or ex-partner, and when the episode occurs at home. Consistent with these results, we find a reduction in female homicides, particularly for homicides at home.

4.4 Mechanisms

In this section we attempt to provide evidence of the mechanisms through which this reduction in violence against women takes place. As discussed previously, the reduction can come from policies implemented by the mayor while in office, or by a role model effect, empowering women to act when experiencing violence. The evidence in the literature suggests that the role model effect is unlikely to be driving the results. First, Iyer et al. (2012) show that female leaders increase reporting of episodes of violence against women, therefore it is unlikely that the role model channel would have generated a decrease in cases of violence. Second, Brollo and Troiano (2016) show that female mayors in Brazil have an effect on outcomes related to women's wellbeing, such as pre-natal visits and non-premature births. Thus in what follows we show evidence which we deem consistent with the policies channel.

In Table 5 we estimate the effect of electing a female mayor for each year of the mayoral term. We can see the effect of a female mayor on the first, second, third and forth year of mandate. Panel A shows results for the full sample, while Panel B restricts the sample to municipalities in which the mayor's full tenure is in the sample. Focusing on Panel A, columns 1-4 show that there is a negative but small and imprecisely estimated effect during the first two years of the mayoral term. On the other hand, in columns 5-8 we find that the effect found in Table 3 is concentrated in the last two years of her mandate. Panel B shows similar results, but less precise given that the sample is much smaller. These results suggest that the effect female mayors on violence takes time to materialize, which is consistent with the public policy channel.

In addition, in Table 6 we estimate the effect of female mayors on violence against women according to the proportion of women in the local council. As discussed in Section 2, councilors have an impact on what public policies mayors can implement, because they have veto power on the mayoral annual budget proposal. Therefore, a larger share of female councilors might help female mayors to enact policies aimed at reducing violence towards women. Columns 1 and 2 give estimates for municipalities where the share of female councilors is less or equal that the median (11 percent), while columns 3 and 4 include municipalities where the share is above the median. We find negative coefficients above and below the median (columns 2 and 4). However, below the median the coefficient is small and not statistically significant, while the opposite is true when the share of female councilors is above the median. These results are consistent with Gagliarducci and Paserman (2012), who find that female mayors are less likely to be sacked when there is a larger share of female councilors.

Finally, in Table 7 we look at other outcomes that could be associated with policies towards women's overall health, such as deaths caused by car accidents, or death caused by tumors or infections (panel A). We also analyze male homicides and sexual violence against men (panel B), which could be associated with an increase in overall safety. In none of these outcomes we find statistically or economically significant effects, suggesting that the effect of female mayors comes from policies directly aimed at curbing violence against women.

5 Conclusions

We study the relationship between female political representation and violence against women. Specifically, we analyze whether electing a female mayor leads to lower rates of gender violence in Brazil. We use data for violence against women from the Ministry of Health and electoral information from the Electoral Superior Court of Brazil. Because the gender of the mayor is endogenous to observable and non-observable municipal characteristics, we employ a Regression Discontinuity Design strategy for mayoral elections.

The results show that female political representation reduces violence against women. In particular, our preferred specification show that electing a female mayor decreases cases of violence in 63 percent. The effect is larger for episodes of sexual violence happening at home, perpetrated by the partner or ex-partner of the victim. The effect is also concentrated on women aged 15-39.

We conjecture that the effect is due to policies that female mayors implement while in office. The effect of female mayors is concentrated towards the end of their mandate, and is larger when the municipality has a larger share of female councilors. However, more research is needed to identify specific policies that reduce violence.

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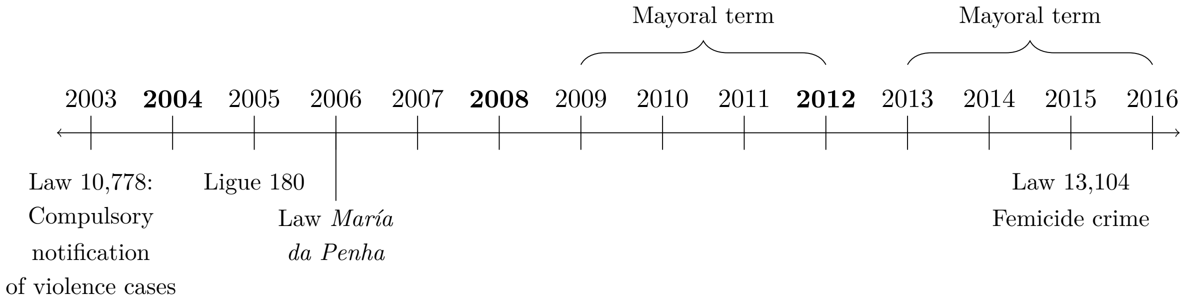
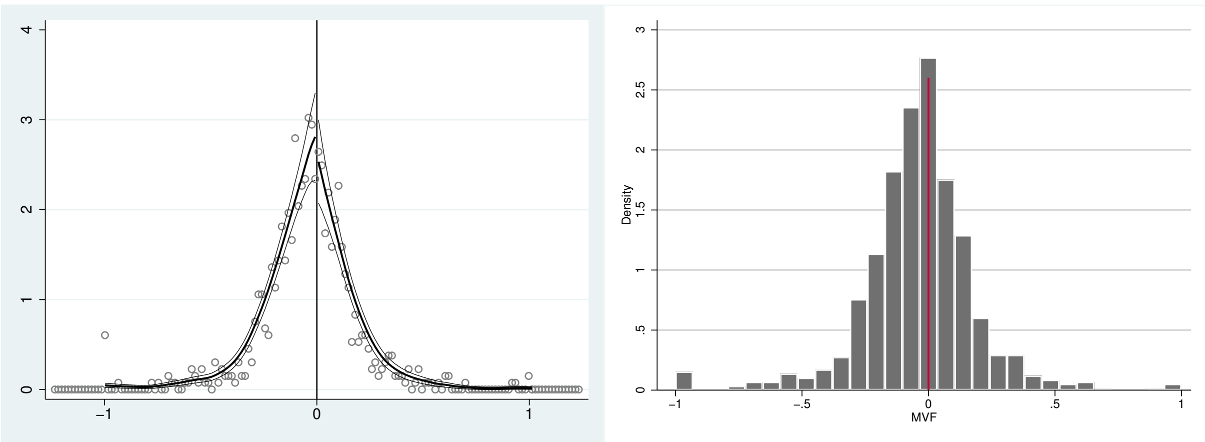
Tables and figures

Figure 1
Laws against gender violence



Notes: Years in bold indicate municipal elections.

Figure 2
Continuity on MVF



(a) **McCrary's Test** (b) **Histogram**

Notes: Female margin of victory of 2008 and 2012. (a) McCrary's test is a kernel estimation of the log density of MVF_{it}. The discontinuity estimation is -0.074 and the standard error is 0.122 (b) The bandwidth is 0.05.

Table 1
Descriptive statistics - Municipalities with a female mayor vs. municipalities with a male mayor

	(1) Female	(2) Obs.	(3) Male	(4) Obs.	(5) p-value
Municipal characteristics					
Population	14,278	349	12,986	494	0.082*
Income per capita (R$)	464	349	455	494	0.562
Literacy rate	0.781	349	0.782	494	0.914
Urban	0.634	349	0.616	494	0.222
Income ratio	0.802	349	0.785	494	0.134
Occupied men	0.510	349	0.506	494	0.681
Secondary education	0.166	349	0.163	494	0.486
Absenteeism	0.126	349	0.126	494	0.910
North	0.072	349	0.081	494	0.617
Noreast	0.330	349	0.330	494	0.989
Center	0.077	349	0.101	494	0.237
South	0.226	349	0.217	494	0.737
Southeast	0.295	349	0.271	494	0.448
Mayoral characteristics					
Age	48	349	48	494	0.898
Primary education	0.037	349	0.126	494	0.000***
Secondary education	0.252	349	0.310	494	0.069*
College	0.688	349	0.445	494	0.000***
Married	0.668	349	0.787	494	0.000***
Incumbent	0.252	349	0.310	494	0.069*
PMDB	0.201	349	0.190	494	0.710
PT	0.115	349	0.121	494	0.762
DEM	0.060	349	0.071	494	0.540
PSDB	0.140	349	0.117	494	0.324
Dependent variables					
Violence against women	11.057	349	10.642	494	0.757
Physical violence	8.858	349	8.574	494	0.772
Sexual violence	1.106	349	1.418	494	0.069*
Psychological violence	5.766	349	4.815	494	0.321
Violence at home	7.990	349	7.453	494	0.582
Violence in the street	1.473	349	1.753	494	0.256
Violence in a public place	1.412	349	1.171	494	0.309
Partner or ex-partner	5.427	349	4.766	494	0.350
Relative	1.923	349	1.711	494	0.451
Other perpetrator	2.735	349	2.816	494	0.820
Physical agression	7.654	349	7.645	494	0.992
Threat	3.123	349	2.718	494	0.537
Object agression	1.448	349	1.734	494	0.126
Recurrent violence	5.524	349	4.728	494	0.248
Alcohol use by perpetrator	4.759	349	4.291	494	0.450
Female homicide	0.517	307	0.556	457	0.395
Female homicide at home	0.195	307	0.246	457	0.106

Notes: Columns (1) and (3) show the variables' average on municipalities with female mayors (treatment group) and male mayors (control group). Columns (2) and (4) show the number of observations for each case. Column (5) displays the p-value of a mean difference test. Dependent variables are measured as the rate per 10,000 women. More detail on the variables in Table A1. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table 2
Discontinuities on municipal and mayoral characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Municipal characteristics	Population	Income	Literacy	Urban	Income ratio	Occupied	Secondary	Absenteeism
Female	0.142	34.003	0.009	0.046	0.019	0.001	0.008	-0.000
	(0.146)	(39.585)	(0.016)	(0.034)	(0.031)	(0.021)	(0.009)	(0.008)
Optimal bandwidth	0.13	0.17	0.18	0.17	0.17	0.19	0.19	0.19
Observations	465	546	567	546	554	592	574	581
Panel B: Brazilian macro-regions	North	Northeast	Center	South	Southeast			
Female	-0.065	0.028	-0.006	-0.007	0.088			
	(0.045)	(0.085)	(0.047)	(0.069)	(0.067)			
Optimal bandwidth	0.16	0.15	0.16	0.19	0.18			
Observations	529	500	529	581	573			
Panel C: Mayoral characteristics	Age	Primary	Secondary	College	Married	Incumbent		
Female	0.274	-0.043	-0.025	0.048	0.080	-0.064		
	(1.489)	(0.035)	(0.081)	(0.085)	(0.082)	(0.068)		
Optimal bandwidth	0.15	0.13	0.13	0.13	0.14	0.16		
Observations	517	477	467	474	488	537		
Panel D: Political parties	PMDB	PT	DEM	PSDB				
Female	0.028	0.011	-0.038	0.010				
	(0.068)	(0.054)	(0.041)	(0.055)				
Optimal bandwidth	0.17	0.15	0.15	0.12				
Observations	543	501	518	444				

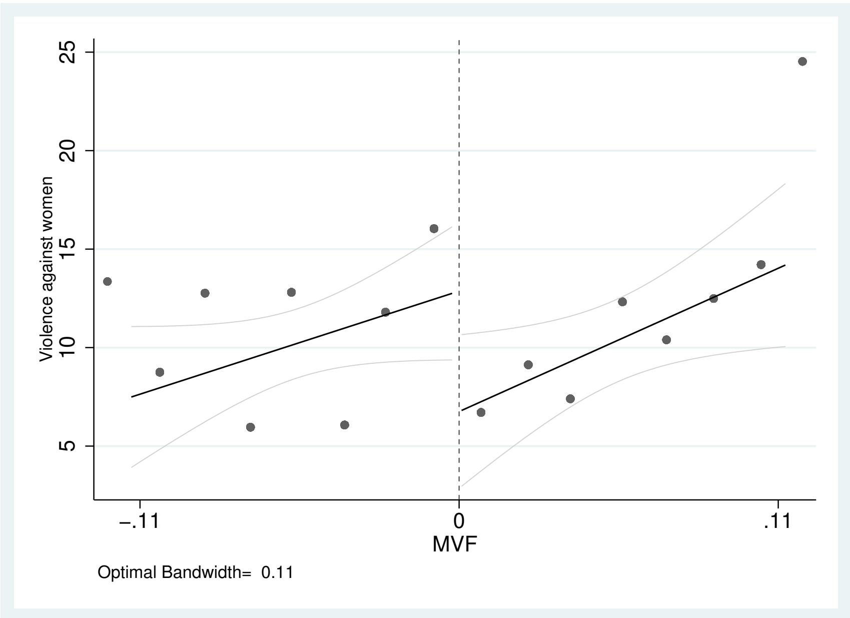
Notes: All columns include year fixed effects. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014). ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table 3
The effect of a female mayor on violence against women

	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.01	-1.39	-6.49**	-6.93***	-10.15**	-1.46	-11.14***	-11.96***
	(1.71)	(1.38)	(2.55)	(2.50)	(4.00)	(1.96)	(3.67)	(3.91)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.06	0.23	0.15	0.24
Output mean	10.81	10.81	10.27	10.27	9.78	10.42	10.83	10.36
Control group mean	10.64	10.64	10.22	10.22	10.96	10.25	10.57	10.16
Observations	843	843	444	444	237	672	547	682

Notes: The dependent variable is cases of violence against women per 10,000 women. All columns include year fixed effects. In columns 2 and 4 municipality controls are log of population, income, literacy, urban, income ratio, occupied, secondary, absenteesim, North, Northeast, Midwest, South, Southeast, and mayoral controls are age, primary education, high-school, college, married, incumbent, PMDB, PT, DEM and PSDB. All variables are defined in table A1 in the Appendix. Optimal bandwidth estimated using the methodology by Calonico et al. (2014). Robust standard errors clustered at the municipality level in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10%, respectively.

Figure 3
The impact of a female mayor on violence against women: Main result



Notes: The black lines represent predicted values of a linear prediction model, while the grey lines show the confidence interval at 95%.

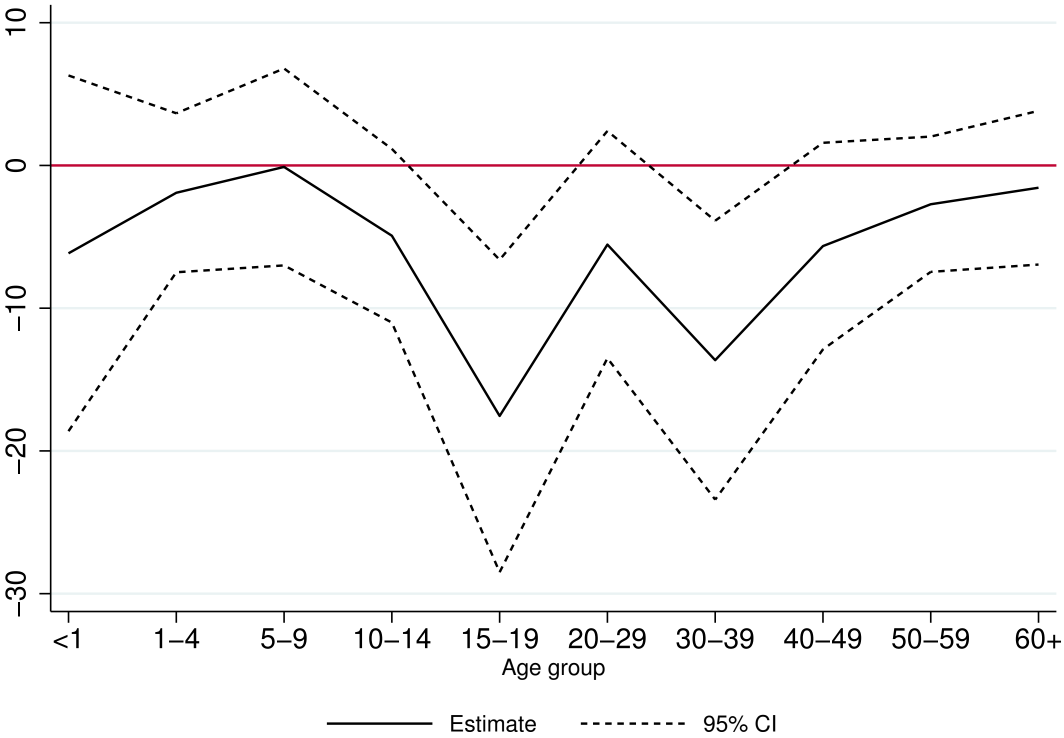
Table 4

The effect of a female mayor on violence against women: Heterogeneous Effects

	OLS (1)	RDD (2)	OLS (3)	RDD (4)	OLS (5)	RDD (6)
Panel A: Type of violence	Physical		Sexual		Psychological	
Female	-0.39	-3.67*	-0.41*	-0.83*	0.94	-2.96*
	(1.30)	(2.20)	(0.22)	(0.48)	(1.29)	(1.65)
Output mean	8.69	8.79	1.29	1.35	5.21	5.09
Observations	843	501	843	517	843	429
Panel B: Place	Home		Street		Public place	
Female	0.38	-6.22**	-0.65**	-0.71	0.19	-0.40
	(1.31)	(2.74)	(0.29)	(0.48)	(0.32)	(0.37)
Output mean	7.68	7.92	1.64	1.53	1.27	1.18
Observations	843	454	843	531	843	444
Panel C: Perpetrator	Partner or ex-partner		Relative		Other	
Female	0.16	-3.35**	0.41	-1.27	-0.28	-1.71**
	(0.94)	(1.39)	(0.37)	(0.78)	(0.46)	(0.81)
Output mean	5.04	4.87	1.80	1.93	2.78	2.72
Observations	843	430	843	454	843	386
Panel D: Means	Physical aggression		Threat		Object agression	
Female	-0.61	-4.39**	0.27	-2.36**	-0.54**	-0.95*
	(1.18)	(2.13)	(0.88)	(1.01)	(0.25)	(0.53)
Output mean	7.65	7.81	2.89	2.67	1.62	1.70
Observations	843	478	843	437	843	531
Panel E: Other characteristics	Recurrent		Alcohol use			
Female	0.84	-2.13	0.22	-2.91**		
	(0.93)	(1.38)	(0.81)	(1.27)		
Output mean	5.06	4.98	4.48	4.34		
Observations	843	445	843	431		
Panel F: Female homicide	Homicide		Homicide at home			
Female	-0.05	-0.11	-0.08*	-0.20**		
	(0.07)	(0.11)	(0.05)	(0.09)		
Output mean	0.55	0.56	0.24	0.26		
Observations	630	432	630	401		

Notes: The dependent variable is cases of violence against women per 10,000 women. All columns were estimated without covariates, include year fixed effects and are estimations of a first-order polynomial. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014). ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Figure 4
Violence against women by age group



Notes:

Table 5

The effect of a female mayor on violence against women: Tenure

	Years after election							
Panel A: Whole sample	$t = 1$		$t = 2$		$t = 3$		$t = 4$	
	OLS	RDD	OLS	RDD	OLS	RDD	OLS	RDD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	2.62	-3.00	2.56	-1.36	-0.63	-6.77*	-0.68	-8.59*
	(2.04)	(3.58)	(2.64)	(3.36)	(2.68)	(3.71)	(2.29)	(4.41)
Covariates	No	No	No	No	No	No	No	No
Polynomial order		1		1		1		1
Optimal bandwidth		0.13		0.10		0.10		0.11
Output mean	13.23	11.85	12.04	9.97	11.15	11.35	10.81	11.75
Observations	488	279	598	275	723	351	843	415
Panel B: Sample with data in the four years	$t = 1$		$t = 2$		$t = 3$		$t = 4$	
	OLS	RDD	OLS	RDD	OLS	RDD	OLS	RDD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	2.62	-3.00	3.54	-2.32	2.23	-5.92	2.17	-9.12
	(2.04)	(3.58)	(3.12)	(4.19)	(3.84)	(5.79)	(3.66)	(7.73)
Covariates	No	No	No	No	No	No	No	No
Polynomial order		1		1		1		1
Optimal bandwidth		0.13		0.10		0.10		0.11
Output mean	13.23	11.85	13.23	10.76	13.23	13.53	13.23	15.18
Observations	488	279	488	225	488	232	488	242

Notes: Dependent variable is cases of violence against women per 10,000 women. All columns were estimated without covariates, include year fixed effects and are estimations of a first-order polynomial. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table 6

The effect of a female mayor on violence against women: Other women in city council

Share women in city council:	Under 11.1%		Above 11.1%	
	OLS	RDD	OLS	RDD
	(1)	(2)	(3)	(4)
Female	0.20	-3.99	-0.21	-7.16**
	(2.03)	(3.58)	(3.10)	(3.24)
Covariates	No	No	No	No
Polynomial order		1		1
Optimal bandwidth		0.12		0.11
Output mean	11.43	10.69	9.99	9.45
Observations	481	269	362	179

Notes: Dependent variable is cases of violence against women per 10,000 women. All columns were estimated without covariates, include year fixed effects and are estimations of a first-order polynomial. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table 7

The effect of a female mayor on violence against women: Other outcomes

Panel A: Women	Death caused by a car accident		Death caused by a tumor		Death caused by an infection	
	OLS	RDD	OLS	RDD	OLS	RDD
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.14	0.02	0.26	0.74	0.02	-0.24
	(0.21)	(0.23)	(0.35)	(0.62)	(0.16)	(0.29)
Covariates	No	No	No	No	No	No
Polynomial order	1	1	1	1	1	1
Optimal bandwidth		0.21		0.16		0.14
Output mean	1.48	1.48	8.10	8.22	2.42	2.42
Observations	678	508	804	536	749	457

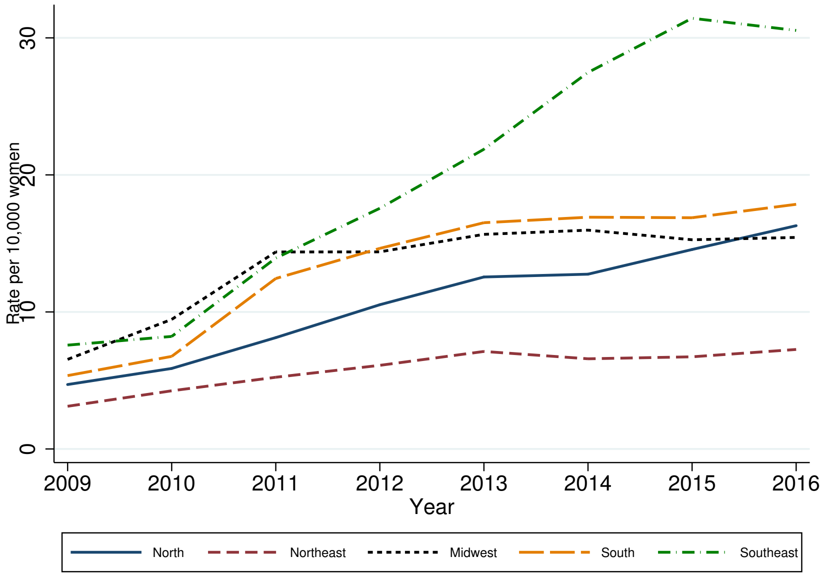
Panel B: Men	Homicide		Homicide at home		Sexual violence	
	OLS	RDD	OLS	RDD	OLS	RDD
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.35	0.89	-0.03	-0.01	-0.08	-0.31
	(0.33)	(0.62)	(0.14)	(0.22)	(0.14)	(0.27)
Covariates	No	No	No	No	No	No
Polynomial order	1	1	1	1	1	1
Optimal bandwidth		0.13		0.15		0.12
Output mean	3.92	3.92	1.13	1.12	0.59	0.57
Observations	747	427	543	354	237	133

Notes: Coefficients represent the rate per 10,000 women or men, depending on the panel. All columns were estimated without covariates, include year fixed effects and are estimations of a first-order polynomial. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014). ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Appendix

Figure A1

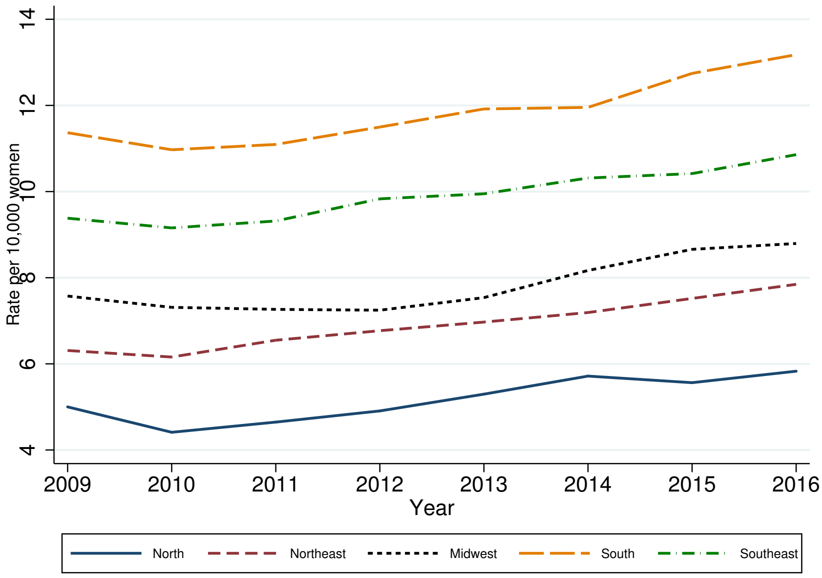
Evolution of cases of violence against women by macroregions



Notes: Own elaboration using information from the Health Ministry and 2010 census.

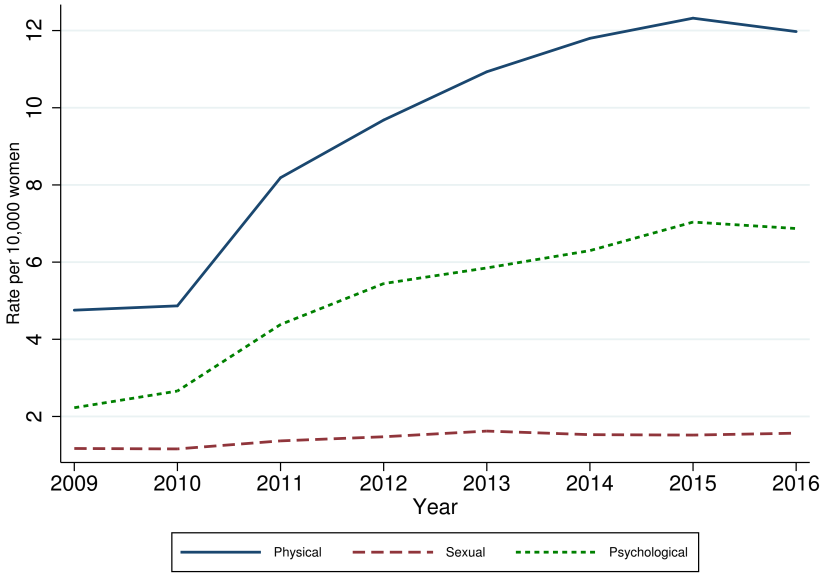
Figure A2

Evolution of female deaths cased by tumors by macroregions



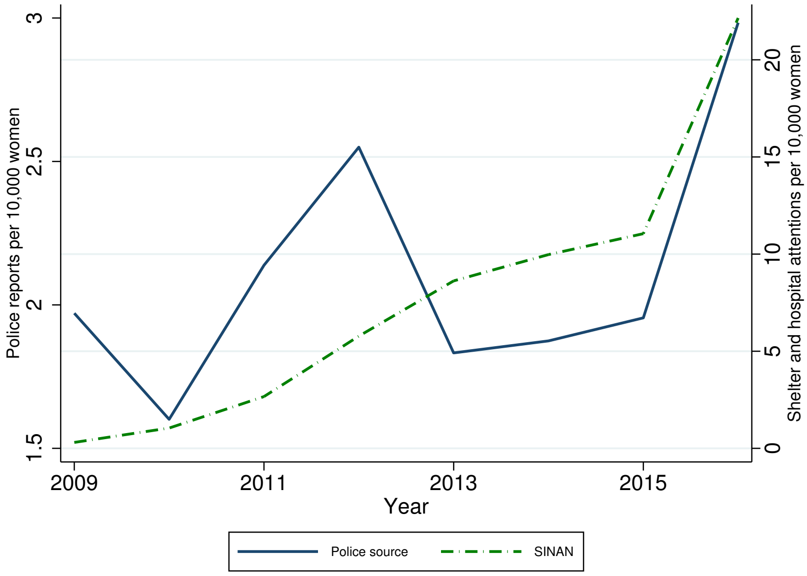
Notes: Own elaboration using information from the Health Ministry and 2010 census.

Figure A3
Evolution of cases of violence against women by type



Notes: Own elaboration using information from the Health Ministry and 2010 census.

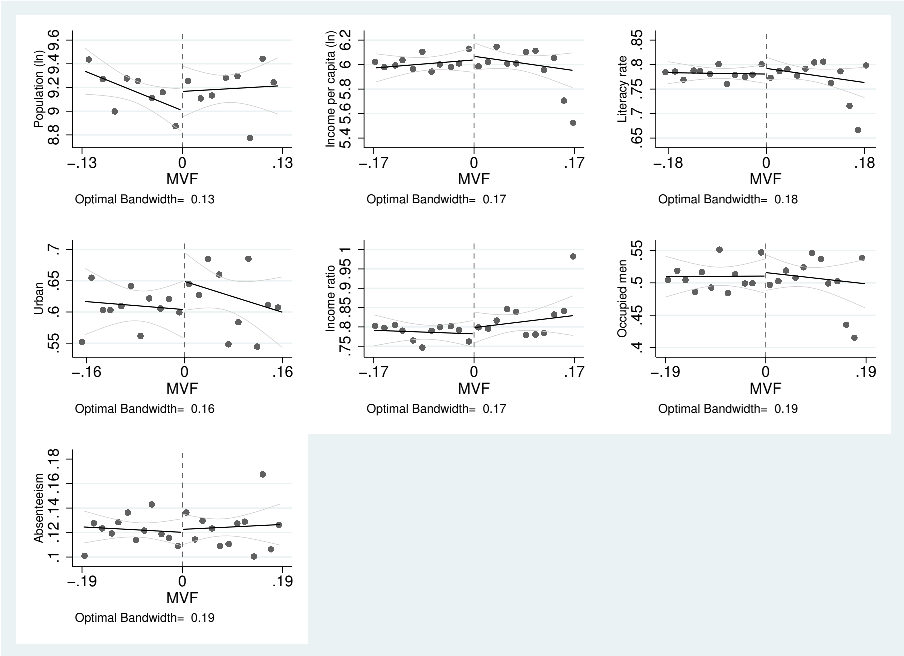
Figure A4
Evolution of cases of violence against women by source in Rio de Janeiro



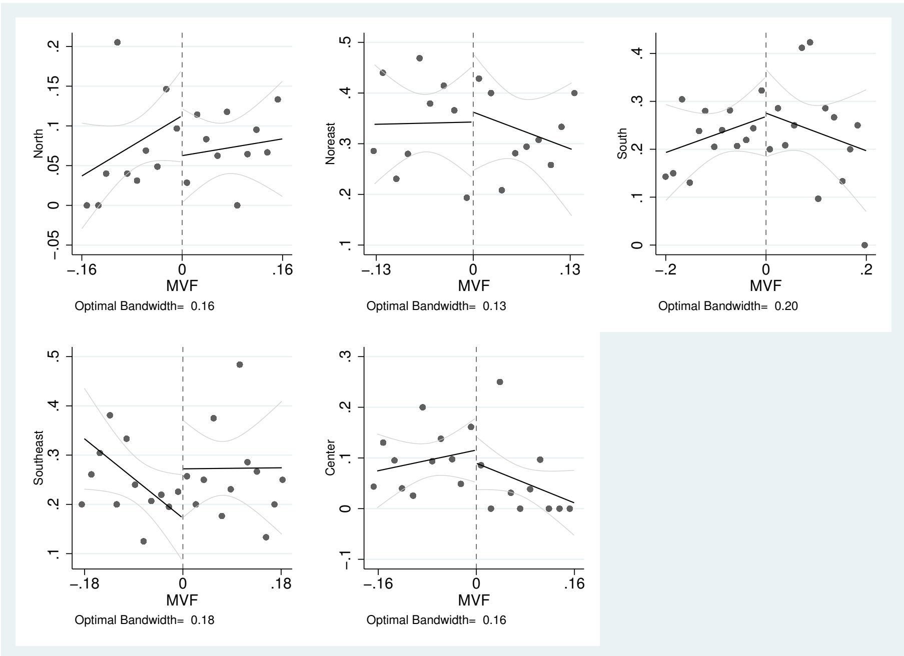
Notes: Own elaboration using information from the Health Ministry and police reports.

Figure A5

Balance tests - Municipalities



(a) **Municipal characteristics**

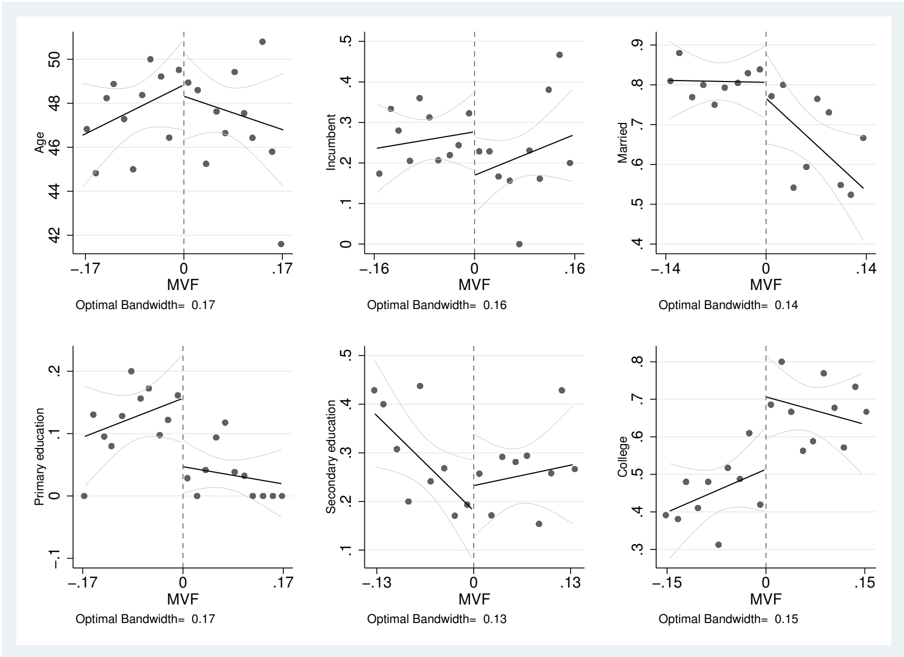


(b) **Brazilian macro-regions**

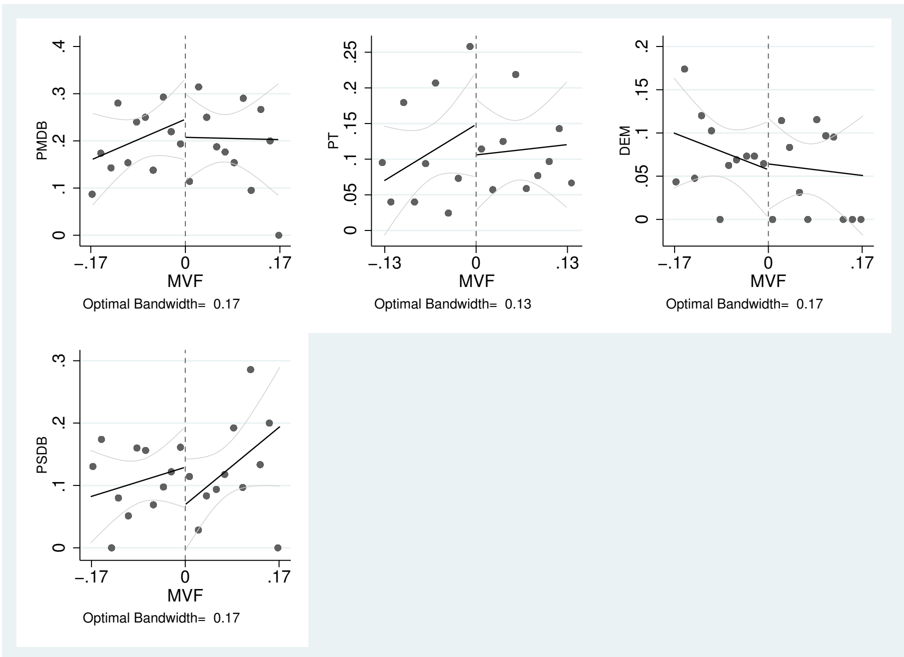
Notes: Pre-treatment characteristics from year 2010. Population and income are measured in thousands. The solid lines represent predicted values of a linear polynomial smoothing, while the dotted lines show the confidence interval at 95%.

Figure A6

Balance tests - Mayors



(a) **Mayoral characteristics**

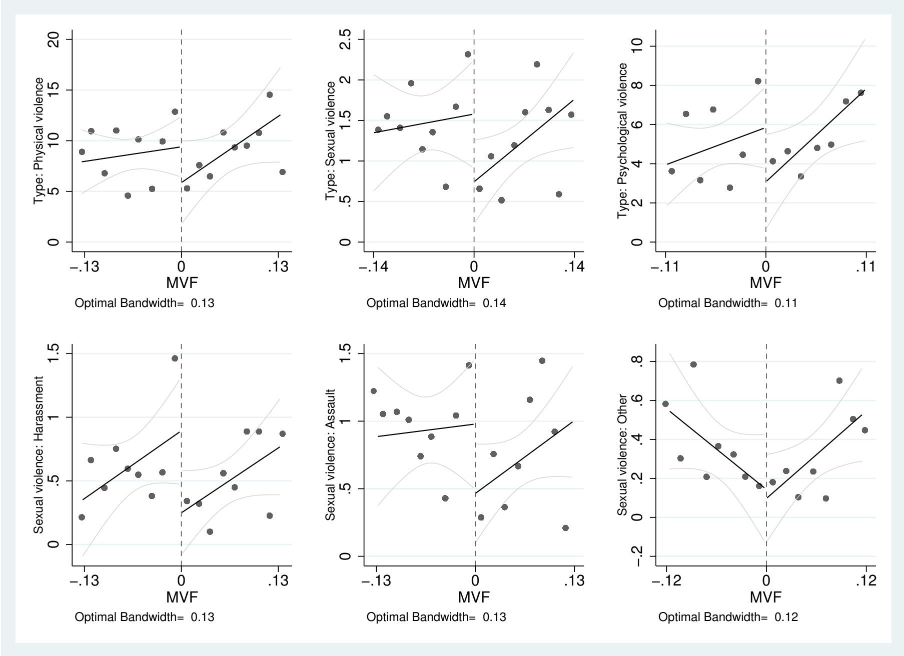


(b) **Political parties**

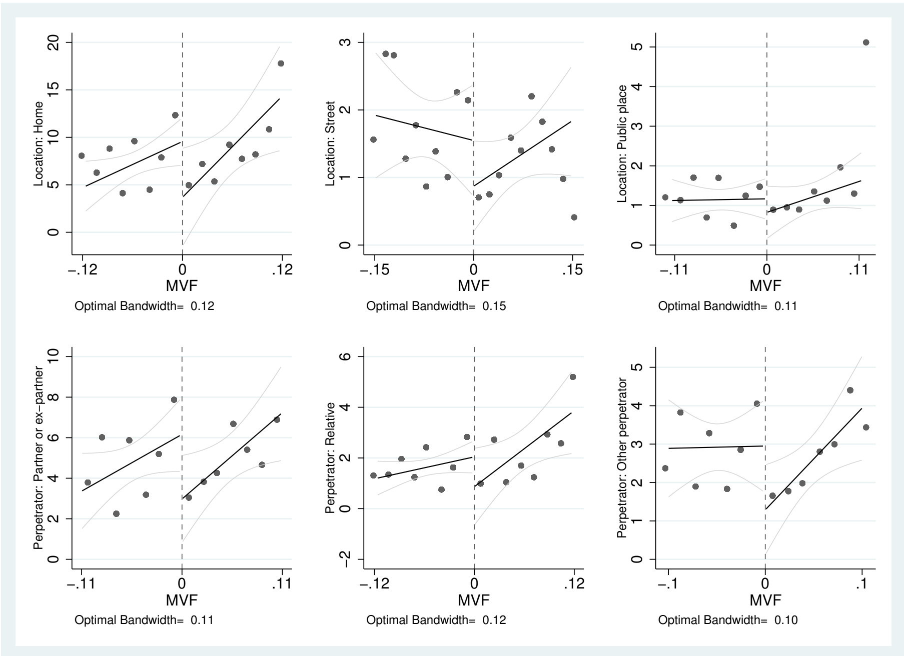
Notes: Pre-treatment characteristics from years 2008 and 2012. Population and income are measured in thousands. The solid lines represent predicted values of a linear polynomial smoothing, while the dotted lines show the confidence interval at 95%.

Figure A7

The impact of a female mayor on different violence-related outcomes



(a) **According to type of violence**

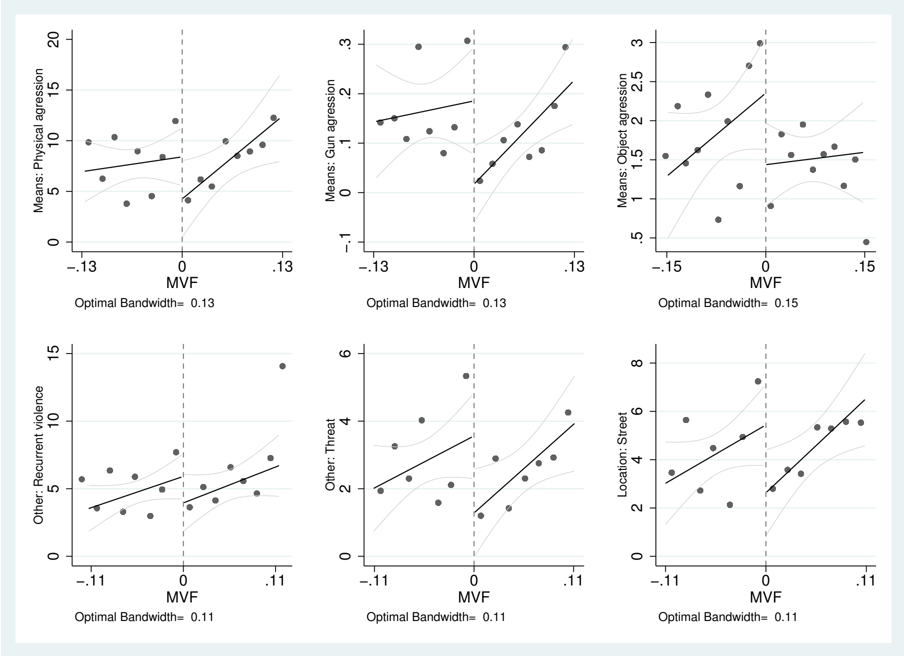


(b) **According to place or perpetrator**

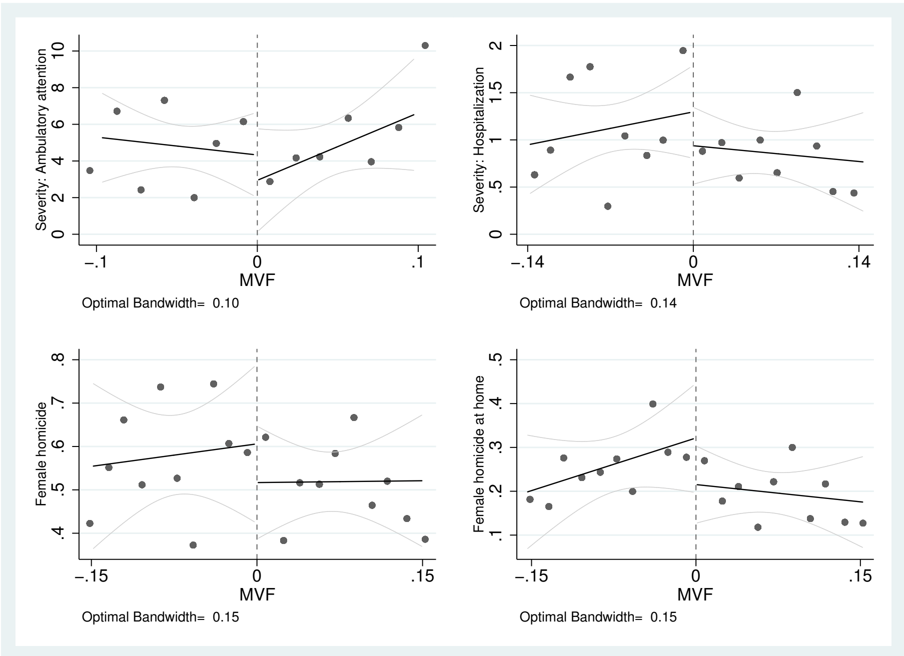
Notes: The solid lines represent predicted values of a linear polynomial smoothing, while the dotted lines show the confidence interval at 95%.

Figure A8

The impact of a female mayor on different violence-related outcomes



(a) **According to means or other characteristics**



(b) **According to severity or female homicide**

Notes: The black lines represent predicted values of a linear prediction model, while the grey lines show the confidence interval at 95%.

Table A1
Description of variables

Municipal characteristics	
Population	Number of inhabitants.
Income	Per-capita income in Brazilian *reais*.
Literacy rate	Share of people above age 20 that can read and write.
Urban	Share of people who live in urban areas.
Income ratio	Ratio between female and male wages for people 15-65 years old.
Occupied men	Share of men between 15 and 65 years old with an occupation.
Secondary education	Share of people with secondary education.
Absenteeism	Share of voters that did not vote.
North	Share of households located in the northern region of Brazil.
Northeast	Share of households located in the northeastern region of Brazil.
Center	Share of households located in the central region of Brazil.
South	Share of households located in the southern region of Brazil.
Southeast	Share of households located in the southeastern region of Brazil.
Mayoral characteristics	
Age	Age of mayor in election year.
Primary	Mayor has primary education.
High school	Mayors has high-school education.
College	Mayor with college education.
Married	Mayor is married.
Incumbent	Mayor is in his/her second consecutive electoral period.
PMDB	Mayor belongs to *Movimento Democrático Brasileiro.*
PT	Mayor belongs to *Partido dos Trabalhadores.*
DEM	Mayor belongs to *Democratas.*
PSDB	Mayor belongs to *Partido da Social Democracia Brasileira.*
Dependent variables	
Violence against women	Cases of violence per 10,000 women.
Physical violence	Cases of physical violence per 10,000 women.
Sexual violence	Cases of sexual violence per 10,000 women.
Psychological violence	Cases of psychological violence per 10,000 women.
Harassment	Cases of harassment per 10,000 women.
Assault	Cases of assault per 10,000 women.
Threat	Cases of reported threats per 10,000 women.
Recurrent violence	Cases of recurrent violence per 10,000 women.
Violence at home	Cases of violence in the victim's household per 10,000 women.
Violence in a public place	Cases of violence occured in the street, school, sport center, pub or commerce per 10,000 women.
Physical aggression	Cases of physical aggression per 10,000 women.
Gun aggression	Cases of gun aggression per 10,000 women.
Object aggression	Cases of heavy, hot or sharp object aggression per 10,000 women.
Ambulatory attention	Cases of ambulatory attention for violence per 10,000 women.
Hospitalization	Cases hospitalized for violence per 10,000 women.
Violence resulting in death	Cases of death because of violence per 10,000 women.
Female homicide	Women murdered.
Female homicide at home	Women murdered at home.

Table A2

Descriptive statistics - Mixed races vs. Other races in Brazil

	(1) Sample	(2) Obs	(3) Other races	(4) Obs	(5) p-value
Municipal characteristics					
Population	17,610	479	12,961	497	0.000***
Income per capita (R$)	474	479	455	497	0.149
Literacy rate	0.784	479	0.782	497	0.687
Urban	0.651	479	0.616	497	0.008***
Income ratio	0.796	479	0.785	497	0.312
Occupied men	0.510	479	0.506	497	0.609
Secondary education	0.172	479	0.163	497	0.021**
Absenteeism	0.131	479	0.126	497	0.190
North	0.086	479	0.080	497	0.773
Noreast	0.326	479	0.332	497	0.834
Center	0.075	479	0.101	497	0.161
South	0.207	479	0.217	497	0.685
Southeast	0.307	479	0.270	497	0.199
Mayoral characteristics					
Age	48	479	48	497	0.949
Primary education	0.040	479	0.125	497	0.000***
Secondary education	0.228	479	0.310	497	0.004***
College	0.704	479	0.447	497	0.000***
Married	0.672	479	0.789	497	0.000***
Incumbent	0.234	479	0.308	497	0.009***
PMDB	0.194	479	0.189	497	0.842
PT	0.109	479	0.123	497	0.489
DEM	0.061	479	0.072	497	0.457
PSDB	0.152	479	0.119	497	0.124
Dependent variables					
Violence against women	10.480	479	10.604	497	0.917
Physical violence	8.421	479	8.546	497	0.886
Sexual violence	1.099	479	1.412	497	0.037**
Psychological violence	5.199	479	4.796	497	0.631
Violence at home	7.513	479	7.424	497	0.919
Violence in the street	1.450	479	1.750	497	0.170
Violence in a public place	1.317	479	1.166	497	0.464
Partner or ex-partner	4.995	479	4.752	497	0.696
Relative	1.792	479	1.704	497	0.723
Other perpetrator	2.688	479	2.806	497	0.716
Physical agression	7.341	479	7.619	497	0.730
Threat	2.829	479	2.704	497	0.828
Object agression	1.354	479	1.729	497	0.022**
Recurrent violence	5.098	479	4.712	497	0.530
Alcohol use by perpetrator	4.527	479	4.274	497	0.649
Female homicide	0.519	366	0.561	380	0.345
Female homicide at home	0.185	366	0.264	380	0.011**

Notes: Columns (1) and (3) show the variables' average in mixed races and other races. Columns (2) and (4) show the number of observations for each case. Column (5) displays the p-value of a mean difference test. Dependent variables are measured as the rate per 10,000 women. More detail on the variables in Table A1. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table A3

The effect of a female mayor on violence against women without southeast

	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-1.60	-1.24	-4.87**	-3.87*	-7.68**	-2.20	-7.40**	-10.88***
	(1.15)	(1.08)	(2.31)	(2.20)	(3.27)	(1.66)	(2.92)	(3.68)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.06	0.23	0.16	0.19
Output mean	8.84	8.84	9.12	9.12	8.82	8.67	8.69	8.72
Observations	576	576	317	317	168	470	399	435

Notes: The dependent variable is cases of violence against women per 10,000 women. All columns include year fixed effects. In columns 2 and 4 municipality controls are log of population, income, literacy, urban, income ratio, occupied, secondary, absenteesim, North, Northeast, Midwest, South, Southeast, and mayoral controls are age, primary education, high-school, college, married, incumbent, PMDB, PT, DEM and PSDB. All variables are defined in table A1 in the Appendix. Optimal bandwidth estimated using the methodology by Calonico et al. (2014). Robust standard errors clustered at the municipality level in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table A4

The effect of a female mayor on violence against women winsoring and trimming the sample

	99%		95%		90%	
	Winsor	Trim	Winsor	Trim	Winsor	Trim
Female	-6.13**	-5.62**	-5.51**	-3.23*	-3.23**	-1.78
	(2.53)	(2.41)	(2.23)	(1.87)	(1.59)	(1.29)
Covariates	No	No	No	No	No	No
Polynomial order	1	1	1	1	1	1
Optimal bandwidth	0.11	0.11	0.11	0.11	0.13	0.13
Control group mean	10.30	9.77	10.22	8.29	10.56	6.41
Observations	441	437	444	426	485	436

Notes: The dependent variable is cases of violence against women per 10,000 women. All columns include year fixed effects. The cases in which the sample was trimmed, the winsor data bandwidth was used. All variables are defined in table A1 in the Appendix. Optimal bandwidth estimated using the methodology by Calonico et al. (2014). Robust standard errors clustered at the municipality level in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10%, respectively.

Table A5

Share of votes of third candidate

	25%		20%		15%		10%		5%		0%	
	OLS	RDD	OLS	RDD	OLS	RDD	OLS	RDD	OLS	RDD	OLS	RDD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	-0.54	-5.29**	-0.25	-6.15**	-0.17	-6.49**	-0.42	-6.07*	-0.53	-7.89*	-0.14	-5.63
	(1.59)	(2.33)	(1.65)	(2.38)	(1.77)	(2.55)	(1.84)	(3.61)	(2.02)	(4.34)	(2.47)	(3.52)
Covariates	No	No	No	No	No	No	No	No	No	No	No	No
Polynomial order		1		1		1		1		1		1
Optimal bandwidth		0.11		0.11		0.11		0.13		0.12		0.10
Output mean	10.74	10.18	10.69	10.30	10.81	10.27	10.74	11.23	10.92	11.33	11.50	11.55
Observations	965	483	916	479	843	444	792	446	711	391	555	250

Notes: The dependent variable is cases of violence against women per 10,000 women. All columns were estimated without covariates, include year fixed effects and are estimations of a first-order polynomial. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014). ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table A6

The effect of a female mayor on violence against women according to type of violence

Panel A: Physical violence	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.39	-1.25	-3.67*	-5.06**	-6.91**	-1.17	-8.62***	-9.44***
	(1.30)	(1.14)	(2.20)	(2.39)	(2.92)	(1.56)	(2.91)	(3.25)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.13	0.13	0.07	0.27	0.15	0.22
Output mean	8.69	8.69	8.79	8.79	8.25	8.18	8.66	8.37
Observations	843	843	501	501	278	710	535	659

Panel B: Sexual violence	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.41*	-0.51**	-0.83*	-0.87*	-1.31*	-0.47	-1.32**	-1.67**
	(0.22)	(0.22)	(0.48)	(0.47)	(0.70)	(0.33)	(0.65)	(0.76)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.14	0.14	0.07	0.28	0.19	0.26
Output mean	1.29	1.29	1.35	1.35	1.20	1.30	1.30	1.31
Observations	843	843	517	517	290	728	615	702

Panel C: Psychological violence	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.94	0.11	-2.96*	-2.65	-2.54	-0.30	-5.29**	-4.85*
	(1.29)	(0.90)	(1.65)	(1.65)	(2.85)	(1.16)	(2.56)	(2.65)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.05	0.22	0.17	0.26
Output mean	5.21	5.21	5.09	5.09	4.64	5.04	5.31	4.93
Observations	843	843	429	429	229	659	572	702

Notes: Coefficients represent the rate of female hospital attention per 10,000 women. All columns include year fixed effects. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table A7

The effect of a female mayor on violence against women according to place of aggression

Panel A: Residence	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.38	-0.46	-6.22**	-6.81**	-6.99**	-0.90	-7.91***	-8.67***
	(1.31)	(1.04)	(2.74)	(3.00)	(3.00)	(1.48)	(2.84)	(3.02)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.12	0.12	0.06	0.23	0.16	0.24
Output mean	7.68	7.68	7.92	7.92	7.11	7.39	7.68	7.35
Observations	843	843	454	454	247	676	553	682

Panel B: Street	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.65**	-0.79***	-0.71	-1.09**	-1.85***	-0.54	-2.36***	-2.41***
	(0.29)	(0.29)	(0.48)	(0.50)	(0.62)	(0.37)	(0.70)	(0.73)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.15	0.15	0.07	0.30	0.15	0.24
Output mean	1.64	1.64	1.53	1.53	1.31	1.54	1.53	1.52
Observations	843	843	531	531	299	738	529	684

Panel C: Public place	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.19	-0.08	-0.40	-0.57	-0.75	-0.05	-0.70	-0.87
	(0.32)	(0.23)	(0.37)	(0.39)	(0.60)	(0.30)	(0.65)	(0.65)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.06	0.23	0.18	0.25
Output mean	1.27	1.27	1.18	1.18	1.03	1.26	1.33	1.24
Observations	843	843	444	444	237	670	593	694

Notes: Coefficients represent the rate of female hospital attention per 10,000 women. All columns include year fixed effects. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table A8

The effect of a female mayor on violence against women according to perpetrator

Panel A: Partner or ex-partner	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.16	-0.51	-3.35**	-3.55**	-5.02**	-0.93	-5.64***	-5.87***
	(0.94)	(0.77)	(1.39)	(1.39)	(2.14)	(1.07)	(1.94)	(2.07)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.05	0.22	0.15	0.26
Output mean	5.04	5.04	4.87	4.87	4.61	4.88	5.05	4.77
Observations	843	843	430	430	229	659	534	696

Panel B: Relative	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.41	0.16	-1.27	-1.33	-1.04	0.07	-1.54**	-1.55**
	(0.37)	(0.28)	(0.78)	(0.85)	(0.76)	(0.40)	(0.75)	(0.77)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.12	0.12	0.06	0.23	0.17	0.24
Output mean	1.80	1.80	1.93	1.93	1.63	1.78	1.85	1.77
Observations	843	843	454	454	247	676	581	682

Panel C: Other	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.28	-0.43	-1.71**	-1.58*	-2.80**	-0.68	-2.88***	-3.22***
	(0.46)	(0.39)	(0.81)	(0.80)	(1.20)	(0.59)	(1.03)	(1.12)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.10	0.10	0.05	0.20	0.16	0.25
Output mean	2.78	2.78	2.72	2.72	2.37	2.70	2.74	2.68
Observations	843	843	386	386	211	630	562	684

Notes: Coefficients represent the rate of female hospital attention per 10,000 women. All columns include year fixed effects. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table A9

The effect of a female mayor on violence against women according to means

Panel A: Physical agression	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.61	-1.30	-4.39**	-4.97**	-6.48**	-1.51	-8.98***	-9.91***
	(1.18)	(1.04)	(2.13)	(2.22)	(2.71)	(1.46)	(2.75)	(3.01)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.13	0.13	0.06	0.25	0.15	0.21
Output mean	7.65	7.65	7.81	7.81	7.00	7.23	7.72	7.30
Observations	843	843	478	478	262	691	520	642

Panel B: Threat	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.27	-0.33	-2.36**	-2.19**	-2.90*	-0.93	-3.72**	-3.40**
	(0.88)	(0.58)	(1.01)	(1.05)	(1.63)	(0.67)	(1.76)	(1.73)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.06	0.22	0.18	0.29
Output mean	2.89	2.89	2.67	2.67	2.37	2.87	2.96	2.86
Observations	843	843	437	437	234	662	601	734

Panel C: Object	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.54**	-0.61**	-0.95*	-1.23**	-2.04**	-0.49	-2.19***	-2.43***
	(0.25)	(0.25)	(0.53)	(0.54)	(0.79)	(0.37)	(0.80)	(0.94)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.15	0.15	0.07	0.30	0.17	0.24
Output mean	1.62	1.62	1.70	1.70	1.77	1.63	1.71	1.64
Observations	843	843	531	531	300	738	571	681

Notes: Coefficients represent the rate of female hospital attention per 10,000 women. All columns include year fixed effects. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table A10

The effect of a female mayor on violence against women according to other characteristics

Panel A: Recurrent	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.84	0.24	-2.13	-2.07	-3.52	-0.10	-4.40**	-4.09*
	(0.93)	(0.73)	(1.38)	(1.32)	(2.17)	(1.06)	(2.02)	(2.11)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.06	0.23	0.17	0.27
Output mean	5.06	5.06	4.98	4.98	4.80	5.02	5.16	4.93
Observations	843	843	445	445	238	672	577	715

Panel B: Alcohol use by perpetrator	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.22	-0.23	-2.91**	-3.08**	-5.16***	-0.72	-5.33***	-4.45**
	(0.81)	(0.66)	(1.27)	(1.23)	(1.93)	(0.98)	(1.81)	(1.92)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.11	0.11	0.06	0.22	0.15	0.29
Output mean	4.48	4.48	4.34	4.34	4.01	4.42	4.58	4.37
Observations	843	843	431	431	230	660	541	730

Notes: Coefficients represent the rate of female hospital attention per 10,000 women. All columns include year fixed effects. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.

Table A11

The effect of a female mayor on female homicides

Panel A: Female homicide	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.05	-0.02	-0.11	-0.04	-0.21	-0.12	-0.07	-0.23
	(0.07)	(0.07)	(0.11)	(0.12)	(0.14)	(0.09)	(0.13)	(0.18)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.17	0.17	0.09	0.34	0.28	0.21
Output mean	0.55	0.55	0.56	0.56	0.57	0.55	0.55	0.55
Observations	630	630	432	432	246	568	537	487

Panel B: Female homicide at home	OLS		RDD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.08*	-0.05	-0.20**	-0.14	-0.21*	-0.16**	-0.21**	-0.19
	(0.05)	(0.05)	(0.09)	(0.09)	(0.11)	(0.07)	(0.10)	(0.12)
Covariates	No	Yes	No	Yes	No	No	No	No
Polynomial order			1	1	1	1	2	3
Optimal bandwidth			0.15	0.15	0.08	0.30	0.23	0.26
Output mean	0.24	0.24	0.26	0.26	0.27	0.24	0.24	0.24
Observations	630	630	401	401	222	549	503	520

Notes: Coefficients represent the rate of female homicide per 10,000 women. All columns include year fixed effects. Robust standard errors clustered at the municipality level on parenthesis. Optimal bandwidth estimated using the methodology by Calonico et al. (2014): a bandwidth equal to 10 represents sample elections where MVF_{it} is between -10% and 10%. ***, ** and * indicate statistical significance at the 99%, 95% and 90%, respectively.