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Rally ‘round the Gun? Drug Battles and
“Tough-on-Crime” Candidates in Rio de Janeiro

Violência afeta preferências eleitorais? Confronto de
Facções e Candidatos “Linha Dura” na cidade do Rio de
Janeiro

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Janeiro**

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RESUMO

Esta dissertação estuda o efeito de exposição a violência em resultados eleitorais das eleições para deputado estadual na cidade do Rio de Janeiro de 2006 a 2018. Usando dados georreferenciados de denúncias anônimas, eu exploro a variação no tempo e no espaço de tiroteios por territórios na cidade do Rio de Janeiro. Os resultados principais indicam que a maior exposição a tiroteios leva a um maior percentual de votos em candidatos “linha dura” em áreas vizinhas a Unidades de Polícia Pacificadora (UPP) - um programa de policiamento comunitário implementado a partir de 2008. Eu argumento que tal programa aumentou a confiança dos eleitores em agentes de segurança e militares, conforme sugerido por pesquisa de opinião, beneficiando candidatos “linha dura”. Não há resultado significativo para participação. Os resultados são robustos a testes de sensibilidade e de falseamento.

Palavras-chave: Tiroteio. Linha Dura. Rio de Janeiro. Eleições. Violência.

ABSTRACT

This thesis studies the effects of violence exposure on electoral outcomes in Rio de Janeiro's state legislature elections from 2006 to 2018. By geo-referencing data from anonymous reports, I explore variation across time and space of gun shooting episodes when gangs battle over territories in the city of Rio de Janeiro. The main results indicate that higher exposure to shootings leads to higher vote share for tough-on-crime candidates in areas close to a Pacifying Police Unit (UPP) – a community oriented policing program introduced in 2008. I argue that such program boosted voters' confidence in law-enforcement and the military as suggested by survey data, benefiting tough-on-crime candidates. I also find null effects on turnout. The results are robust to a number of sensitivity checks and placebo analyses.

Keywords: Gunshooting. Tough-on-Crime. Rio de Janeiro. Elections. Violence.

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Rally ‘Round the Gun? Drug Battles and “Tough-on-Crime” Candidates in Rio de Janeiro *

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Abstract

This thesis studies the effects of violence exposure on electoral outcomes in Rio de Janeiro’s state legislature elections from 2006 to 2018. By geo-referencing data from anonymous reports, I explore variation across time and space of gun shooting episodes when gangs battle over territories in the city of Rio de Janeiro. The main results indicate that higher exposure to shootings leads to higher vote share for tough-on-crime candidates in areas close to a Pacifying Police Unit (UPP) – a community oriented policing program introduced in 2008. I argue that such program boosted voters’ confidence in law-enforcement and the military as suggested by survey data, benefiting tough-on-crime candidates. I also find null effects on turnout. The results are robust to a number of sensitivity checks and placebo analyses.

Keywords: Gunshooting, Tough-on-Crime, Rio de Janeiro, Elections, Violence

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1 Introduction

Brazil's 2018 elections were dominated by one single man: Jair Bolsonaro. Although early presidential polls indicated he would lose in various scenarios, Mr. Bolsonaro almost won on the first round, obtaining 46% of valid vote share, and, on the runoff, defeated Fernando Haddad from the Workers' Party (PT) to become the 38th president of Brazil. His party for less than a year, the Liberal Social Party (PSL), went from 1 to 52 seats in the lower house, becoming the second largest, and newcomer governor candidates attached to his image outpaced traditional politicians in Rio de Janeiro and Minas Gerais states.

Many factors could explain such phenomenon. Widespread rejection to PT, anti-corruption and anti-establishment statements, an alliance with liberal economist Paulo Guedes, signalling pro-market policies, and even being victim of a knife attack during campaign are possible reasons. But, most of all, Jair Bolsonaro has always been a "tough-on-crime" politician and, in a country such as Brazil, with high violence levels and growing concerns about public security, voters might support candidates whose platform promises to fix violence and crime once and for all.

A former army captain and federal representative for almost 30 years, Mr Bolsonaro has voted against gun prohibition and in favour of age of criminal responsibility reduction. His government plan for presidency includes gun liberalization to ensure citizens' right of self-defense and stricter parole decisions ("arresting and keeping arrested"). On January 15th, two weeks after taking office, he decreed more flexible rules for gun ownership and reassured his commitment to make carrying firearm easier as well in a near future. Besides that, and perhaps more simbolic, a gesture adopted by him and his supporters is making a finger gun.

Following this trend, candidates have opted to add rank to their name on the ballot, a way to better sinalize adherence to platform. Comparing to 2014, there was a 39% increase in candidates with rank in 2018 elections. Most of them (313 out of 553) have run for state

representative position, which are responsible for public security, and Mr Bolsonaro's party is the leading one in absolute number of "rank candidates".¹ According to DIAP, Public Security Parliamentary bench (also known as "bullet bench", *bancada da bala*) has grown from 35 to 61 representatives in Congress, half of them from PSL party.² Rio de Janeiro state, which had been under federal-military intervention on the security area since February, elected 8 of them, including Major Fabiana, a policewoman who got famous after stopping a bus from being ignited on fire while in heels back in 2014.

A public opinion poll by DataFolha in October 2017 revealed 72% of Rio de Janeiro's capital inhabitants would leave town because of violence and 83% of them support Army Forces participating in public security actions.³ At first, it is plausible to associate violence concerns and military support, but even in a scenario of public security calamity, which led governor Luiz Fernando Pezao to request forementioned federal backup, Rio has elected around the same number of "tough-on-crime" candidates as its neighboring states Sao Paulo and Minas Gerais. So, does violence or criminality affect demand for such candidates?

Looking at the data, business newspaper *Valor Economico* published an article⁴ assessing the correlation between homicide data from Violence Map (*Mapa da Violencia*) and Mr Bolsonaro's performance. In fact, the most violent municipalities voted **less** for Mr Bolsonaro. Economist Claudio Ferraz has made a similar analysis in an opinion article of his⁵ using state-level homicide rate variation and found the same result: where violence grew, his vote share was lower. But these are correlations and should **not** be interpreted as causal effect of violence. There is a clear bias, for example, if violence is correlated with poverty and poorer communities are aligned with left wing parties, such as PT, as disclaimed by researcher Bruno Paes Manso

¹<https://exame.abril.com.br/brasil/nome-militar-nas-urnas-cresce-39-nas-eleicoes/>

²<https://www.diap.org.br/index.php/noticias/agencia-diap/28531-eleicoes-2018-bancada-linha-dura-da-seguranca-publica-cresce-na-camara-e-no-senado>

³<https://www.valor.com.br/politica/5329425/ibope-mostrou-que-preocupacao-com-violencia-dobrou-em-um-ano>

⁴<https://www.valor.com.br/politica/5914559/bolsonaro-vai-pior-nos-locais-mais-violentos>.

⁵<https://www.nexojournal.com.br/colunistas/2018/O-que-causou-o-furac%C3%A3o-da-extrema-direita-nas-eleic%C3%A7%C3%B5es>

on the first piece. Sociologist Julio Jacobo Waiselfisz makes another fair point: if exposed to violence voters think reacting would only make it worse, this correlation can still be negative.

It is not clear if “tough-on-crime” candidates benefit or not from the rise in crime. On one hand, there is evidence on a support reaction after suffering attacks ((ONEAL; BRYAN, (1995)); (BERINSKY, (2009))) and punishment for “being soft” ((DRAGO; GALBIATI; SOBBRIO, (2018))). On the other hand, part of the literature has focused on social and psychological mechanisms which may play a decisive role and point to different directions ((DAVIS; SILVER, (2004)), (HUDDY et al., (2005)), (KRAUSE, (2014))). Several studies highlight trust in police and institutions as determinants (TYLER; HUO, (2002)), (CALDEIRA, (2002)). When looking at turnout, effects are in general positive: exposed individuals engage more in politics ((BATESON, (2012)), (BLATTMAN, (2009)), (BELLOWS; MIGUEL, (2009))).

In this paper, I estimate the causal effect of violence exposure on political preferences by exploiting exogenous variation of drug battles across Rio de Janeiro municipality between 2006 and 2018, following closely (MONTEIRO; ROCHA, (2017)). I test if being exposed leads to higher vote share for “tough-on-crime” state representative candidates, those who promise tougher responses to public security issues, identified by their registered profession and by adopting military rank as name on the ballot. With a database of anonymous reports provided by Disque Denuncia, a hotline service that collaborates with state authorities, the occurrence of gun shooting conflicts was mapped across town and is used as an explanatory variable in a panel model.

I find positive and significant effects for this type of candidate, but only in areas near a Pacifying Police Unit, a community oriented policing program which reconquers territories controlled by drug gangs with Military Forces backup. Due to this policy success, one possible explanation is that it benefited “tough-on-crime” candidates by improving police and military’s images, specially in direct contact areas. Once security forces are often perceived as corrupt

and not efficient, witnessing different behavior under the program seemed to have enhanced trust in such institutions and its agents⁶. Additional regressions show there is also no effect for turnout: being exposed to violence does not cause an increase of engagement as measured by attending on election day.

To the extent of my knowledge, there is no other work that has explored demand for “tough-on-crime” candidates caused by violence in a quasi-experimental electoral context, this research’s main contribution. The remainder of this paper proceeds as follows. Section 2 reviews related literature and Section 3 provides institutional background information and a description of the data and its sources. Section 4 presents the econometric model and identification strategy. Section 5 contains results and checks and Section 6 concludes.

⁶Forementioned DataFolha poll also revealed 67% of respondents fear more than trust Military Police and 34% believe most police officers are corrupt. Nonetheless, they believe UPP should only be remodeled, and not be terminated (Table 4)

2 Literature Review

2.1 Crime, Violence and Politics

Literature relating crime or violence to politics is often concentrated on extreme events such as terrorist attacks and civil wars. For instance, the *rally 'round the flag* effect characterizes the President's popularity upsurge in the aftermath of an external threat ((ONEAL; BRYAN, (1995)); (BERINSKY, (2009))). Others find higher support for right-wing parties, as they would be perceived as more competent to deal with such crises ((BERREBI; KLOR, (2006)); (KIBRIS, (2011))), or a combination of both: higher benefit for right-wing incumbent ((MEROLLA; ZECHMEISTER, (2009))). On a similar ground, (DRAGO; GALBIATI; SOBBRIO, (2018)) explore a natural experiment after a collective pardon for prisoners in Italy and found that support of this policy cost votes for the proponent and incumbent left-center coalition and even right-wing politicians that voted in favour, depending on municipal recidivism rates ("political cost of being soft on crime").

There is also a more extensive body of work which focus on politically-motivated violence, violence by the state and state capacity. (COLLIER; VICENTE, (2014)) describes how a anti-violence campaign affected elections in Nigeria through a field experiment. (ACEMOGLU; ROBINSON; SANTOS, (2013)) and (ALESINA; PICCOLO; PINOTTI, (2018)), on the other hand, model the action of Colombia paramilitary groups and Sicilian mafia, respectively, and strategic use of violence against politicians and/or with electoral goals. It is important to state that the conflicts I analyze are not politically-motivated and there is no record of drug gangs acting intentionally to divert electoral outcomes.⁷

Causality might work the other way around: (DELL, (2015)) shows that, when Mexican conservative PAN party wins in close elections, drug-related violence increases using an RD

⁷I use conflicts from January to September in electoral years since elections are held in the beginning of October. During most of this period, it is not clear who will run or how they will perform in order to strategically use violence in favour of some electoral group.

approach. This party’s “tough-on-crime” actions have cracked down incumbent gangs, but new groups have used this an opportunity to dominate, causing conflict to escalate. Violence also increased in alternative drug routes, as illegal activity found new ways to operate.

Surveys show, nonetheless, that support for tougher reactions depends on other factors. For instance, (DAVIS; SILVER, (2004)) ask about people’s willingness to give up civil liberties in exchange for more security. Responses vary according to trust in government, race and whether you are a liberal or a conservative. (HUDDY et al., (2005)), on the other hand, identify two different and opposing mechanisms: anxiety and perceived threat. While the latter would increase support as a need to retaliate, the former would reduce, accounting for a higher level of uncertainty on the political scenario. Finally, (KRAUSE, (2014)) argues perception of crime is more relevant than crime itself by exploiting media coverage on crime for Guatemala.

Violence exposure also affects political participation. (BATESON, (2012)) finds increase for a range of measures, from protests to community meetings, and support of authoritarianism and vigilantism, for the average individual that falls victim to a criminal act. (BLATTMAN, (2009)) shows Ugandan former combatants engage themselves politically as a post-trauma reaction. In Sierra Leone, according to (BELLOWS; MIGUEL, (2009)), meetings’ turnout and likelihood of voting were higher on areas directly exposed to the country’s civil war. Considering the voting paradox ((DOWNS, (1957)); (RIKER; ORDESHOOK, (1968))), these evidences suggest that violence seems to increase participation through civil duty utility, strengthening social bonds.

2.2 Public Security in Rio de Janeiro

Specifically for Rio de Janeiro and public security, (FERRAZ; OTTONI, (2013)[b]) assess the political return of the pacification strategy adopted by former governor Sergio Cabral. The Pacifying Policy Unit (or *Unidade de Polícia Pacificadora* - UPP) consisted on police operations backed by Military Forces to reconquer territories under control of drug gangs. UPP

was the main public security policy in Rio de Janeiro’s metropolitan region. Near occupied *favelas*, Sergio Cabral’s vote share increased by 22 percentage points. Spillover effects benefited same-party mayor Eduardo Paes as well.

Some works claim, nonetheless, crime reduction is not a universal effect. First of all, UPP might also affect reporting rates. (CANO; BORGES; RIBEIRO, (2012)) show an increase on some crimes’ denouncement. (FERRAZ; OTTONI, (2013)[a]), for instance, observe opposing effects on different crimes: higher drug apprehension and lower police killings. Second, UPP might have only displaced crime. (MAGALONI; FRANCO; MELO, (2015)) outline evidence on this. Other benefits accompanied the program. According to (FRISCHTAK; MANDEL, (2012)), UPP had effect on property value, appreciating house prices via crime reduction. (CUNHA; MELLO, (2011)) describe an impact on formalization of services, such as electric power provision, once crime reduction enabled market entry. Lastly, (JÚNIOR, (2019)) finds UPP improved birth outcomes for pregnancies within its borders.

(D. HIDALGO; LESSING, (2015)) analyze militia’s expansion as a paramilitary agent affecting vote in 2006 election. Areas where militia took control casted more votes for candidates whose profession was on the security area (namely police and military), compared to those without such presence. Furthermore, once elected, these politicians used their political power to befriend this group’s action and dominance.

Finally, (MONTEIRO; ROCHA, (2017)) is the closest one to this paper in terms of methodology. Authors show that schools located in slums exposed to gun shooting conflicts had lower Mathematics test score in padronized exams. Violence caused the disruption of school activities, absence of teachers and headmasters turnover, affecting negatively their human capital accumulation process and future test performance.

2.3 Trust in Police and Legitimacy

Finally, a third branch of research this work relates to discusses public's relation with police. One possible way to interpret our results is that the Pacifying Police Program improved citizens' vision of the police and military institutions and electoral performance of these categories. (TYLER; HUO, (2002)) and (TYLER, (2005)) distinguish racial bias by police and lower levels of trust for minorities. (GOLDSMITH, (2005)) describes police and trust-building reform process in developing and post-authoritarian countries. (CALDEIRA, (2002)) studies democratization reform inside police in Brazil, focused in São Paulo, and states the coexistence of support for a 'violent police' and a negative view of the institutions. (WEITZER, (2002)) documents incidents and negative but short-lived impacts on police image in New York and Los Angeles.

This thesis complements the existing literature about public security, endemic violence in Rio de Janeiro and its consequences, especially focusing on a period of a major program's creation and demise, the Pacifying Police, although it does not investigate the effect of the program alone. Moreover, it uses quasi-experimental variation of non-political conflicts, which contributes to a body of work in political science which normally resorts to external threats, victimization and opinion surveys, rather than internal threats and electoral context. Finally, the proposed mechanism potentially relates to studies on developing countries and trust in institutions (i.e. the police/Army) and how policies are able to shift public's beliefs.

3 Institutional Background and Data Description

The current section briefly describes some relevant information concerning context and application of this paper’s strategy to Rio de Janeiro municipality, besides data and its sources.

3.1 Drug battles

Rio de Janeiro has been dominated by three main drug gangs (*facções*) since around the 70’s and the conflicts between these groups for the dominance of strategic slums (*favelas*) and points of sale have spread across town. These conflicts have escalated with the usage of war equipment such as machine guns and rifles, which made drug commerce an extremely lethal activity. Drug trafficking, nonetheless, still recruits young men in these poor communities, attracted by large and fast gains and lack of better opportunities elsewhere, and replacing easily any “soldiers” lost. It is important to note that, since slums are spread around city’s hillsides, they also happen close to some of the richest neighbors on South Zone.⁸ These groups do not have political motivation during such battles, distancing themselves from terrorist and paramilitary organizations. (MONTEIRO; ROCHA, (2017)) provides more complete historical outlook of violence undertaken by these groups.

My treatment variable was constructed from gunshooting location, provided by Disque Denuncia, an anonymous hotline service maintained by an NGO with state government support. Citizens report via phone call the occurrence of different crimes, providing an address and a brief description. “Drug gangs gun shooting conflict” is one specific category and contains 7545 reports between May 2002 and October 2018 in Rio de Janeiro’s municipality. I turn my attention to the ones in state election years and, since elections are held the first Sunday of October, I have considered reports from January to September. Then I verify by description if they are actual conflicts, instead of threats or other related crimes, and remove duplicate events, reported by more than one phone call, based on time of the call and location of the event. Figures 1 to 4 plot occurrences on state election years from 2006 to 2018 on Rio de

⁸Check figures 1-4 and A1-A3.

Janeiros's map. Figures A1-A3 map conflicts on the following years (except 2019), which were used as placebos in Subsection 5.4

In order to argue that Disque Denuncia phone call reports are a good measure, I follow once again (MONTEIRO; ROCHA, (2017)), assessing correlation between homicide rates and number of days with conflicts. Public Security Institute (ISP-RJ) has provided data on homicide rates, organized by AISP (city's public security division unit). These figures are presented in the Appendix (A4-A10). Strong and stable correlations across years suggest there is no change in reporting rates overtime and no bias due to measurement error in my estimates. Town Hall provided shapefile for administrative division of Rio de Janeiro.

3.2 Pacifying Police Program

In 2008, state governor Sérgio Cabral Filho and public security secretary José Mariano Beltrame started the Pacifying Police Program, which involved military police and military forces joint operations to reconquer territories dominated by drug gangs. Over 30 units were created until 2016 all over town. Figure 5 depicts UPP map, as disclosed by ISP-Rio. The project included a community-oriented police, followed by progressive provision of services (UPP Social), and was a success at the beginning, as mentioned evidence from the literature supports. The operation in *Morro do Alemão* was televised and even yielded Rede Globo an Emmy Award. Recovering *Rocinha*, one of the biggest *favelas*, was done without one single shot fired.⁹

Nonetheless, police abuse episodes and state's fragile fiscal situation have contributed to its downfall. Second phase was never implemented and recently some units were dismantled. Data from Violence Atlas (*Atlas da Violência*) from 2017 show homicide rate has returned to 2008 levels, when program was implemented,¹⁰ and it nowadays perceived as a partial failure¹¹,

⁹(GLENNY, (2016))

¹⁰<https://extra.globo.com/noticias/brasil/atlas-da-violencia-em-uma-decada-taxa-de-homicidios-do-rio-volta-ao-nivel-pre-upps-23718932.html>

¹¹<https://noticias.uol.com.br/cotidiano/ultimas-noticias/2017/08/22/rio-nas-favelas-quase-70-veem-falencia-de-upps-mas-maioria-quer-permanencia.htm>

people believe the program needs changes to continue.¹²

Table 1 presents summary statistics for variables on our dataset and its second panel is violence data. Main analysis uses dummy for over 2 conflicts in neighborhoods within 1000 meters of a given voting locale. 20% of locales were exposed to violence considering the four years altogether. The number of conflicts per locale peaks 26 when considering 1 kilometer as distance. The share of locales close to UPP is also around 20%, but interaction reveals only 3% experience violence even though close to an UPP by the same 1000 meters distance.

3.3 Brazilian Elections

Brazilian elections happen every two years alternating in two levels, municipal and state-federal. Voting is mandatory, facing fines and other legal sanctions in case of absence without proper justification.¹³ Voters must register themselves when completing 18 years old, although they can also do it voluntarily when turning 16. During registration, a voting section and address in voter's neighbourhood are assigned. Thus, it is safe to assume that citizens vote near their homes, with few exceptions of people who move and do not change their electoral address to another voting zone. Voting addresses often remain the same throughout the years. Some reallocation might happen, but always keeping voters within their neighbourhood. This is important to our assumption that voters are exposed the same way their voting addresses are and to make voting addresses comparable between years. In case voting addresses changed or were far from voters' households, it could be the case violence in those places would not affect their behaviour.

Electoral Courts publicly disclose election data such as voting addresses, how many votes each candidate received, voters' characteristics by ballot¹⁴ and candidates' registration. Although many positions could be influenced by violence exposure, state representatives are the ones directly involved in public security as established by Brazilian Constitution and will

¹²For further detailing, check (**ferraz2016state**) and (FERRAZ; OTTONI, (2013)[a]).

¹³For further detailing on this, check (CEPALUNI; F. D. HIDALGO, (2016))

¹⁴Since it first became available in 2008, I use 2008 voters' characteristics as proxy for 2006.

be the focus of the following analysis.

In order to identify candidate stance, I use profession in his/her official registration submitted to Superior Electoral Court, assuming candidates in security area are aligned to “tough-on-crime” platforms, often adopting rank as part of name on the ballot. Since we do not have the same candidates running every year, I opt for summing vote share of this group of candidates. Forementioned professions include:

- Military Police – Military Firefighter – Reformed Military
- Civilian Police – Member of the Army – Security Guard

Just as the conflicts, electoral ballots (or voting sections) are also georeferenced. However, the ballot itself is not the relevant unit, but the building where it is. An illustrative example: two classrooms of one single school are different ballots, but belong to the same locale, the school. So I aggregate results from both sections and whichever more to keep one observation by address. Unbalanced panel contains 5290 addresses, each one with at least one section in at least two consecutive state elections, although not always the same group of sections. These addresses account for about 90% of ballots across the years included in the sample and are depicted in Figure 6.

The first panel on Table 1 consists on the electoral outcomes of interest. Voters cast around 7.8% of **valid**¹⁵ votes to “tough-on-crime” candidates, but some locales reached about half of valid votes. Out of those, 3.1% of votes are for candidates whose name included rank. Turnout averages 79%, even though voting is mandatory in Brazil. Last panel includes our controls, i.e. voters’ profile information as shares in each locale and year. Characteristics are gender, marital status, age range and education level.

¹⁵Results are unchanged by whether using valid, nominal or total vote share, as described in Robustness Checks subsection (5.3).

4 Econometric Model

In this section, I describe how I combine election and violence data into one single dataset in order to estimate the causal effect of violence exposure on results and turnout. I built an unbalanced panel of voting locations from 2006 to 2018 and hypothesize a model regression such as below:

$$P_{lt} = \theta T_{lt} + \omega UPP_{lt} + \beta T_{lt} \times UPP_{lt} + \mu_l + \gamma_t + X'_{lt} \psi + \epsilon_{lt} \quad (1)$$

where P_{lt} is the political outcome of interest (i.e. “tough-on-crime” candidates vote share) in voting location l and electoral year t . Variable T_{lt} is a dummy which indicates whether the location l was exposed to violence in electoral year t . It is defined as:

$$T_{lt} = \begin{cases} 1, & \text{if } \sum \mathbf{1}\{D_l < B\} \vartheta_t \geq n \\ 0, & \text{otherwise} \end{cases}$$

where ϑ_t is the number of days in which there was a conflict report close to l in electoral year t . Since elections are held in October, I have considered reports from January to September. D_l represents the distance of voting locale l to conflict coordinates and $\mathbf{1}\{D_j < B\}$ indicates when conflict is located in at least B meters. Thus, T_{lt} captures the occurrence of conflicts in B meters buffer whose duration exceeds n days.¹⁶ In section 5.3, I carry a sensitivity analysis of my main results by considering different values of these parameters.

I consider that the effect of violence exposure also differs whether the locale is close or not to an UPP. The program proximity dummy (UPP_{lt}) is constructed using same B as T_{lt} and varies over time and space, since was adopted in 2008 and shrank in 2017, after several expansion years. This is captured by coefficient β , which represents the additional effect of being exposed to violence while close to an UPP, relative to areas neither exposed nor close. It

¹⁶(MONTEIRO; ROCHA, (2017))’s measure is slightly different as it considers distance to slums’ borders. They use 250 and 2 as standard values for B and n , respectively.

is important to note that I do not attribute causal interpretation to the UPP_{lt} coefficient by itself (ω).

Terms μ_l and γ_t capture locale and year fixed effects, respectively. Including them, we are able to capture particular time-invariant local behaviours and overall electoral tendencies throughout the years. X_{lt} is a vector of local variables for voters' profile as shares in each local-year: age range, gender, marital status and education level. I have included a Herfindal Index to account for local concentration of votes ¹⁷.

Other targeted outcome (Y_{lt}) is turnout, which we model such as Equation (2) below. Variables' description remain the same as in Equation (1). In contrast, UPP_{lt} is included as control, although I do not differentiate effects with regards to it.

$$Y_{lt} = \theta T_{lt} + \mu_l + \gamma_t + X'_{lt} \psi + \epsilon_{lt} \quad (2)$$

The identification strategy relies on the fact that treatment (i.e. violence exposure via gun shooting conflicts) is random, once controlled by other local characteristics. In other words, conditional on year and local fixed effects and voters' profile, drug battles are uncorrelated to other determinants of candidate choice. If this is true, I am able to identify the causal effect of violence in political preferences, as our variable T_{lt} is orthogonal to the error term. As described by (MONTEIRO; ROCHA, (2017)), drug battles occurrence is associated to gangs and drug lords' strategic behaviour for control of territory and points of sale. The authors list evidences of triggers involving idiosyncratic episodes, such as leaders' arrest or release, betrayal and revenge. Besides this qualitative argument, two results of mine corroborate with the application of this hypothesis: first, the inclusion of controls are not relevant to our estimates; and second, a placebo exercise with post-election conflicts. Next section will provide further detailing on these.

¹⁷A "supply" side argument could imply our findings are driven by candidates campaigning in exposed areas

5 Results

5.1 Main Results

Table 2 illustrates my baseline results for aggregate “tough-on-crime” vote share. All five specifications use $B=1000$ and $n=2$ as parameters and standard errors clustered by locale.¹⁸ Panel A considers candidates whose profession is on security area and Panel B the subset of those who added rank in the name on the ballot. Column 1 specification includes only fixed effects for year and locale and coefficient is not significant. In column 2, I include UPP dummy, and then in 3, the interaction, which is highly significant. Once controls are added, in column 4, the coefficient does not change qualitatively: still positive and significant, although a bit smaller. Finally, when including Local Herfindal Index as a control, which proxies supply variation, estimates remain the same. This is my preferred specification.

For profession candidates, being exposed to violence close to an UPP causes, on average, an increase of 1.05 p.p. on aggregate vote share. For rank candidates, the effect is 0.65 p.p. Both correspond to about 18%-22% of respective dependent variable’s standard deviation, a sizeable magnitude. I interpret these coefficients as a net effect, since, close to an UPP, there could be voters with positive as well as negative vision of the program. Taking into consideration cases of police abuse, it is possible that residents from UPP areas are likely to vote against security agents, while those who live right outside and do not suffer from this might vote in favour. Data does not allow me to explore this variation, as they are likely to vote at the same place.

5.2 Turnout

Table 3 displays baseline results for turnout as modeled by Equation 2. Although in Column 1, violence exposure seems to increase participation, once controlled for voters’ profile, the effects become non significant. Observe that drug battles should not physically prevent

¹⁸Clustering using Conley standard errors do not change my results’ significance. These are available upon request.

people from voting, as conflicts are counted before election day, differently than preventing students from learning in (MONTEIRO; ROCHA, (2017)). Thus, any effect, if found, should be credited to motivation/mobilization. Once again, I interpret this a net effect: while violence exposure could repel and attract voters to participate, finding non-significant result might be either a “true zero” or caused by not being able to separate individuals within the voting locale.

5.3 Robustness Checks

Tables A1-A6 present robustness checks for “tough-on-crime” results. The first pair of tables includes every combination of n and B , for either profession or rank, a sensitivity test with regards to the treatment variable parameters. We replicate Table 1, Column 5 specification using $B=\{500,1000\}$ across panels and $n=\{1,...,10\}$ across columns within the same panel. Baseline results are located in Column 2, Panel B ($B=1000$, $n=2$). Overall, coefficients do not change sign and significance, with slight changes in magnitude, for both groups of candidates.

I have reported results using alternative vote shares in Tables A3-A6. The first pair considers only nominal vote shares, i.e. eliminates votes cast to parties from total. The last pair uses total vote share, not eliminating neither votes for parties nor non-valid votes. Results remain unchanged.

Finally, Table A7 repeats the sensitivity test for parameter combination used in Tables A1-A2, this time for turnout. Effect on turnout is not significant in any combination except for one.

5.4 Placebo test

For a placebo test, I proceed in two ways. First, I use conflicts after the election instead of same year events. Since data from 2019 is not available yet, I drop 2018 and run regressions again on Tables A8-A9. Results remain unchanged. This is interesting because rules out the possibility

of having one leading Executive postulant such as Mr. Bolsonaro driving estimates in state Legislative via platform spillovers in 2018. For Tables A10 and A11, I replace pre election by post election violence. Coefficients are not significant in most of parameters combination, as expected since election has already taken place. At last, in Tables A12-A15, when including both dummies, pre and post, and interactions coefficients remain same magnitude and significance as in regressions separately. This reinforces the argument of random variation of violence. If conflicts from one year to another were somehow correlated, the inclusion of following year exposure dummy would eliminate bias from current year estimates, and vice-versa. The same procedure is done for turnout: first, turnout without 2018 (Table 16); then post election conflict (Table 17); and finally including both (Table 18). Coefficients are mostly non-significant as in Table 3.

The second placebo resorts to simulation. I run 5000 simulations randomizing which locales are exposed, maintaining the proportion of exposed and non-exposed within each year according to baseline parameters $B=1000$ and $n=2$. In each round I draw a vector of zeros and ones to replace my exposure variable T_{lt} and reestimate Equations (1) and (2) with this pseudo-data. Then I plot the frequency distribution of estimations (Figures A4 to A6). It is important to note that, for Profession and Rank (A4-A5), I plot the interaction between Violence Exposure and UPP, which means this is not centered around zero, as UPP effect shifts positively the distribution. Red tick marks magnitude of baseline estimates. My estimates are on the tails of simulations for aggregate vote share, strengthening our findings. For turnout, treatment was already non significant.

6 Conclusion

While familiar with “tough-on-crime” candidates and their platform to be more aggressive in order to control crime and violence, evidence of how appealing this speech is to crime vulnerable citizens is quite sparse. Theories point in many directions and (quasi) experimental variation is scarce. In this context, this paper provides causal impact estimation of how being exposed to violence may shift political preferences. In the case of voters registered in the city of Rio de Janeiro, I find robust evidence that violence-related events do improve “tough-on-crime” candidates vote share, but only when police and military institutions possess credibility, such as near Pacifying Police Units in Rio de Janeiro.

I exploit exogenous variation of gun shooting conflicts in Rio de Janeiro’s municipality to explain vote share cast to candidates whose profession is on security area. Comparing same places without UPP near when exposed and when not, I find exposure does not affect demand for such candidates. Only places near UPP, violence exposure has a positive effect, which I credit to higher trust in security categories after the program. This is in line with the effect captured by (DAVIS; SILVER, (2004)). Depending on trust, people have different inclinations towards supporting police and military platforms. When looking at data in public opinion poll ((CESOP-DATAFOLHA/RJ17.OUT-04424, /por/banco_de_dados/v/4254, accessed 05/09/2019)), we find, even with program dismantling, that 70% of citizens consulted would still maintain it, making some changes (Table 4). Unfortunately, there is no fine-grained data on trust in police, which could allow me to better analyze the proposed mechanism.

Moreover, results for participation measures are not in line with previous findings. Although literature reports an increase in turnout, my regressions do not show any effect on turnout. It is possible, nonetheless, that this derives from positive and negative effects cancelling each other within the same location. Since other works use individual survey answers, electoral data by location might not be able to correctly separate both effects.

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Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Local Agregate Vote Share Profession Candidates	7.847	5.823	0	48.214
Local Agregate Vote Share Rank Candidates	3.136	2.947	0	42.592
Turnout	79.428	6.108	22.345	96.563
Number of conflicts within 500 meters	0.281	0.985	0	15
Number of conflicts within 1000 meters	1.069	2.277	0	26
Violence Exposure Dummy - within 1000 meters and at least 2 conflicts (baseline)	0.205	0.404	0	1
Located within 500 of an UPP area	0.106	0.308	0	1
Located within 1000 of an UPP area	0.197	0.398	0	1
Interaction - within 1000 meters of at least 2 conflicts and an UPP area (baseline)	0.032	0.176	0	1
Herfindal Index	0.074	0.037	0.017	0.815
Share Female Voters	54.59	3.198	3.636	75.479
Share Single Voters	64.45	8.521	40.441	100
Share Married Voters	29.441	7.172	0	52.921
Share Divorced Voters	2.145	1.161	0	8.333
Share Separated Voters	1.746	1.12	0	7.453
Share Voters Age 16-17	0.61	1.216	0	44.186
Share Voters Age 18-24	12.765	9.672	0	66.737
Share Voters Age 25-59	63.193	9.09	0	92.764
Share Voters Age 60-79	18.048	7.061	0	45.196
Share Illiterate	2.346	1.613	0	15.934
Share Reads and Writes	10.928	5.73	0	34.312
Share Unfinished Middle School	37.904	16.168	1.215	100
Share Finished Middle School	19.943	6.995	0	40.212
N	5280			

This table reports summary statistics of dataset's variables. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Rank aggregates a subset of those who adopted military rank as part of their name on the ballot. Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. UPP dummy uses same distance as violence exposure dummy across every specification. Voters' profile in 2006 is proxied by 2008, when it became first available. Conflict location obtained from *Disque Denuncia* reports' address and georeferenced with Google Maps API and geocode command in R. UPP location obtained from Public Security Insitute (ISP-Rio) shapefile's. See Figures 1-6 for maps.

Table 2: Effect of Violence Exposure on Law and Order Vote Share

Panel A: “Profession” Candidates

	(1)	(2)	(3)	(4)	(5)
Violence Exposure	-0.0214 (0.153)	0.0525 (0.151)	-0.179 (0.179)	-0.146 (0.175)	-0.147 (0.176)
UPP dummy		1.576*** (0.207)	1.385*** (0.210)	1.081*** (0.207)	1.081*** (0.208)
Violence Exposure * UPP dummy			1.197*** (0.358)	1.045*** (0.358)	1.045*** (0.359)
Local Herfindal Index					0.499 (4.360)
Observations	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458
Adj. R-squared	0.57	0.57	0.57	0.59	0.59
Year and Local FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes

Panel B: “Rank” Candidates

	(1)	(2)	(3)	(4)	(5)
Violence Exposure	0.126 (0.0782)	0.181** (0.0766)	0.0425 (0.0814)	0.0511 (0.0803)	0.0600 (0.0815)
UPP dummy		1.172*** (0.105)	1.058*** (0.0994)	0.951*** (0.0959)	0.956*** (0.0952)
Violence Exposure * UPP dummy			0.713*** (0.273)	0.654** (0.270)	0.652** (0.272)
Local Herfindal Index					-3.843* (2.023)
Observations	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458
Adj. R-squared	0.59	0.61	0.61	0.62	0.62
Year and Local FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local vote share on violence exposure dummy, UPP dummy and interaction of both. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Rank aggregates a subset of those who adopted rank as part of their name on the ballot. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table 3: Effect of Violence Exposure on Turnout

	(1)	(2)
Violence Exposure	0.483*** (0.167)	0.189 (0.139)
Observations	5280	5280
Clusters	1458	1458
Adj. R-squared	0.52	0.63
Year and Local FE	Yes	Yes
Controls	No	Yes

This table reports the coefficients from regressing turnout on violence exposure dummy. Controls include UPP dummy, local Herfindal Index and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table 4: Opinion Poll 10/2017

Variable	Mean	Std. Dev.
Continue the program, with changes	0.701	0.458
Continue the program, without changes	0.073	0.26
Discontinue the program	0.208	0.406
Don't know	0.018	0.135
N		812

This table reports share of respondents by answer to the question "Do you think UPP should continue?" in DATAFOLHA questionnaire from October 2017.

Figure 1: Heat Map Conflicts 2006

This figure presents heat map of drug battles in Rio de Janeiro municipality in 2006. Scale from yellow to red indicates geographical concentration of events. Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Figure 2: Heat Map Conflicts 2010

This figure presents heat map of drug battles in Rio de Janeiro municipality in 2010. Scale from yellow to red indicates geographical concentration of events. Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Figure 3: Heat Map Conflicts 2014

This figure presents heat map of drug battles in Rio de Janeiro municipality in 2014. Scale from yellow to red indicates geographical concentration of events. Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Figure 4: Heat Map Conflicts 2018

This figure presents heat map of drug battles in Rio de Janeiro municipality in 2018. Scale from yellow to red indicates geographical concentration of events. Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Figure 5: Map Pacifying Police Units

This figure presents map of Pacifying Police Units (UPPs, ochre areas). Shapefiles provided by Rio de Janeiro Town Hall and Public Security Institute (ISP-Rio).

Figure 6: Map Voting Locals

This figure presents map of voting locals in our sample, i.e. 5290 places that held at least one ballot (section) in at least two consecutive elections from 2006 to 2018. Addresses provided by Electoral Court and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Table A1: Robustness Check - Varying Parameters for “Profession” Candidates

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.00874 (0.193)	-0.273 (0.240)	-0.225 (0.342)	-0.169 (0.496)	0.136 (0.668)	-0.00925 (0.627)	-0.0199 (0.749)	0.577 (0.692)	0.401 (1.084)	0.388 (1.181)
UPP dummy	0.749*** (0.211)	0.757*** (0.208)	0.830*** (0.210)	0.843*** (0.209)	0.863*** (0.209)	0.860*** (0.209)	0.860*** (0.208)	0.867*** (0.210)	0.865*** (0.210)	0.865*** (0.210)
Violence Exposure * UPP dummy	0.811* (0.483)	2.115* (1.205)	1.532** (0.738)	3.250** (1.495)	1.249* (0.756)	1.394* (0.724)	1.405* (0.834)	.	.	.
Local Herfindal Index	0.642 (4.352)	0.692 (4.365)	0.637 (4.365)	0.643 (4.366)	0.581 (4.366)	0.594 (4.363)	0.594 (4.367)	0.563 (4.360)	0.577 (4.359)	0.578 (4.359)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.221 (0.159)	-0.147 (0.176)	-0.0516 (0.188)	0.131 (0.232)	0.150 (0.279)	0.262 (0.372)	0.0837 (0.385)	0.0641 (0.482)	0.0181 (0.595)	-0.143 (0.726)
UPP dummy	1.048*** (0.233)	1.081*** (0.208)	1.179*** (0.204)	1.185*** (0.203)	1.245*** (0.205)	1.253*** (0.203)	1.243*** (0.204)	1.242*** (0.203)	1.241*** (0.203)	1.239*** (0.203)
Violence Exposure * UPP dummy	0.490* (0.273)	1.045*** (0.359)	0.866* (0.509)	1.324** (0.667)	0.532 (0.435)	0.0658 (0.607)	0.662 (0.571)	0.714 (0.664)	0.760 (0.753)	0.795 (0.870)
Local Herfindal Index	0.572 (4.373)	0.499 (4.360)	0.505 (4.354)	0.281 (4.338)	0.359 (4.344)	0.322 (4.329)	0.460 (4.380)	0.473 (4.380)	0.489 (4.375)	0.522 (4.372)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59	0.59
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates’ aggregate local vote share on violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Controls include local Herfindal Index (reported) and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A2: Robustness Check - Varying Parameters for “Rank” Candidates

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.0172 (0.0842)	0.154 (0.135)	0.130 (0.189)	0.322 (0.256)	0.492 (0.327)	0.443 (0.389)	0.183 (0.459)	0.714*** (0.199)	0.507** (0.222)	0.516** (0.261)
UPP dummy	0.621*** (0.102)	0.612*** (0.0977)	0.662*** (0.107)	0.685*** (0.106)	0.691*** (0.106)	0.689*** (0.106)	0.683*** (0.106)	0.688*** (0.109)	0.685*** (0.109)	0.685*** (0.109)
Violence Exposure * UPP dummy	0.443 (0.416)	1.731 (1.130)	1.518*** (0.504)	2.040* (1.230)	0.411 (0.470)	0.459 (0.517)	0.721 (0.573)	.	.	.
Local Herfindal Index	-3.651* (2.028)	-3.730* (2.023)	-3.687* (2.026)	-3.686* (2.028)	-3.713* (2.029)	-3.696* (2.026)	-3.684* (2.030)	-3.704* (2.018)	-3.688* (2.018)	-3.687* (2.018)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.0343 (0.0762)	0.0600 (0.0815)	0.0992 (0.0783)	0.270*** (0.102)	0.258** (0.117)	0.246* (0.142)	0.223 (0.152)	0.209 (0.191)	0.173 (0.219)	-0.0446 (0.257)
UPP dummy	0.914*** (0.0936)	0.956*** (0.0952)	1.015*** (0.0934)	1.017*** (0.0935)	1.060*** (0.0996)	1.055*** (0.0989)	1.052*** (0.0991)	1.050*** (0.0991)	1.048*** (0.0992)	1.045*** (0.0991)
Violence Exposure * UPP dummy	0.340** (0.163)	0.652** (0.272)	0.644 (0.438)	0.974* (0.586)	0.454** (0.210)	0.930*** (0.232)	1.132*** (0.224)	1.166*** (0.260)	1.202*** (0.286)	1.357*** (0.317)
Local Herfindal Index	-3.724* (2.020)	-3.843* (2.023)	-3.857* (2.028)	-4.025** (2.012)	-3.974* (2.045)	-3.959* (2.056)	-3.868* (2.037)	-3.848* (2.037)	-3.821* (2.036)	-3.774* (2.034)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates’ aggregate local vote share on violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Rank aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002 and adopted Rank as part of their name on the ballot. Controls include local Herfindal Index (reported) and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A3: Robustness Check - “Profession” Nominal Vote Share

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.0130 (0.214)	-0.289 (0.266)	-0.222 (0.380)	-0.132 (0.553)	0.233 (0.745)	0.0888 (0.700)	0.0996 (0.836)	0.754 (0.794)	0.530 (1.250)	0.493 (1.355)
UPP dummy	0.811*** (0.235)	0.819*** (0.231)	0.898*** (0.233)	0.914*** (0.232)	0.936*** (0.232)	0.932*** (0.231)	0.932*** (0.231)	0.939*** (0.233)	0.937*** (0.233)	0.936*** (0.233)
Violence Exposure * UPP dummy	0.871* (0.527)	2.277* (1.307)	1.668** (0.805)	3.501** (1.623)	1.304 (0.852)	1.449* (0.816)	1.438 (0.938)	.	.	.
Local Herfindal Index	1.741 (5.019)	1.792 (5.032)	1.731 (5.032)	1.736 (5.033)	1.668 (5.034)	1.683 (5.030)	1.680 (5.034)	1.650 (5.027)	1.667 (5.026)	1.669 (5.025)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.258 (0.176)	-0.164 (0.195)	-0.0598 (0.211)	0.151 (0.259)	0.178 (0.311)	0.302 (0.415)	0.115 (0.431)	0.110 (0.540)	0.0558 (0.669)	-0.129 (0.817)
UPP dummy	1.134*** (0.259)	1.168*** (0.231)	1.275*** (0.226)	1.282*** (0.226)	1.347*** (0.227)	1.357*** (0.225)	1.346*** (0.225)	1.345*** (0.225)	1.343*** (0.225)	1.340*** (0.225)
Violence Exposure * UPP dummy	0.528* (0.303)	1.135*** (0.395)	0.939* (0.556)	1.448** (0.728)	0.610 (0.486)	0.116 (0.677)	0.773 (0.639)	0.816 (0.743)	0.870 (0.844)	0.923 (0.978)
Local Herfindal Index	1.668 (5.041)	1.588 (5.025)	1.595 (5.019)	1.342 (5.004)	1.420 (5.010)	1.379 (4.994)	1.533 (5.047)	1.543 (5.046)	1.564 (5.042)	1.604 (5.038)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.59	0.59	0.58	0.59	0.58	0.58	0.58	0.58	0.58	0.58
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates’ aggregate local **nominal** vote share on violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. “Profession” aggregates every candidate whose registered profession is in security area in Electoral Court in any year since 2002. Controls include local Herfindal Index (reported) and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A4: Robustness Check - “Rank” Nominal Vote Share

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.0172 (0.0934)	0.180 (0.150)	0.162 (0.208)	0.382 (0.281)	0.583 (0.358)	0.531 (0.425)	0.252 (0.503)	0.830*** (0.217)	0.580** (0.249)	0.587** (0.290)
UPP dummy	0.696*** (0.113)	0.686*** (0.108)	0.740*** (0.117)	0.765*** (0.116)	0.771*** (0.117)	0.769*** (0.116)	0.763*** (0.116)	0.767*** (0.119)	0.765*** (0.119)	0.764*** (0.119)
Violence Exposure * UPP dummy	0.469 (0.452)	1.859 (1.224)	1.651*** (0.546)	2.200* (1.323)	0.436 (0.525)	0.486 (0.575)	0.768 (0.636)	.	.	.
Local Herfindal Index	-3.698 (2.288)	-3.787* (2.284)	-3.740 (2.286)	-3.739 (2.287)	-3.768* (2.288)	-3.748 (2.286)	-3.737 (2.289)	-3.756* (2.277)	-3.737 (2.277)	-3.737 (2.277)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.0500 (0.0854)	0.0603 (0.0911)	0.106 (0.0881)	0.301*** (0.114)	0.289** (0.131)	0.274* (0.158)	0.250 (0.167)	0.240 (0.210)	0.198 (0.240)	-0.0441 (0.283)
UPP dummy	1.013*** (0.103)	1.062*** (0.105)	1.127*** (0.103)	1.129*** (0.103)	1.175*** (0.110)	1.170*** (0.109)	1.167*** (0.109)	1.165*** (0.109)	1.162*** (0.109)	1.158*** (0.109)
Violence Exposure * UPP dummy	0.378** (0.180)	0.712** (0.297)	0.689 (0.476)	1.053* (0.637)	0.524** (0.241)	1.079*** (0.265)	1.319*** (0.250)	1.351*** (0.289)	1.392*** (0.317)	1.555*** (0.349)
Local Herfindal Index	-3.774* (2.280)	-3.904* (2.284)	-3.919* (2.291)	-4.108* (2.273)	-4.057* (2.308)	-4.040* (2.320)	-3.939* (2.298)	-3.918* (2.299)	-3.887* (2.297)	-3.834* (2.295)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.61
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates’ aggregate local **nominal** vote share on violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. “Rank” aggregates every candidate whose registered profession is in security area in Electoral Court in any year since 2002 and also adopted Rank as part of ballot name. Controls include local Herfindal Index (reported) and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A5: Robustness Check - “Profession” Total Vote Share

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.0302 (0.169)	-0.190 (0.205)	-0.137 (0.289)	-0.0868 (0.416)	0.155 (0.563)	-0.0157 (0.538)	-0.0193 (0.645)	0.463 (0.581)	0.458 (0.914)	0.484 (1.001)
UPP dummy	0.777*** (0.187)	0.794*** (0.184)	0.854*** (0.187)	0.864*** (0.185)	0.881*** (0.186)	0.877*** (0.185)	0.877*** (0.185)	0.883*** (0.187)	0.883*** (0.187)	0.882*** (0.187)
Violence Exposure * UPP dummy	0.753* (0.433)	1.742 (1.105)	1.229* (0.683)	2.899** (1.428)	1.009 (0.653)	1.180* (0.634)	1.184 (0.729)	.	.	.
Local Herfindal Index	-3.655 (3.789)	-3.620 (3.805)	-3.661 (3.804)	-3.651 (3.804)	-3.702 (3.804)	-3.688 (3.801)	-3.687 (3.804)	-3.713 (3.798)	-3.706 (3.798)	-3.706 (3.798)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.183 (0.137)	-0.0873 (0.152)	0.00704 (0.162)	0.175 (0.202)	0.201 (0.243)	0.316 (0.324)	0.152 (0.330)	0.136 (0.413)	0.116 (0.514)	-0.0183 (0.628)
UPP dummy	1.060*** (0.205)	1.098*** (0.183)	1.175*** (0.179)	1.181*** (0.178)	1.239*** (0.180)	1.244*** (0.179)	1.233*** (0.179)	1.232*** (0.179)	1.230*** (0.179)	1.228*** (0.179)
Violence Exposure * UPP dummy	0.425* (0.238)	0.866*** (0.313)	0.834* (0.454)	1.195** (0.600)	0.358 (0.382)	-0.156 (0.526)	0.345 (0.505)	0.383 (0.586)	0.403 (0.664)	0.426 (0.766)
Local Herfindal Index	-3.712 (3.808)	-3.794 (3.796)	-3.813 (3.788)	-4.007 (3.773)	-3.940 (3.778)	-3.984 (3.763)	-3.831 (3.815)	-3.818 (3.815)	-3.801 (3.811)	-3.769 (3.809)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates’ aggregate local **total** vote share on violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Controls include local Herfindal Index (reported) and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A6: Robustness Check - “Rank” Total Vote Share

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.0371 (0.0723)	0.166 (0.116)	0.152 (0.162)	0.323 (0.217)	0.452 (0.281)	0.378 (0.336)	0.162 (0.398)	0.612*** (0.160)	0.502*** (0.176)	0.525** (0.208)
UPP dummy	0.586*** (0.0884)	0.581*** (0.0847)	0.625*** (0.0946)	0.645*** (0.0937)	0.649*** (0.0944)	0.647*** (0.0940)	0.642*** (0.0936)	0.646*** (0.0964)	0.645*** (0.0964)	0.644*** (0.0964)
Violence Exposure * UPP dummy	0.421 (0.374)	1.515 (1.032)	1.339*** (0.461)	1.903 (1.185)	0.356 (0.413)	0.429 (0.454)	0.647 (0.502)	.	.	.
Local Herfindal Index	-5.055*** (1.773)	-5.130*** (1.769)	-5.088*** (1.771)	-5.084*** (1.773)	-5.106*** (1.773)	-5.089*** (1.771)	-5.079*** (1.774)	-5.096*** (1.764)	-5.084*** (1.764)	-5.083*** (1.764)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.60	0.61	0.61	0.60	0.60	0.60	0.60	0.60	0.60	0.60
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.0223 (0.0654)	0.0785 (0.0704)	0.116* (0.0672)	0.269*** (0.0876)	0.264*** (0.1000)	0.254** (0.121)	0.234* (0.130)	0.224 (0.163)	0.203 (0.189)	0.0141 (0.222)
UPP dummy	0.841*** (0.0810)	0.881*** (0.0818)	0.927*** (0.0804)	0.930*** (0.0804)	0.972*** (0.0871)	0.966*** (0.0864)	0.963*** (0.0866)	0.961*** (0.0865)	0.960*** (0.0866)	0.956*** (0.0865)
Violence Exposure * UPP dummy	0.297** (0.141)	0.563** (0.237)	0.642 (0.394)	0.926* (0.530)	0.380** (0.174)	0.747*** (0.198)	0.911*** (0.195)	0.942*** (0.226)	0.963*** (0.249)	1.101*** (0.277)
Local Herfindal Index	-5.114*** (1.763)	-5.232*** (1.765)	-5.256*** (1.769)	-5.405*** (1.754)	-5.359*** (1.785)	-5.345*** (1.795)	-5.251*** (1.778)	-5.233*** (1.779)	-5.209*** (1.778)	-5.166*** (1.777)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.61	0.61	0.61	0.62	0.61	0.61	0.61	0.61	0.61	0.61
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates’ aggregate local **total** vote share on violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Rank aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002 and adopted Rank as part of their name on the ballot. Controls include local Herfindal Index (reported) and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A7: Robustness Check - Turnout

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.176 (0.196)	0.297 (0.327)	-0.0796 (0.454)	-0.0832 (0.747)	-0.499 (1.076)	-1.008 (1.317)	-1.626 (1.567)	-2.071 (2.513)	-3.126 (4.064)	-3.712 (4.591)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.308** (0.143)	0.189 (0.139)	0.0836 (0.193)	0.143 (0.239)	0.198 (0.272)	-0.0258 (0.361)	0.201 (0.445)	0.122 (0.549)	0.239 (0.686)	-0.117 (0.759)
Observations	5280	5280	5280	5280	5280	5280	5280	5280	5280	5280
Clusters	1458	1458	1458	1458	1458	1458	1458	1458	1458	1458
Adj. R-squared	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing turnout on violence exposure dummy. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Controls include local Herfindal Index, UPP dummy and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)). UPP dummy uses same distance as Violence Exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A8: Profession without 2018

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.148 (0.226)	-0.626** (0.287)	-0.760* (0.420)	-0.835 (0.596)	-0.641 (0.854)	-0.332 (1.004)	-0.173 (1.208)	0.634 (1.224)	0.247 (1.305)	0.312 (1.559)
UPP dummy	0.804*** (0.246)	0.792*** (0.239)	0.905*** (0.240)	0.932*** (0.238)	0.975*** (0.238)	0.987*** (0.237)	0.992*** (0.236)	1.009*** (0.241)	1.004*** (0.241)	1.004*** (0.241)
Violence Exposure * UPP dummy	1.108* (0.631)	3.257** (1.526)	2.322*** (0.735)	3.929** (1.543)	2.002** (0.970)	1.691 (1.112)	1.530 (1.302)	.	.	.
Local Herfindal Index	29.36*** (8.860)	29.73*** (8.889)	29.64*** (8.895)	29.47*** (8.878)	29.33*** (8.877)	29.26*** (8.879)	29.25*** (8.880)	29.19*** (8.874)	29.19*** (8.877)	29.19*** (8.878)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.165 (0.181)	0.0219 (0.192)	0.0696 (0.216)	0.139 (0.278)	-0.0211 (0.330)	-0.0149 (0.475)	-0.247 (0.479)	-0.367 (0.617)	-0.310 (0.749)	-0.520 (0.857)
UPP dummy	1.092*** (0.299)	1.154*** (0.249)	1.277*** (0.243)	1.284*** (0.241)	1.332*** (0.242)	1.340*** (0.240)	1.325*** (0.241)	1.321*** (0.241)	1.326*** (0.241)	1.320*** (0.241)
Violence Exposure * UPP dummy	0.567 (0.362)	1.274*** (0.492)	1.039 (0.659)	1.279 (0.830)	0.455 (0.506)	0.0287 (0.618)	0.734 (0.569)	0.936 (0.687)	0.879 (0.813)	1.116 (0.924)
Local Herfindal Index	28.47*** (8.978)	28.14*** (8.944)	28.11*** (8.946)	28.10*** (8.922)	28.48*** (8.934)	28.51*** (8.901)	28.61*** (8.993)	28.61*** (8.985)	28.60*** (8.989)	28.71*** (8.986)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local vote share on violence exposure dummy, UPP dummy and interaction of both from 2006 to 2014. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A9: Rank without 2018

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.0576 (0.0834)	-0.110 (0.142)	-0.310 (0.221)	-0.222 (0.316)	-0.137 (0.436)	-0.139 (0.599)	-0.505 (0.729)	0.287 (0.237)	0.166 (0.247)	0.146 (0.294)
UPP dummy	0.523*** (0.120)	0.558*** (0.108)	0.639*** (0.116)	0.668*** (0.114)	0.686*** (0.114)	0.687*** (0.112)	0.678*** (0.111)	0.696*** (0.120)	0.695*** (0.120)	0.694*** (0.120)
Violence Exposure * UPP dummy	0.876 (0.581)	2.424 (1.550)	1.591*** (0.501)	2.230* (1.289)	0.626 (0.618)	0.628 (0.751)	0.999 (0.861)	.	.	.
Local Herfindal Index	-1.574 (2.854)	-1.409 (2.869)	-1.435 (2.873)	-1.557 (2.868)	-1.631 (2.877)	-1.643 (2.863)	-1.626 (2.856)	-1.671 (2.845)	-1.672 (2.846)	-1.671 (2.846)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.107 (0.0864)	-0.00573 (0.0812)	-0.0131 (0.0827)	0.0622 (0.108)	0.0211 (0.126)	-0.0642 (0.157)	-0.149 (0.175)	-0.229 (0.226)	-0.236 (0.259)	-0.426 (0.292)
UPP dummy	0.849*** (0.109)	0.972*** (0.103)	1.042*** (0.102)	1.054*** (0.102)	1.102*** (0.108)	1.096*** (0.106)	1.093*** (0.105)	1.090*** (0.105)	1.091*** (0.105)	1.086*** (0.105)
Violence Exposure * UPP dummy	0.584*** (0.217)	0.873** (0.401)	0.820 (0.588)	0.998 (0.752)	0.275 (0.250)	0.682** (0.300)	1.078*** (0.251)	1.188*** (0.290)	1.196*** (0.326)	1.340*** (0.364)
Local Herfindal Index	-2.359 (2.817)	-2.565 (2.775)	-2.582 (2.750)	-2.618 (2.732)	-2.366 (2.862)	-2.262 (2.884)	-2.240 (2.860)	-2.241 (2.851)	-2.237 (2.861)	-2.135 (2.877)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local vote share on violence exposure dummy, UPP dummy and interaction of both from 2006 to 2014. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Rank aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002 and adopted Rank as part of their name on the ballot. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)) UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A10: Post Election Conflicts - Profession

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure (t+1)	-0.310 (0.199)	-0.226 (0.248)	-0.0970 (0.311)	0.315 (0.409)	0.651 (0.490)	0.207 (0.492)	-0.930 (1.022)	-1.014 (1.177)	-1.014 (1.177)	-1.066 (1.250)
UPP dummy	0.968*** (0.227)	0.897*** (0.233)	0.895*** (0.231)	0.911*** (0.231)	0.913*** (0.231)	0.898*** (0.231)	0.975*** (0.234)	0.974*** (0.234)	0.974*** (0.234)	0.974*** (0.234)
Violence Exposure (t+1)* UPP dummy	0.0520 (0.902)	2.048 (1.766)	4.559 (3.067)	4.306 (3.146)	4.102 (3.187)	5.297 (3.950)	.	.	.	.
Local Herfindal Index	29.05*** (8.839)	29.02*** (8.836)	29.32*** (8.840)	29.39*** (8.842)	29.46*** (8.839)	29.27*** (8.822)	29.13*** (8.856)	29.12*** (8.854)	29.12*** (8.854)	29.11*** (8.853)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure (t+1)	0.125 (0.170)	0.311* (0.187)	-0.0566 (0.189)	0.121 (0.197)	0.426* (0.238)	0.453** (0.225)	0.312 (0.296)	0.193 (0.311)	0.130 (0.418)	0.0391 (0.520)
UPP dummy	1.438*** (0.291)	1.440*** (0.250)	1.326*** (0.238)	1.351*** (0.238)	1.368*** (0.237)	1.291*** (0.242)	1.394*** (0.245)	1.380*** (0.244)	1.351*** (0.243)	1.343*** (0.243)
Violence Exposure (t+1)* UPP dummy	-0.202 (0.366)	-0.320 (0.574)	0.0987 (1.032)	0.0971 (1.183)	-0.146 (1.234)	1.764 (1.623)	-1.940** (0.958)	-1.797 (1.095)	-0.862 (0.713)	-0.157 (0.725)
Local Herfindal Index	28.66*** (8.975)	28.71*** (8.994)	28.50*** (8.966)	28.57*** (8.952)	28.62*** (8.962)	28.55*** (8.957)	28.56*** (8.983)	28.48*** (8.985)	28.50*** (8.985)	28.50*** (8.984)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local valid vote share on post-election violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. "Profession" aggregates every candidate whose registered profession is in security area in Electoral Court in any year since 2002. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A11: Post Election Conflicts - Rank

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure (t+1)	-0.180 (0.110)	-0.120 (0.145)	0.0962 (0.161)	0.161 (0.194)	0.0579 (0.187)	0.155 (0.219)	-0.937 (0.673)	-1.103 (0.774)	-1.103 (0.774)	-1.077 (0.823)
UPP dummy	0.507*** (0.111)	0.581*** (0.106)	0.595*** (0.103)	0.596*** (0.103)	0.592*** (0.102)	0.583*** (0.103)	0.667*** (0.111)	0.664*** (0.110)	0.664*** (0.110)	0.665*** (0.110)
Violence Exposure (t+1)* UPP dummy	1.310* (0.686)	2.367 (1.690)	4.496 (2.988)	4.446 (3.016)	4.512 (3.019)	5.626 (3.718)	.	.	.	.
Local Herfindal Index	-1.680 (2.823)	-1.809 (2.743)	-1.511 (2.755)	-1.507 (2.753)	-1.520 (2.752)	-1.599 (2.700)	-1.744 (2.798)	-1.755 (2.792)	-1.755 (2.792)	-1.760 (2.788)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure (t+1)	0.0428 (0.0744)	0.155* (0.0796)	0.0314 (0.0884)	0.163 (0.103)	0.218* (0.112)	0.271** (0.123)	0.134 (0.179)	0.0695 (0.195)	-0.121 (0.230)	-0.286 (0.285)
UPP dummy	1.032*** (0.123)	1.073*** (0.104)	1.053*** (0.101)	1.060*** (0.100)	1.054*** (0.101)	1.042*** (0.101)	1.130*** (0.109)	1.125*** (0.109)	1.103*** (0.107)	1.094*** (0.106)
Violence Exposure (t+1)* UPP dummy	0.217 (0.226)	0.416 (0.381)	0.865 (0.749)	1.281 (0.869)	1.217 (0.891)	1.874 (1.472)	-1.008*** (0.228)	-1.040*** (0.244)	-0.683* (0.358)	-0.224 (0.395)
Local Herfindal Index	-2.336 (2.802)	-2.347 (2.785)	-2.142 (2.883)	-2.074 (2.856)	-2.083 (2.854)	-2.292 (2.774)	-2.302 (2.825)	-2.345 (2.823)	-2.329 (2.827)	-2.322 (2.826)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local valid vote share on post-election violence exposure dummy, UPP dummy and interaction of both. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. "Rank" aggregates every candidate whose registered profession is in security area in Electoral Court in any year since 2002 and also adopted Rank as part of ballot name. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)) UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A12: Pre and Post Election Conflicts Profession - Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.159 (0.225)	-0.491* (0.263)	-0.488 (0.378)	-0.604 (0.530)	-0.185 (0.698)	0.429 (0.742)	0.314 (1.054)	1.211 (1.188)	0.964 (1.295)	1.261 (1.586)
Violence Exposure (t+1)	-0.351* (0.200)	-0.256 (0.249)	-0.115 (0.305)	0.447 (0.399)	0.622 (0.442)	-0.00475 (0.457)	-1.172 (0.858)	-1.449 (1.143)	-1.392 (1.148)	-1.557 (1.217)
UPP dummy	0.898*** (0.246)	0.863*** (0.238)	0.953*** (0.231)	0.970*** (0.230)	0.989*** (0.229)	0.991*** (0.229)	1.063*** (0.232)	1.069*** (0.234)	1.068*** (0.234)	1.066*** (0.234)
Violence Exposure * UPP dummy	1.241** (0.572)	2.586** (1.184)	0.382 (1.388)	-1.563 (4.931)	-4.332 (3.909)	0.650 (0.938)	0.747 (1.202)	.	.	.
Violence Exposure (t+1)* UPP dummy	-0.444 (0.880)	1.084 (1.459)	4.350 (3.782)	4.636 (4.768)	4.973 (4.070)	5.545 (4.047)	.	.	.	.
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local valid vote share on both pre-election and post-election violence exposure dummy, UPP dummy and interactions. Each column represents a combination of parameters n , varying along columns, and B , constant at 500 meters. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A13: Pre and Post Election Conflicts Profession - Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.180 (0.179)	-0.0170 (0.183)	0.0994 (0.206)	0.112 (0.269)	-0.0176 (0.314)	0.167 (0.512)	-0.313 (0.478)	-0.459 (0.631)	-0.295 (0.798)	-0.377 (0.869)
Violence Exposure (t+1)	0.0813 (0.170)	0.298* (0.181)	-0.0445 (0.189)	0.102 (0.203)	0.389 (0.239)	0.403* (0.237)	0.361 (0.289)	0.277 (0.305)	0.232 (0.415)	0.165 (0.488)
UPP dummy	1.270*** (0.338)	1.348*** (0.262)	1.387*** (0.244)	1.399*** (0.240)	1.465*** (0.239)	1.393*** (0.237)	1.473*** (0.241)	1.458*** (0.240)	1.437*** (0.239)	1.428*** (0.239)
Violence Exposure * UPP dummy	0.696* (0.360)	1.568*** (0.468)	1.711*** (0.657)	1.932** (0.781)	0.647 (0.998)	-0.196 (0.638)	0.689 (0.557)	0.909 (0.690)	0.760 (0.848)	0.812 (0.923)
Violence Exposure (t+1)* UPP dummy	-0.341 (0.359)	-0.703 (0.549)	-1.086 (1.114)	-1.045 (1.177)	-0.481 (1.581)	1.841 (1.670)	-2.055** (0.919)	-2.096** (1.059)	-1.000 (0.742)	-0.305 (0.669)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local valid vote share on both pre-election and post-election violence exposure dummy, UPP dummy and interactions. Each column represents a combination of parameters n , varying along columns, and B , constant at 1000 meters. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A14: Pre and Post Election Conflicts Rank - Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.0322 (0.0847)	-0.0716 (0.136)	-0.191 (0.184)	0.00822 (0.235)	0.324 (0.219)	0.592*** (0.228)	-0.211 (0.551)	0.702* (0.385)	0.605 (0.426)	0.691 (0.542)
Violence Exposure (t+1)	-0.168 (0.112)	-0.0892 (0.148)	0.116 (0.167)	0.215 (0.208)	0.123 (0.181)	-0.00662 (0.233)	-0.861 (0.532)	-1.256 (0.829)	-1.234 (0.837)	-1.237 (0.914)
UPP dummy	0.426*** (0.136)	0.515*** (0.115)	0.581*** (0.106)	0.585*** (0.104)	0.584*** (0.103)	0.586*** (0.103)	0.657*** (0.110)	0.664*** (0.113)	0.664*** (0.113)	0.665*** (0.113)
Violence Exposure * UPP dummy	0.536 (0.419)	1.784* (1.052)	-0.0325 (1.268)	-3.771 (4.552)	-5.693 (3.698)	-0.0617 (0.482)	0.726 (0.697)	.	.	.
Violence Exposure (t+1)* UPP dummy	1.110** (0.552)	1.565 (1.238)	4.522 (3.463)	5.678 (4.338)	5.779 (3.689)	5.957 (3.673)	.	.	.	.
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local valid vote share on both pre-election and post-election violence exposure dummy, UPP dummy and interactions. Each column represents a combination of parameters n , varying along columns, and B , constant at 500 meters. "Rank" aggregates every candidate whose registered profession is in security area in Electoral Court in any year since 2002 and also adopted Rank as part of ballot name. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)) UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A15: Pre and Post Election Conflicts Rank - Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.112 (0.0876)	-0.0207 (0.0802)	-0.0115 (0.0843)	0.0729 (0.106)	0.0419 (0.109)	-0.0364 (0.123)	-0.258 (0.167)	-0.344 (0.218)	-0.233 (0.231)	-0.380 (0.243)
Violence Exposure (t+1)	0.0658 (0.0756)	0.177** (0.0781)	0.0462 (0.0904)	0.164 (0.106)	0.220** (0.111)	0.283** (0.129)	0.204 (0.175)	0.162 (0.185)	-0.0416 (0.212)	-0.174 (0.251)
UPP dummy	0.859*** (0.120)	0.981*** (0.109)	1.026*** (0.104)	1.045*** (0.104)	1.050*** (0.103)	1.030*** (0.102)	1.110*** (0.110)	1.104*** (0.109)	1.087*** (0.108)	1.075*** (0.107)
Violence Exposure * UPP dummy	0.569** (0.223)	0.818** (0.357)	0.537 (0.400)	0.515 (0.512)	-0.842 (0.740)	0.690** (0.277)	1.182*** (0.240)	1.301*** (0.276)	1.198*** (0.298)	1.306*** (0.316)
Violence Exposure (t+1)* UPP dummy	0.00149 (0.232)	0.147 (0.330)	0.557 (0.590)	1.010 (0.670)	1.527 (1.122)	1.858 (1.465)	-1.141*** (0.239)	-1.216*** (0.258)	-0.774** (0.371)	-0.321 (0.373)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state representatives law and order candidates' aggregate local valid vote share on both pre-election and post-election violence exposure dummy, UPP dummy and interactions. Each column represents a combination of parameters n , varying along columns, and B , constant at 1000 meters. "Rank" aggregates every candidate whose registered profession is in security area in Electoral Court in any year since 2002 and also adopted Rank as part of ballot name. Controls include local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. (Panel B, column (2)) UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A16: Turnout without 2018

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.0241 (0.249)	0.319 (0.441)	-0.0300 (0.572)	-0.371 (0.935)	-0.711 (1.376)	-1.490 (1.883)	-2.318 (2.289)	-3.025 (3.752)	-3.396 (4.095)	-4.315 (4.962)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.361** (0.184)	0.216 (0.171)	0.141 (0.244)	0.235 (0.287)	0.352 (0.329)	0.0180 (0.456)	0.448 (0.554)	0.413 (0.681)	0.446 (0.820)	0.0150 (0.829)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state elections' turnout on violence exposure dummy from 2006 to 2014. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Controls include UPP indicator, local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A17: Post Election Conflicts - Turnout

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure (t+1)	0.305 (0.235)	0.332 (0.279)	0.276 (0.274)	0.241 (0.364)	0.296 (0.480)	0.780 (0.531)	1.345* (0.697)	0.986* (0.560)	0.986* (0.560)	1.077* (0.588)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure (t+1)	0.252 (0.168)	0.247 (0.183)	0.336* (0.202)	0.704** (0.277)	0.258 (0.286)	0.330 (0.334)	0.441 (0.391)	0.438 (0.326)	0.553 (0.408)	0.325 (0.379)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state elections' turnout on post-election violence exposure dummy. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. "Profession" aggregates every candidate whose registered profession is in security area in Electoral Court in any year since 2002. Controls include UPP indicator, local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Table A18: Pre and Post Election Conflicts - Turnout

Panel A: Distance (B) = 500

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	-0.00460 (0.251)	0.315 (0.424)	-0.0250 (0.577)	-0.450 (1.033)	-0.760 (1.435)	-1.704 (1.960)	-3.022 (2.522)	-3.591 (3.987)	-4.019 (4.373)	-5.296 (5.392)
Violence Exposure (t+1)	0.292 (0.238)	0.278 (0.277)	0.257 (0.282)	0.355 (0.505)	0.395 (0.563)	1.102* (0.661)	2.288** (1.111)	1.773 (1.149)	1.870 (1.228)	2.335 (1.546)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Distance (B) = 1000

Intensity (n):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Violence Exposure	0.336* (0.187)	0.203 (0.169)	0.112 (0.251)	0.130 (0.309)	0.343 (0.342)	-0.00464 (0.463)	0.388 (0.553)	0.333 (0.684)	0.298 (0.843)	-0.0435 (0.863)
Violence Exposure (t+1)	0.199 (0.172)	0.215 (0.182)	0.312 (0.212)	0.665** (0.305)	0.163 (0.305)	0.327 (0.342)	0.342 (0.392)	0.351 (0.318)	0.455 (0.393)	0.342 (0.396)
Observations	3915	3915	3915	3915	3915	3915	3915	3915	3915	3915
Clusters	1386	1386	1386	1386	1386	1386	1386	1386	1386	1386
Adj. R-squared	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Year and Local FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients from regressing state elections' turnout on both pre-election and post-election violence exposure dummy. Each column represents a combination of parameters n , varying along columns, and B , varying between panels. Controls include UPP indicator, local Herfindal Index (reported) and voters' characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$ (Panel B, column (2)). UPP dummy uses same distance as violence exposure dummy across every specification. Clustered by locale standard errors in parenthesis. Significance levels: 0.10 *, 0.05 **, 0.01 ***

Figure A1: Heat Map Conflicts 2007

This figure presents heat map of drug battles in Rio de Janeiro municipality in 2007. Scale from yellow to red indicates geographical concentration of events. Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Figure A2: Heat Map Conflicts 2011

This figure presents heat map of drug battles in Rio de Janeiro municipality in 2011. Scale from yellow to red indicates geographical concentration of events. Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Figure A3: Heat Map Conflicts 2015

This figure presents heat map of drug battles in Rio de Janeiro municipality in 2015. Scale from yellow to red indicates geographical concentration of events. Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Shapefiles provided by Rio de Janeiro Town Hall and Public Security Insitute (ISP-Rio).

Figure A4: Placebo Profession

This figure reports histogram of the interaction between Violence Exposure and UPP dummies coefficient from regressing state representatives “profession” law and order candidates’ aggregate local vote share on violence exposure dummy, UPP dummy and interaction of both. I have simulated 5000 samples replicating within year average distribution of Violence Exposure dummy at baseline (i.e. shuffling exposed and non-exposed locales). Profession aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002. Controls include local Herfindal Index and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. UPP dummy uses same distance as violence exposure dummy across every specification.

Figure A5: Placebo Rank

This figure reports histogram of the interaction between Violence Exposure and UPP dummies coefficient from regressing state representatives “rank” law and order candidates’ aggregate local vote share on violence exposure dummy, UPP dummy and interaction of both. I have simulated 5000 samples replicating within year average distribution of Violence Exposure dummy at baseline (i.e. shuffling exposed and non-exposed locales). Rank aggregates every candidate who has registered in Electoral Court with profession in security area in any year since 2002 and adopted military rank as part of their name on the ballot. Controls include local Herfindal Index and voters’ characteristics (share by age group, education level, gender and marital status). Exposure dummy constructed as explained in Section 5. Baseline parameters used: Distance $B=1000$ and Intensity $n=2$. UPP dummy uses same distance as violence exposure dummy across every specification.

Figure A8: Correlation Conflicts Homicide 2014

This figure presents scatter plot of number of conflicts and homicide rate in 2014. Correlation: 0.3594. Each point represents one AISP (city's public security division unit). Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Homicide rates calculated as number of occurrences per 10.000 inhabitants according to Public Security Insitute (ISP-Rio). Shapefile provided by ISP-Rio.

Figure A9: Correlation Conflicts Homicide 2018

This figure presents scatter plot of number of conflicts and homicide rate in 2018. Correlation: 0.3283. Each point represents one AISP (city's public security division unit). Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Homicide rates calculated as number of occurrences per 10.000 inhabitants according to Public Security Insitute (ISP-Rio). Shapefile provided by ISP-Rio.

Figure A10: Correlation Conflicts Homicide 2007

This figure presents scatter plot of number of conflicts and homicide rate in 2007. Correlation: 0.9204. Each point represents one AISP (city's public security division unit). Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Homicide rates calculated as number of occurrences per 10.000 inhabitants according to Public Security Insitute (ISP-Rio). Shapefile provided by ISP-Rio.

Figure A11: Correlation Conflicts Homicide 2011

This figure presents scatter plot of number of conflicts and homicide rate in 2011. Correlation: 0.4801. Each point represents one AISP (city's public security division unit). Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Homicide rates calculated as number of occurrences per 10.000 inhabitants according to Public Security Insitute (ISP-Rio). Shapefile provided by ISP-Rio.

Figure A12: Correlation Conflicts Homicide 2015

This figure presents scatter plot of number of conflicts and homicide rate in 2015. Correlation: 0.4164. Each point represents one AISP (city's public security division unit). Drugbattles are obtained from anonymous phonecalls from *Disque Denuncia* hotline service and georeferenced using *geocode* command and Google Maps API in R. Homicide rates calculated as number of occurrences per 10.000 inhabitants according to Public Security Insitute (ISP-Rio). Shapefile provided by ISP-Rio.