Voting for Violence:

Crime and the Election of Law-and-order Politicians in Brazil.

Tiago Ventura *

University of Maryland, College Park

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Abstract

This paper discusses how criminal violence affects voting behavior and citizens' demand for security policies on unequal and violent societies. I propose a theory considering both the micro-level dynamics behind preferences for security policies, and the supply of politicians framing the menu of security policies available to voters. I argue that, rather than priming valence consideration, security policies work as a wedge issue in which voters' security preferences overlap with prior partisan identities and income status, as the salience of violence increases. Using the Brazilian case, one of the most violent countries in the world, I apply a combination of fine-grained observational data on crime and voting, computational text analysis on thousands of congressional speeches, and a novel factorial experiment to support my theory. Observational results show that crime shocks increase law-and-order candidates' vote share, specially on more conservative municipalities. Within each city, the greater electoral support comes, particularly, from wealthier neighborhoods. Similar results are replicated using a factorial experiment on an online sample of Brazilian voters.

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Introduction

Crime and violence have spiked in Latin America's democracies, not only in urban centers but all over the continent. Survey data indicates that, on average, 20 percent of the population in every Latin American country has been a victim of crime during the past 12 months, and personal security has peaked among citizens' concerns (Muggah and Tobón, 2018; Pérez, 2015). As crime has risen on the continent, politicians advancing more punitive policies based on populist, anti-liberal platforms are becoming more numerous, and are increasingly enacting war-type policies with evident human and social costs (Bueno, 2012; Flores-Macías and Zarkin, 2019; Mummolo, 2018; Bonner, 2019). In the realm of both personal safety and threats to individual human rights, the rise of crime and its likely political consequences have become a fundamental threat to democratic politics and deserve detailed attention from political science scholarship.

Despite a recent explosion of studies on the attitudinal effects of victimization on voters (Malone, 2010; Krause, 2014; Merolla et al., 2013; Fernandez and Kuenzi, 2010; Carreras, 2013; Bateson, 2012; Ley, 2017; Visconti, 2019; Garcia-Ponce et al., 2019), we still know relatively little about how criminal violence shape the electoral arena, voters' behavior, and party strategies.

Much of the previous literature relies on theories of party competence and issue ownership to argue that conservative parties have a comparative advantage when campaigning on security policies in an environment where violence is on a rise (Kaplan et al., 2006; Petrocik, 1996; Beckett, 1999; Beckett and Western, 2001; Cohen and Smith, 2016; Holland, 2013). Arguments viewing security as a valence issue assumes voters have homogeneous responses to security appeals. Seen as a valence issue, behavioral effects from exposure to crime victimization are argued to enter in the electoral arena merely as competence shock in which voters more afflicted by violence increase their support to candidate who can credibly signal about their competence to reduce crime.

This paper outlines an alternative explanation to how criminal violence affects voting behavior and citizens' demand for security policies. I propose a theory considering both the micro-level dynamics behind preferences for security policies, and the supply of politicians framing the menu of security policies available to voters. In this model, I argue that security appeals enter into the electoral arena as a wedge issue, in which voters have sharply divisive preferences about the best political strategies to reduce crime. Rather than having a blanket effect on voters, I argue that security serves as a wedge issue, contingent on existing socioeconomic and political cleavages among voters.

Voters more afflicted by violence increase their subjective concerns about personal security, and as recent scholarship has shown victimization in Latin America these voters develop a greater taste for punitive penal policies (Visconti, 2019; Garcia-Ponce et al., 2019). I posit that this effect follows a simple insurance dynamic in which voters more exposed to risks of victimization are willing to increase the amount of punishment delivered by the state apparatus as a form of protection. However, absent in these previous studies is considerations about the externalities and human costs of these harsh-on-crime policies. Although benefits of these policies are arguably spread among the entire society, the *costs* are mainly concentrated on underprivileged sectors and social and racial minorities (Magaloni et al., 2020; Mummolo, 2018; Denyer Willis, 2015; Gelman and Hill, 2007). I argue that this difference makes wealthier, usually politically conservative groups, less risk-averse and more willing to support candidates campaigning on punishment. Consequently, the effects of crime shocks become a wedge issue dividing voters on the best strategies to reduce crime, and overlapping with partisan identities and economic status.

These changes on the demand side, with some voters growing a greater taste for more punitive policies, affect partisans and candidates strategies. I argue that as violence becomes more salient, candidates with professional experience in law-and-order agencies, who can credibly signal about their *mano dura* preferences, will receive greater electoral support. Former police officers, members of the army, and other law-and-order candidates strategically use their personal history to convince voters concerned with crime control about their capacity and willingness to prioritize security *at all* costs while in office. The importance of occupation as an heuristic for voters is a consequence of party labels' fluidity in newly democratized countries (Lupu, 2017; Samuels and Zucco, 2018; Baker et al., 2016), but also a historical consequence of the strong historical pattern of abuses and violence committed by security forces in Brazil (Bueno, 2012; Caldeira, 2002; Denyer Willis, 2015; Cano, 1997; Misse, 2011).

I show empirical evidence for my theory using data from the election of law-and-order candidates in Brazil. In 2018, the populist leader Jair Bolsonaro, a former captain of the Brazilian Army, won in a landslide presidential election, and together with Bolsonaro, the public security caucus became the largest in the Congress with several candidates from police forces, the military, or other enforcement agencies elected to the House in recent years . In a country where 57,358 people were violently murdered just in 2019 (Cerqueira et al., 2019), making Brazil one of the most violent democracies in the world, law-and-order candidates ran and won on promises of being tough on crime. This dynamic makes Brazil an ideal case to understand the effects of criminal violence on voting behavior.

The empirical sections of this paper use a unique combination of computational text-analysis on thousands of congressional speeches, fine-grained observational data with causal models, and an online factorial experiment. Each section builds an important piece of my theoretical work. The text-analysis from congressional speeches shows evidence of the crucial assumption of my model: law-and-order candidates dedicate greater attention in their speeches, more than other conservative parties, to public security and are more likely to be associated with more punitive issues. Observational data indicates that House candidates from enforcement agencies received greater support in municipalities where a random crime shock occurred right before the election, and is mostly driven by voters from wealthier neighborhoods in Brazil. And the factorial experiment provides evidence that voters do pay more attention to public security messages from law and order candidates, that wealthier and more conservative voters are on average more punitive, and that punitive preferences also increase support for messages from candidates with a military background.

The rest of the paper is structured as follows: the next section introduces the theory and positions the paper within the broader literature on the political effects of violence in electoral democracies. The following section describes the Brazilian case and provides evidence about the growth of law and order politics. I then present the empirical sections of the paper. I conclude with a discussion about the main findings and contributions of the manuscript.

Violent Democracies, Attitudes and Issue Ownership Theory.

Research on the intersection between criminal violence and political behavior has received increased attention from political scientists in the last few years. Measuring citizens' attitudes, recent comparative studies have found that victims of violence are less trusting of democratic institutions (Krause, 2014; Pérez, 2015; Merolla et al., 2013) and criminal justice agencies (Malone, 2010), and are less supportive of democratic attitudes (Fernandez and Kuenzi, 2010; Carreras, 2013; Bateson, 2012). Considering political participation, the effects of criminal victimization and exposure to violence are more mixed; evidence suggests that while crime is associated with higher levels of non-electoral forms of participation, victimization is also associated with diminishing electoral turnout (Ley, 2017; Bateson, 2012; Trelles and Carreras, 2012).

The effects of violence on mass policy preferences, particularly with regard to penal policy, have also been a topic of increased attention. Using cross-national survey data in Latin America and the Caribbean, some studies suggest that victimization and fear of crime is strongly associated with approval of repressive institutions and vigilantism (Bateson, 2012; Singer et al., 2020). Visconti (2019) finds that subjects who were victims of crime are more likely than non-victims to support strong-arm policies to reduce crime in Brazil, while experimental studies also indicate that exposure to news about violence and victimization elicits similar effects on preferences for punitive crime control policies (Garcia-Ponce et al., 2019; Krause, 2014). These studies have substantially shaped our knowledge about political behavior and citizens' attitudes in violent democracies. Nevertheless, our understanding of how these political attitudes shape the electoral arena, candidates' competitiveness, and party strategies amid high-levels of violence is still limited.

The majority of the scholarship discussing the effects of crime on voting behavior and party dynamics often relies on the assumptions of issue ownership and party competence to explain who wins and who loses when crime increases in democratic societies (Holland, 2013; Beckett, 1999; Beckett and Western, 2001; Kaplan et al., 2006; Petrocik, 1996; Berens and Dallendörfer, 2019; Calvo and Murillo, 2019). The issue ownership argument usually runs on two mechanisms: first, voters afflicted by violence are more likely to vote on candidates they perceive as more credible and capable of reducing crime, a purely non-policy effect. Second, conservative parties "own" the issue of security (Kaplan et al., 2006; Petrocik, 1996). Therefore, when crime becomes a salient topic, conservative candidates have a valence advantage commonly perceived by voters as more competent and credible to fight against crime.

In the following paragraphs, I propose an alternative theory in which security policies work as a wedge issue and expand on how these preferences affect voting behavior and partisan strategies.

Theory: Security as a Wedge Issue

Lower crime rates are a desirable goal for every society. However, the way one achieves this goal is not a matter of competence, but rather involve some crucial trade-offs on voters' mind. Conservative voters, usually coming from the upper-echelon of society, see harsh-on-crime policies as an effective strategy to reduce crime, while liberal voters point to redistribution as a path to be followed. These differences are not new (Beckett, 1999; Beckett and Western, 2001), but this distinction is crucial to understand how voting in violent democracies is affected by crime.

Taking this distinction into consideration, I argue that as concerns about violence and crime in a particular society increase, security appeals enter the electoral arenas as a wedge issue in which voters react differently to policy strategies to reduce crime. Thus, policy preferences by voters will play the strongest role in how crime shocks impact the electoral arena, rather than valence concerns that bluntly favor a given party or candidate.

The wedge dimension of security concerns is a consequence of micro-level dynamics behind the support for punitive policies. Recent scholarship has pointed out to attitudinal effects emerging from crime victimization resulting in increased support for punitive penal policies (Visconti, 2019; Garcia-Ponce et al., 2019). In this argument, as victimization increases, voters become more punitive and likely to support the adoption of harsh-on-crime policies. I consider this policy effect as an insurance decision. As the risk of being a victim of crime increases, voters make a decision to invest more on protection, allowing the security apparatus to adopt more punitive security policies.

However, even assuming that these punitive policies are indeed effective reducing crime and all the society equally enjoys their benefits, which recent research has question (Weintraub and Blair, 2020), the costs of these policies are not equally spread across socioeconomic groups and ethnic and racial minorities. For example, iron-fist policies usually come associated with the adoption of large-scale crackdowns against criminal, often involving strong military deployment. Research, in most developing countries, and some developed countries like the U.S., has shown that police militarization has deep humans costs against social and racial minorities (Mummolo, 2018; Flores-Macías and Zarkin, 2019; Lessing, 2017; Durán-Martínez, 2015). In Latin America specifically, security forces have used legal instruments to justify and hide the indiscriminate use of violence (Denyer Willis, 2015; Misse, 2011), taking advantage of weak vertical and horizontal mechanisms of oversight from other institutions (Brinks, 2007; Ahnen, 2007).

This unequal distribution of the risks and costs associated with the adoption of punitive policies suggests that the formation of punitive preferences emerge as an insurance dynamic. As criminal violence and personal risk increases, the salience of security appeals goes up; because the changes of being caught on a arbitrary police action are lower for rich voters, and the benefits of harsh-on-crime policies are equal to the entire society, better-off voters have more incentives to support candidates promising these policies. In the language of a insurance dynamic, when afflicted by violence, rich voters become less risk-averse on their security decision, and become more supportive of punitive candidates.

This argument converges with findings of victimization making voters more punitive (Visconti, 2019; Garcia-Ponce et al., 2019). However, when considering also the costs and risks of adopting punitive policies, my argument adds a direct income effect on how voters update their preferences when crime becomes a salient issue. In this format, my theory connects the effects of victimization with existing work on the established association between conservatism and more punitive views about the society (Cohen and Smith, 2016; Gerber and Jackson, 2016). Due to the intersection between income differences and conservatism in unequal societies like Brazil, punitivism as policy dimension will overlap with socioeconomic and partisan dynamics, substantiating the idea of security concerns as a wedge policy, rather than a valence, non-policy shock in the electoral market.

The wedge dimension of security preferences adds pervasive incentives to law enforcement officials in Brazil. As crime increases, conservative and wealthier voters are more receptive to punitive appeals from law-and-order officials. And, as a consequence to be more competitive at the polls, hopeful candidates use more punitive practices while working in security forces in order to build around them a personal reputation. This electoral dimension potentially explains the persistence of punitive actions and cases of state-sponsored violence among security forces in Brazil; delivering punishment in the present increases the credibility of specific candidates, and is commonly rewarded with votes from conservative and wealthier classes.

A possible alternative argument to my theory should be considered. Canonical economic models relate a growth in crime with high levels inequality (Becker, 1968). And as such, voters afflicted by violence may choose between two different strategies to reduce crime: invest more on redistribution or adhere to more punitive policies promising a reduction on crime in the short-run. Rueda and Stegmueller (2015) has shown the former scenario is prevalent in Europe, where wealthier voters are on average more redistributive where inequality is high, suggesting fear of crime works as the main mechanism turning the affluent more redistributive.

This is a unlikely path in Latin America. While in Europe, welfare schemes controlled or regulated by the state work indeed as redistributive and insurance tools (Moene and Wallerstein, 2001, 2003), in Latin America, social expenditures historically have done little to aid the poor (Díaz-Cayeros and Magaloni, 2009; Haggard and Kaufman, 2020). As this "truncation" of the welfare states has been used to explained poor's diminishing expectations about social speding and publicly funded redistribution (Holland, 2018), I argue these institutional effects on behavio also affect the strategies of the wealthy. In a context of ineffective redistribution, invest in the state become pointless, therefore, promises of punishment and tough-on-crime crackdowns become the main policy strategy to fight against crime.

Occupational Heuristics: Voting for Law and Order in Fragmented Democracies

In democracies more afflicted by violence, one should expect that the number of candidates campaigning on security increases. However, not all candidates have the same set of endowments (Calvo and Murillo, 2019) to convince voters about their best predicates for the office. Issue ownership theory solves this puzzle by arguing that some parties are perceived as more competent in some particular policy areas, and therefore, as this issue increases in salience, these parties win elections at higher rates (Petrocik, 1996; Kaplan et al., 2006). For the issue of crime, this theory has been used to argue that conservative parties "own" the issue of security and would therefore win elections at higher rates when crime grows (Holland, 2013; Beckett, 1999; Beckett and Western, 2001).

While this argument might reflect dynamics on long-standing democracies, in newly-democratized countries, where party labels are often uninformative, more fluid, and brand dilution frequently occurs (Lupu, 2017; Samuels and Zucco, 2018; Baker et al., 2016), issue ownership theory requires some scope conditions. And particularly because countries with a more recent party system often intersect with societies where crime is more widespread, a proper understanding of changes in party and candidates' strategies makes is yet more critical.

I expect that in the absence of strong party labels, heuristics at the candidate level will be more relevant than party labels, as suggested by the literature on source cues (Botero et al., 2015; Lupia, 2002; McDermott, 2005). When parties are less informative, the candidates' professional experience serves as the heuristic voters rely upon to infer about the candidates' credibility and competence. For voters concerned about crime, a candidate's previous professional history in law enforcement agencies supplies the information needed, rather than one's party affiliation. For example, a police officer might argue that having years of experience patrolling the streets, interacting with criminals, or possessing an extensive network of contacts on criminal justice agencies makes one a more credible candidate to fight against crime.

This distinction about how criminal violence affects the supply of politicians and the weight of particular heuristics on voters' mind is far from trivial. In most developing countries, candidates emerging from the police and the military are historically committed with punitive practices, and usually campaign on, and once in office defend the adoption of law-and-order policies (Bueno, 2012; Cano, 1997; Denyer Willis, 2015; Brinks, 2007; Caldeira, 2002). Therefore, different than a simple non-policy issue advantage bluntly attributed to party labels, the candidates with criminal justice system experience that are the one whom hew more closely to those voters that have more punitive preferences.

My theory of security as a wedge issue forms the hypotheses of this paper. Based directly on the occupational advantages argument, I expect higher exposure to violence to have a substantial, positive effect on the electoral support for law-and-order candidates (*h1*), and that these effects are larger among candidates from law enforcement agencies than on candidates from more conservative parties (*h1a*). To show how the crime issue is divisive among voters, I discuss how the support for law-and-order candidates is driven by politically conservative voters (*h2*) voters, and voters living close to olling stations located at wealthier neighborhoods in Brazil (*h2a*). I analyze these predictions using observational electoral data, with well-identified statistical models leveraging random variation on pre-electoral shocks on crime at the local level for all municipalities in Brazil in three electoral cycles. I conclude by replicating the macro-level findings from observational data on a novel factorial endorsement experiment providing micro-level evidence of my theory.

Police, Politics and law-and-order Candidates in the Brazilian Lower-Chamber

Brazilian federalism delegates most public security and policing responsibilities to state-level authorities. At the state level, the police are divided into a civil and a military arm. The former shares the duties of investigation; they do not patrol the streets, generally does not use uniforms, and is directly subordinate to the state government. The military police are in charge of maintaining order, patrolling the streets, and imprisoning criminal suspects.

Police forces in Brazil were built historically as an institution for the deployment of state-level repressive strategies, particularly against social and racial minorities, such as slaves, former slaves, and city dwellers (Rose, 2005; Caldeira, 2002). The periods of military authoritarianism (1930-1945 and 1964-1985) exacerbated police officers' roles in repressive enterprises, including not only minorities, but also political dissidents. Through these years, regular police officers, together with highly trained military forces, became key components of extralegal violence as a mechanism to sustain the authoritarian regime. Consequently, police forces in Brazil carry an institutional history of illegal use of violence, weak accountability, and generations of officials trained under non-democratic practices (Caldeira, 2002; Brinks, 2007).

More importantly, when these specialists in security and repression enter politics, their actions overwhelmingly replicate their previous experiences with illegal use of force and the adoption of more punitive security policies. Several recent papers show these historical legacies affect levels of criminal violence and state-sponsored abuses even in post-authoritarian periods (Frantz, 2018; Trejo et al., 2018). In Brazil, after thirty years of democratization, few institutional reforms were implemented in the police and military forces, and a persistent pattern of excessive use of force by security forces targeting more underprivileged neighborhoods and social and racial minorities persists (Bueno, 2012; Cano, 1997; Denyer Willis, 2015; Brinks, 2007; Caldeira, 2002).

The country electoral and legal system imposes no restrictions on military members and police officers who decide to run for elected positions. During the electoral campaign, these candidates are legally forced to request a leave absence from work, losing their access to the institution and other benefits momentarily; however, after the elections, all the benefits are immediately reinstated for candidates who were not elected.

While several studies and news reports use a broader set of factors to classify law-and-order politicians in Brazil, including participation in the Public Security Caucus, policy and attitudinal preferences, and their past history in criminal agencies, (Medeiros and Fonseca, 2016; Faganello, 2015), I opt for a more restrictive definition. Both theoretical and methodological reasons explain this decision. I classify law-and-order candidates as actors who previously held an occupation in police and/or military forces before entering politics. Theoretically, this classification is substantiate from my argument about occupation working as the main heuristic voters rely upon to make decision in a context of fluid party labels. Methodologically, this straightforward definition can be retrieved directly from the electoral data available from official sources. [1]

Table 1 presents descriptive evidence for the growth of law-and-order candidates in the Brazilian elections over time. These descriptive results showcase a consistent upward trend on the absolute number of House candidates with a professional experience on security forces. In the last three electoral cycles, working in public security is among the top three most reported occupations by House candidates – only behind lawyers and businessmen. With a growth in the number of candidates, their electoral support has increased substantially over the years. In the last 2018 House election, 35 law-and-order candidates were elected for the House (6% of the total); this number gives security actors their biggest presence in legislative politics since the years of the military dictatorship in Brazil. If unified in a single party, these candidates would represent the third-largest party in the House.

Table 1 also indicates how spread across different parties these candidates are; in total, in 2014 and 2018, twelve parties had at least one member of security forces elected as a House member [2] Overall though, as expected, small conservative parties, with basically no strong party labels, have been the

[1] I present more information about this classification in the appendix.

[2] Most of these candidates and elected representatives are members of the center and the center-right parties in Brazil. In particular, in 2018 the PSL, the party of President Bolsonaro, was responsible for electing a large group of former security officers to the House. However, a detailed investigation shows that even leftist parties, such as the PSB, PDT and PSOL, have succeeded in electing law-and-order officials to the House.

Table 1 Descriptive Statistics for the Law and Order Candidates for the House Elections in Brazil (2002-2018)

House Election	# Candidates	# Elected	Total Votes	Share of Votes	Number of Parties (Only Elected)
2002	230	5	1,188,900	1.5\%	5
2006	299	5	1,457,570	1.7\%	4
2010	302	6	2,055,477	2.3\%	6
2014	292	16	3,370,487	3.8\%	12
2018	458	35	8,884,020	9.7\%	12

favorite choice of law-and-order candidates.

Analyzing Congressional Speeches: Examining Issue Ownership among law-and-order Representatives

This paper's theoretical framework is built upon the assumption that candidates occupations on enforcement agencies signal to voters a commitment to enact more punitive policies. In this section, I validate this central assumption using computational text analysis. Using data from congressional speeches for House members from 2002-2019 [3], I estimate a Structural Topic Model (STM) (Roberts et al., 2014a) to identify the prevalence of security as an policy issue in Congress. Then, I use multilevel modeling to explain determinants of these issues across the speeches, particularly how law-and-order representatives, and not conservative parties, dedicate more attention to security and crime in their House speeches.

In the appendix, I provide an in-depth discussion about data collection and pre-processing for the congressional speeches and the statistical model behind the STM; here I provide only a summary of the model. After using standard pre-processing techniques in the corpus, I am left with a corpus of 133,485 speeches, in which I fit a STM model with 60 topics. [4]

[3] The speeches were collected through the Congress API, available here https://dadosabertos.camara.leg.br/

[4] I estimate models with different number of topics, and the results for the security topics are relatively stable, without any substantive change in the words associated with these topics. In the appendix, I provide measures performance measure for the models corroborating my choice of the number of topics.

Table 2 Violence and Security on Congressional Speeches in the Brazilian House (2002-2019)

Topics	Most Likely Words	FREX Words
Topic 9: Police and Military	milit,seguranc,polic,polic,forc, policial,armad,públic,exércit,civil	polic,milit,armad,bombeir,policial, seguranc,exércit,civ,forc,polic
Topic 11 : Gender and Violence	mulh,violênc, homens,contr,lut,tod,feminin,direit,aind,gêner	mulh,homens,violênc, feminin,gêner,igualdad, lut,comemor,internacional,contr
Topic 25: Children and Violence	crianc,jovens,adolescent,anos,idad, menin,sexual,infantil,explor,jov	crianc,adolescent,jovens,menin,sexual, idad,infantil,infânc,jov,adult
Topic 37: Crime	crim,violênc,pres,seguranc,crimin,penal, organiz,armas,combat,públic	crim,crimin,armas,pres,penal,criminal, homicídi,assassin, violênc,tráfic
Topic 45: Race and Violence	pobr,negr,popul,fom,pobrez, desigualdad,social,viv,ric,misér	negr,pobr,desigualdad,pobrez,misér, fom,ric,branc,igualdad,rac

Note: Results are estimated using a Structural Topic Model with 60 topics, in a corpus of 133,485 speeches from Representative in the Brazilian Lower Chamber. The table presents only the five topics addressing issues of violence, crime, and public security. For each topic, I present the word with i) highest probability to be part of the topic, and ii) highest FREX (Frequency and Exclusivity) (Roberts et al., 2014a))

I find five topics that address issues related to violence and security. I present the most prevalent and FREX words (Roberts et al., 2014a) for each of the five topics in table 2. Two topics are more directly connected with crime and public security; the first one focuses on policy issues related to the police and the army (Topic 9: Police and the Military), and the speeches are focused on better wages, retirement, and investment in security, among others; and the second topic (Topic 37: Crime) appears in words such as crime, violence, drugs, victim, and refers to speeches discussing the context of violence in Brazil. The other three topics deal with minorities (Children, Women, and Brazilian Afro-descendants) and violence: some of the speeches on these topics address episodes and statistics of violence against these minorities, while others are more general about social inequalities and minority rights in Brazil.

Modelling Issue Attention

To understand the degree to which law-and-order members of the House strategically give greater attention to crime and security issues in the speeches, I use the outputs from the STM to classify the most prevalent issue in each of the 133,485 speeches. Out of the entire corpus, 8,872 documents were classified as being about security. With this classification in hand, I estimate a set of multilevel generalized logistic models using the speeches' classification from the STM as the dependent variable. The main independent variable in the models is whether the House member is a law-and-order candidate, which I measure using the same classification previously described. I add in the model dummies for six specific parties to show how occupation differs from partisan effect, as well as the vote share at the state-level for each of the speakers. Finally, to address overdispersion in the data (the fact that some politicians make more speeches than others), I add three families of random intercepts to the model: at the speaker level, at the legislature, and the electoral district for each House member (Zheng et al., 2006).

Table 3 presents the results. The models provide support for the main assumption of the paper: candidates with a history in criminal agencies rely more heavily on security and crime issues in their public statements in the House. On average, law-and-order House members are more than two times more likely ($exp(1.154) = 3.16$) to use the floor to make a speech about public security and violence. This effect is positive when pooling all the topics, and stronger when considering only the topics dealing with Public Security and Crime (topics 9 and 37). However, the effect of being a law-and-order House member is negative for speeches about violence against minorities and social inequalities. As theorized, law-and-order House members dedicate more attention on their public speeches to public security and crime issues, however, these politicians also dedicate less attention about how some social and ethnic minorities are the main victims of violence, including abuses from state forces.

Effects across the parties deserve an extended discussion. Before Bolsonaro, Brazilian electoral politics was polarized between PT, on the left, and PSDB and PFL-DEM on the right; results from all the three models in table 3 show how the later conservative parties do not explore public security in their public stances in the House; the PP, the heir to the civil-military party which ruled Brazil during the years of dictatorship during the 60s, also appears with a negative and statistically significant coefficient in the regression models. Finally, the party more closely connected to President Bolsonaro also shows no positive coefficient. In conclusion, former members of enforcement agencies, who were elected to the House prioritize crime and security, indeed make public efforts to signal about their commitment.

Table 3 Regression Models: Issue Attention, Public Security, and Law-and-Order House Members

	Dependent variable: House Speeches about Crime and Violence		
	All	Public Security/Crime	Minorities/Violence
Intercept	-2.932^{***}	-3.506^{***}	-3.599^{***}
	(0.059)	(0.079)	(0.085)
Law-and-Order Representative	1.154^{***}	1.681^{***}	-0.882^{***}
	(0.150)	(0.149)	(0.230)
Vote Share	-2.129^{***}	-2.407^{*}	-2.338^{***}
	(0.774)	(1.370)	(0.742)
PT	0.052	-0.236^{***}	0.249^{***}
	(0.082)	(0.091)	(0.089)
PSL	−0.101	-0.276^{*}	0.152
	(0.133)	(0.147)	(0.203)
PSDB	-0.546^{***}	-0.524^{***}	-0.351^{***}
	(0.102)	(0.112)	(0.118)
PFL-DEM	-0.273^{***}	-0.301^{***}	−0.111
	(0.089)	(0.103)	(0.105)
PMDB-MDB	0.038	0.041	−0.059
	(0.075)	(0.087)	(0.098)
PP	-0.411^{***}	-0.492^{***}	−0.074
	(0.131)	(0.147)	(0.146)
State Random Effects	yes	yes	yes
Representative Random Effects	yes	yes	yes
Legislature Random Effects	yes	yes	yes
Observations	131,125	131,125	131,125
Log Likelihood	−28,821.230	−19,433.120	−19,663.770
Akaike Inf. Crit.	57,666.460	38,890.250	39,351.550
Bayesian Inf. Crit.	57,783.860	39,007.650	39,468.960

Notes: All the models use Generalized Multilevel Logit Models benchmark OLS estimation. Models 1 uses all the speeches classified as addressing issues of violence, crime, and public security. Model 2 uses only the topics 2 (police and military) and 5 (crime), while the model 3 uses the other topics addressing issues of violence and social minorities. All the models uses random intercepts at the speaker, state, and legislature level.

The Effects of Crime Electoral Shocks on Voting for law and order.

This section explores the effects of criminal violence on the electoral support for law-and-order House candidates across Brazil's three more recent electoral cycles (2010-2018). To causally identify the effects of violence on punitive voting choices, I explore month-to-month granular homicide count data from all Brazilian municipalities to isolate exogenous effects of crime on voting behavior. I build a treatment group of cities with a sudden pre-election growth in violence in the three months before an election and a control group with a similar shock but during the three months after an election. I add a set of control variables, state and year fixed effects to improve the causal parameters' identification and efficiency. I have three main predictions from this analysis. First, municipalities with pre-electoral violence will show more significant support for law-and-order candidates. Second, more violent municipalities, using the overall homicide rates in all the months before the election, will also increase the vote share of these candidates. Third, pre-electoral shocks will have greater effects in municipalities in more violent municipalities, where the salience of appeals to fight against crime will be higher.

Data

I rely on several official data sources to estimate the effects of violence shocks on support for law-and-order candidates across the three more recent electoral cycles for the House. Electoral results aggregated for all Brazil's 5.570 municipalities come from the Superior Electoral Court (TSE), and municipal level socio-demographics, except for the violence data, comes from official census information. The outcome variable for all the models uses the logarithm of the vote share of law-and-order candidates. As previously described, I use the candidates' official electoral registration to identify those who reported being a member of criminal justice agencies (military, civil and any private police, armed forces, and firefighters) or reference their law-and-order occupation in their ballot names.

Brazil has no month-to-month official data on crime. Therefore, I use homicides information from the Death Certificates data extracted from the Brazilian System of Death Registration (SIM/Datasus). This is widely recognized as the most reliable and granular information source on homicides in Brazil. [5] Although homicides rates are not an perfect equivalent of criminal violence, several recent studies

[5] All deaths with codes X85 to Y09 and Y87.1 in ICD-10 were counted as homicides, which corresponds with the coding

have relied on this statistic to measure the level of criminal conflict where finer-grained data are not available (Magaloni et al., 2020; Murray et al., 2013; Menezes et al., 2013; Dube et al., 2013). I also use data from census information and the National Institute of Geography and Statistics (IBGE) as a battery of municipal level control variables, such as population, Gini index, rural population, income per capita, and others.

All the models control for the vote share of the front-runner conservative presidential candidate and the his party vote share for the House election in each respective year. This set of controls are instrumental to provide robustness to the results. The fact that results hold, even when controlling out the vote share of conservative party provides evidence voters reward at higher levels law-and-order candidates when afflicted by violence, and this variation rules out explanations based solely on partisan issue ownership.

Model

To isolate the effect of crime from unobserved factors that might also be correlated with support for law-and-order candidates, I leverage short-term variation in the monthly homicide rates right before and right after the House elections for each municipality. My main identification assumption states that the variation over a short period of time in homicides is exogenous to the overall homicide rate and other socio-demographic characteristics in a given municipality, as well as from other observed and unobserved covariates. Under this assumption, spikes in homicides are equally likely to occur before and after the election. This approach borrows from previous empirical studies in corruption and news cycle in Brazil and México (Ferraz and Finan, 2008; Marshall, 2019).

The empirical models compare municipalities with a spike in crime in the months before the election with municipalities with a spike right after the election. Let's formalize the research design. Considering municipality m, on the election month t, I assume a pre-electoral shock occurs when the number of homicides h_{pop} per 100.000 population in city m in the three months before the election is strictly higher than in the three months after the election. On the other side, I classify as post-electoral shock when municipality m experiences the same or higher number of homicides in the three months after

of violent deaths from previous studies (Murray et al., 2013; Cerqueira et al., 2019) the election (including t). To make comparisons more reliable, all the municipalities where no homicide occurred between t_{-3} to t_{+2} are not included in the analysis. Equation 1 presents a formal definition of the main variable of interest:

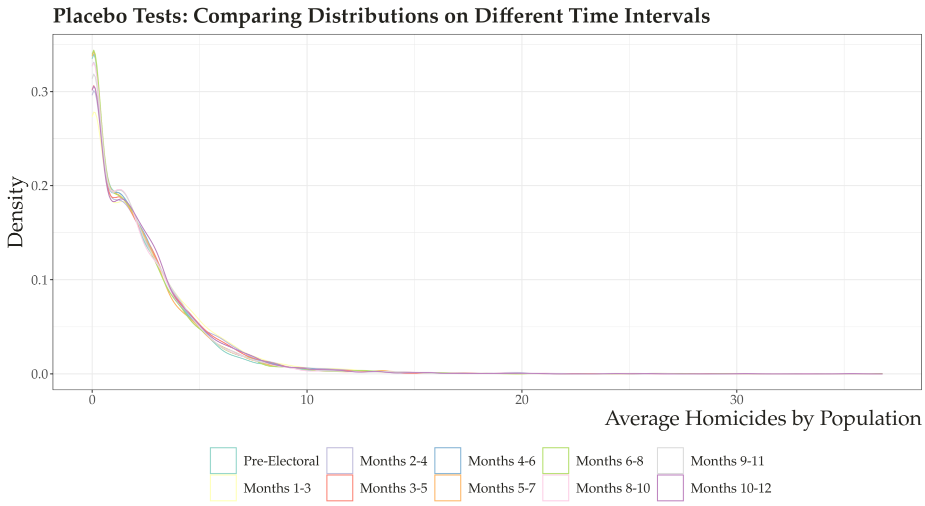
$$\text{Homicide Shock} = \begin{cases} \text{if } \sum_{i,t_{-3}}^{t} h_{i,pop} > \sum_{i,t}^{t+2} h_{i,pop}, \text{ then = 1} \\ \text{if } \sum_{i,t_{-3}}^{t} h_{i,pop} \leq \sum_{i,t}^{t+2} h_{i,pop}, \text{ then = 0} \\ \text{if } \sum_{i,t_{-3}}^{t} h_{i,pop} and \sum_{i,t}^{t+2} h_{i,pop} = 0, \text{ then = .} \end{cases} \tag{1}$$

As mentioned before, the identification of the causal effects assumes that the potential outcomes for electoral support to law-and-order candidates are ignorable conditional on the timing of homicides around elections occurs. The first threat for the causal design relates to the plausibility of the exogeneity assumption on observable covariates. To ensure the validity of this assumption, I demonstrate in the appendix that the pre-election homicide shocks are not systematically affected by a wide variety of observable pre-treatment covariates, including the municipal monthly homicide rate for the same year, and also compare the distributions of crime rate over time. No violations are detected.

Another identification threat relates to the possibility of sorting of the use of violence conditional on the electoral months. Two distinct problems emerge here: first, criminal organizations can use violence to affect electoral outcomes, as argued by the recent scholarship on Drug Trafficking Organizations (DTOs) (Daniele and Dipoppa, 2017; Trejo and Ley, 2018), or local officials might respond to the electoral cycles by investing more on security right before the elections. I argue that both processes are unlikely in the Brazilian case. First, DTOs in Brazil are, particularly the largest one (*Comando Vermelho*), are mainly present in major metropolitan areas of the country, and evidence of their direct electoral engagement has not been identified by the specialized literature (Feltran, 2018; Denyer Willis, 2015). Second, House elections in Brazil do not coincide with local races, which means mayors have no incentives to adjust policies, particularly in long-term structural areas such as public security, in response to these upper-level races.

To conclude, I report results comparing the average levels of violence between the pre-electoral period and all the other three months intervals across a year. I perform this test for all the three electoral years in my data. If changes in the crime rate before the election were not exogenous, we would expect to find differences in their distributions when comparing our target distribution with some placebo examples. Results are presented in figure 1, and visually, results indicate that the average crime rate across ten distinct time periods all seem to emerge from a common distribution, reducing concerns of strategic manipulation of violence around the elections. More rigorously, I use Kolmogorov-Smirnov tests to compare these distributions, and the results fail to reject equality of distributions.

Figure 1 Validity Tests for the Pre-Electoral Shocks



After showing evidence of the plausibility of my identification strategy, I estimate the models using standard OLS Estimators. I report models using several control variables, and two-way fixed effect at the state and election cycle. The pre-electoral violence shock represents the main causal effect of interest, and I present models with the average effect for electoral violence shock and interact it with the overall trend in violence in a municipality i.

Results: The Effects of Violence and Pre-electoral Crime Shocks

Table 4 presents the results from the main statistical model. I report only the coefficients for the effect of pre-electoral homicide shocks, the homicide rate before the campaign starts, and the interactive effect between both variables. Overall, I find no support for a direct effect of pre-electoral homicide shocks on the support for law-and-order candidates. Using the different specifications on models 1, 3, and 5, none of the coefficients for pre-electoral homicides shocks is statistically different from zero.

Table 4 Regression Models: Average and Interactive Effect of Pre-electoral Homicide Shock.

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-8.751^{***}	-8.691^{***}	-9.001^{***}	-8.897^{***}	-9.702^{***}	-10.121^{***}
	(0.734)	(0.734)	(0.723)	(0.724)	(0.652)	(0.605)
Pre-Electoral Homicide Shock	0.031	-0.052	0.042	-0.045	-0.038	-0.080^{**}
	(0.034)	(0.046)	(0.029)	(0.039)	(0.030)	(0.033)
Pre-Electoral Homicide Shock x Homicides Before Electoral Campaign		0.006^{***}		0.007^{***}		0.004^{**}
		(0.002)		(0.002)		(0.002)
Homicides Before Electoral Campaign	0.015^{***}	0.012^{***}	0.015^{***}	0.012^{***}	0.009^{***}	0.006^{***}
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	yes	yes	yes	yes	yes	yes
State Fixed Effects	no	no	yes	yes	yes	yes
Time Fixed Effects	no	no	no	no	yes	yes
Observations	8,628	8,628	8,628	8,628	8,628	8,628
Adjusted R^2	0.135	0.136	0.371	0.371	0.320	0.562
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$					

Note: Regression models using benchmark OLS Estimation. Models 1 and 2 controls for several socio-demographics variables. Model 3 and 4 adds State fixed effects. Model 5 and 6 use electoral year fixed effect. The outcome variables uses the logarithmic of the vote share for law and order candidates, and the homicide data report total counts over months before the electoral campaign starts (January to July) in a given electoral year, and by 100.000 municipal population

However, I find strong and robust interactive effects for pre-electoral shocks conditional on each municipality's overall levels of violence. Interactive models between the homicide shocks and the homicide rate before the electoral campaign are positive and statistically different from zero, in all the three models using local controls, state fixed effects, and time and state fixed effects.

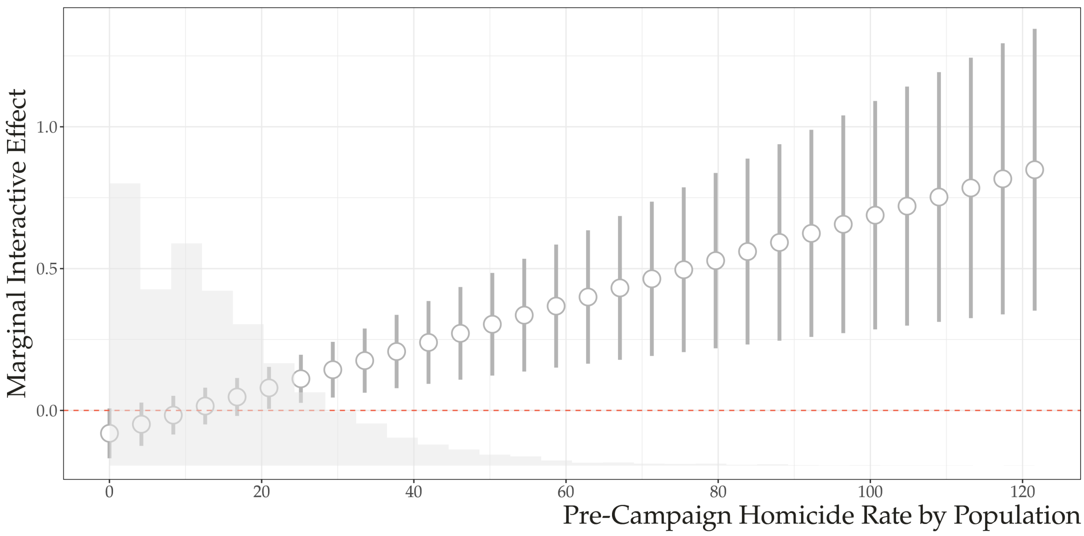
To give a sense of electoral crime shocks' substantive effect on more violent cities, let us consider an example. Consider a municipality with a homicide rate of 20 deaths per 1.000 people in the six months before the electoral campaign – this value, according to figure 2, has marginal effects of pre-electoral shocks that are distinguishable from zero, and represent third quartile (75%) of the moderator. For these violent municipalities, an electoral shock increases by 12% ((exp(0.115) − 1) * 100) the voter share of law-and-order candidates, on average. Considering the high level of competition for House Seats in Brazil, an increase of 12% of the vote share of a few candidates indeed represent the difference between winning or losing a seat.

To ensure robustness for the findings, in the appendix, I estimate models directly controlling for the alternative explanation positing that issue ownership explains how criminal violence makes some parties more competitive. Instead of using the vote share of law-and-order candidates, I model the log odds ratio between the vote share of law-and-order candidates and the House vote share of the front-runner conservative party [6], and evaluate how electoral shocks and violence affect support for law-and-order in comparison with their main conservative competitors. Results go on similar direction, and confirm the hypothesis that voters rely more heavily on occupational heuristics, and not party labels, when municipalities are affected by pre-electoral violence shocks.

In conclusion, these results indicate that an exogenous shock before an election is not enough alone to increase the support for law-and-order candidates. However, when such random variation occurs in a municipality with high levels of crime, there is a substantial increase in support for candidates who own the crime issue in Brazil. There at least two different explanations for why these effects are heterogeneous. On the demand side, in more violent places, crime is likely to be a greater concern for voters, and a random increase in violence right before the election makes voters more willing to support these candidates. Second, on the supply side, law-and-order candidates are also more likely

[6] I use the PSDB for the years of 2010 and 2014, and the PSL for 2018. These parties had both the front-runners in the Presidential elections and won the most House seats among conservative parties for the each respective electoral cycle

Figure 2 Marginal Effects of Pre-Electoral Homicide Conditional on Municipal Homicide Trends



Note: The plot shows marginal effects from model 2 presented in table 4. The figure presents marginal effects with 95% confidence intervals, and in the background the figures plots the density of the moderator variables.

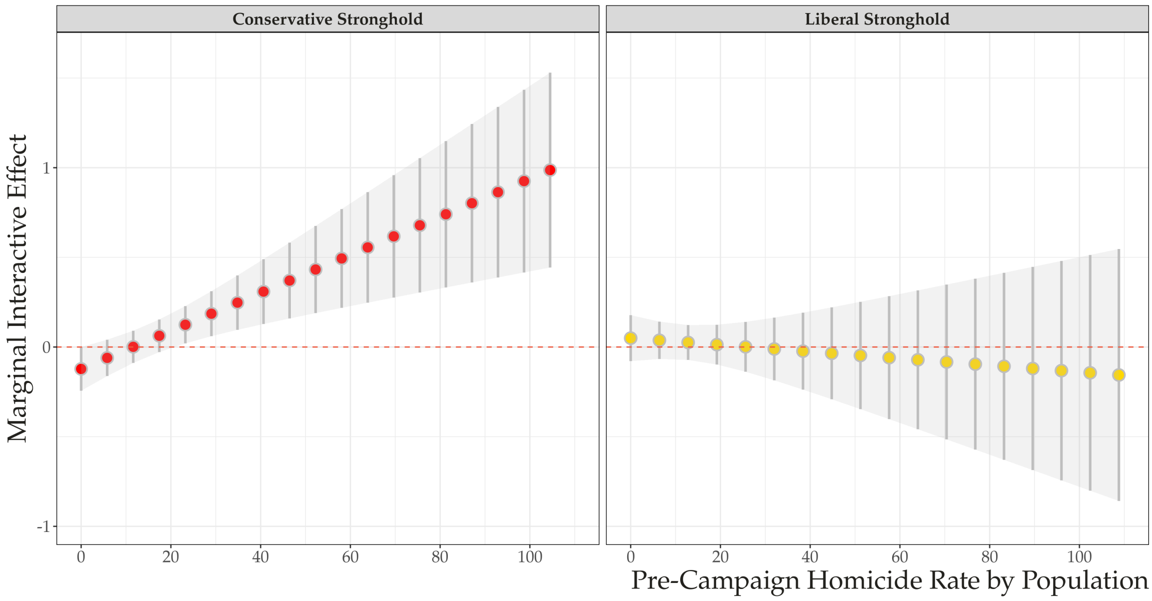
to campaign and target campaign resources in places where crime rates are high, and then reducing the effort on the voters' side to pick a law-and-order candidate when a random, and exogenous crime shock around the election occurs.

Who responds to law and order Heuristics? Violence as a Wedge Issue

I now analyze which voters more strongly activate law-and-order as an informational heuristics, and show strong evidence for my theory of security as an wedge issue. My first question is simply whether pre-electoral shocks have the same effects on electoral strongholds from conservative and liberal presidential candidates [7]. I estimate the same set of models from the previous section after splitting the data between municipalities where conservative/liberal presidential candidates between 2010-2018 performed above their state-level median vote share. Figure 3 presents the marginal interactive effects of the pre-electoral shocks.

[7] In Brazil, presidential elections occur on the same day as House elections

Figure 3 Marginal Effects of Pre-Electoral Homicide Shock Conditional on Municipalities Political Alignment on Presidential Elections



Note:The plot shows marginal effects from model 1 presented in table 12 in the appendix. The figure presents marginal effects with 95% confidence intervals. I consider an municipality i in the state j to be a stronghold when the vote share of the front runner presidential candidates for each party in i is larger than their median vote share in j

Results in figure 3 depict a substantial heterogeneity on the effects of pre-electoral crime shocks on voting for law-and-order candidates. In municipalities "won" by conservative presidential candidates, exogenous crime shocks push voters to use occupational heuristics and support former law-and-order officials in the ballots. Meanwhile, the effects disappear on municipalities dominated by the leftists' presidential candidates. Such heterogeneity suggests that law-and-order heuristics carry considerable information about policy preferences, becoming particularly attractive for politically conservative voters. This dynamic is therefore conclusive to the theory of security as a wedge issue: conservative voters are the ones increasing their support to more punitive candidates upon a crime shock, while voting patterns in leftists strongholds reamain the same.

Then, to conclude, I assemble a unique dataset with voter information at the voting station level. I show how better-off voters display stronger support for these punitive candidates and how the effects of crime shocks are mostly driven by more significant electoral support, conditional on a pre-electoral crime shock, on voting stations located at wealthier neighborhoods in Brazil. Using information about levels of education at the moment of the voters' registration, I estimate a set of multilevel models identifying the between and within-effects of higher share of voters who attended college, and further examine how the occurrence of a pre-electoral shocks increase support at a greater rate in more educated areas, where better off voters live. [8]

Table 5 presents a summary of the results. Results are robust across all three models, and uncover a strong association between better-off voters and support for law-and-order candidates. More importantly, the results also indicate how crime shocks are perceived differently as we move towards voting stations located in wealthier neighborhoods. The interaction term between electoral shocks and the within-city variation on college voters is strong and positive, indicating that the greater support for more punitive candidates emerges mostly in wealthier neighborhoods due to a pre-electoral sudden increase in crime. This dynamic recover the social bases of security as a wedge issue, and not a valence concern: as crime increases, wealthier and more conservative voters show greater tastes for candidates campaigning on punishment.

[8] I estimate the following multilevel model:

$$\begin{aligned} y_{ivt} = \alpha_1 * City_i + \alpha_2 * Year_t + \beta_1 * \text{Shock}_i + \beta_2 * (X_{iv} - \bar{X}_i) + \\ \beta_3 * \bar{X}_i + \beta_4 * \text{Municipal Controls} + \\ \beta_5 * \text{Political Controls} + \epsilon_{ivt} + \mu_i + \mu_t \end{aligned} \quad (2)$$

Table 5 Regression Models: Effects of Crime Shocks on Better-Off Voters

	Dependent Variable: Log Law and Order Vote Share		
	(1)	(2)	(3)
Intercept	-0.338	3.037^{***}	3.236^{***}
	(0.439)	(0.669)	(0.665)
Pre-Electoral Homicide Shock	-0.037^{***}	-0.010^{***}	-0.019^{***}
	(0.002)	(0.003)	(0.003)
Mean College Voters (Voters)	0.805^{***}	1.796^{***}	1.837^{***}
	(0.032)	(0.036)	(0.037)
College Voters Within Effect	0.651^{***}	0.731^{***}	0.743^{***}
	(0.009)	(0.011)	(0.011)
Pre-Electoral Homicide Shock x College Voters Within	0.146^{***}	0.488^{***}	0.479^{***}
	(0.017)	(0.023)	(0.022)
Voting Station Variables	yes	yes	yes
Municipal Socio Economic Controls	no	yes	yes
Political Controls	no	no	yes
Observations	898,379	740,384	735,035
Log Likelihood	$-1{,}056{,}352.000$	$-875{,}311.400$	$-867{,}444.500$
Akaike Inf. Crit.	2,112,727.000	1,750,665.000	1,734,935.000
Bayesian Inf. Crit.	2,112,868.000	1,750,907.000	1,735,200.000

Note: *p<0.1; **p<0.05; ***p<0.01

Experimental Evidence: The Effects of Endorsement From law-and-order Politicians on Voters' Support to Messages about Public Security

Now I present results from an online factoral endorsement experiment to measure the effects of endorsement from law-and-order politicians on support for different messages about security policies. The experimental design provides individual-level evidence of the macro-dynamics highlighted using observational data. The effects discussed below show how partisanship, wealth and overt punitive preferences are key explaining support for punitive preferneces and law-and-order endorsement presented in the experimental task.

To assure make the experiment more realistic, its design measures support by replicating the format of social media messages, and ask respondents to answer which of two social media type of messages they would be more likely to share in their walls. The experiment was included in a national online survey in Brazil with 2.400 respondents. The survey was fielded by Netquest-Vanderbilt, with probabilistic samples drawn by the LAPOP team in Vanderbilt from users registered with Netquest. More details about the survey are provided in the appendix. Each respondents answers only once to the experiment.

Experimental Design

The experiment uses a factorial design combined with an endorsement experiment on edited social media messages. During the survey, each respondent was exposed to a pair of edited tweets created solely for this experiment; and the messages replicates politicians talking about crime and public security in Brazil. The messages vary on four dimensions: the author of the tweet, the content of the message, an associated image, and the support of a law-and-order politician for the text. The latter feature is the primary variable of interest. In the appendix, I present the full combination and the images of the edited social media messages.

Each of the components varies as follows. The tweets' authors can be two news media outlets, one liberal, and another with conservative leaning. The content of the tweet simulates a message from news media broadcasting a speech about public security from a member of the Brazilian Lower-Chamber; the text is either a punitive message, asking for harsh punishment against criminals and support for the use of violence by police officers, and or a redistributive approach reinforcing the importance of investing in education and social policy as strategies to reduce crime. The author of the speech is either a Congressman with a military rank attached to his name, or one without a military rank; to increase the validity of the experiment, I use names of factual House Members elected in the last election. Lastly, the tweets' image rotate between three options: a kid going to school, a heavily armed police officer entering in a slum, and a neutral image of police officers close to a school bus. Since the attributes are randomized independently for each candidate, causal effects can be simultaneously estimated using simple OLS regression models (Hainmueller et al., 2014).

The decision to use social media messages can be justified on several grounds. First, voters are constantly exposed to social media environments in their daily lives. In my sample, 97 % of respondents reported using at least one of the three largest social media platforms in Brazil (Twitter, Facebook, or Whatsapp) at least once a day, and 85 % reported using social media to learn about politics and keep themselves informed; Therefore, the experiment does not require subjects to make any strong cognitive effort when performing the experimental task. Besides, by using an experimental exercise mirroring a social media support, I can capture the treatment effects on a more realistic setting than using to other vignette's designs (Horiuchi et al., 2018; Knudsen and Johannesson, 2019).

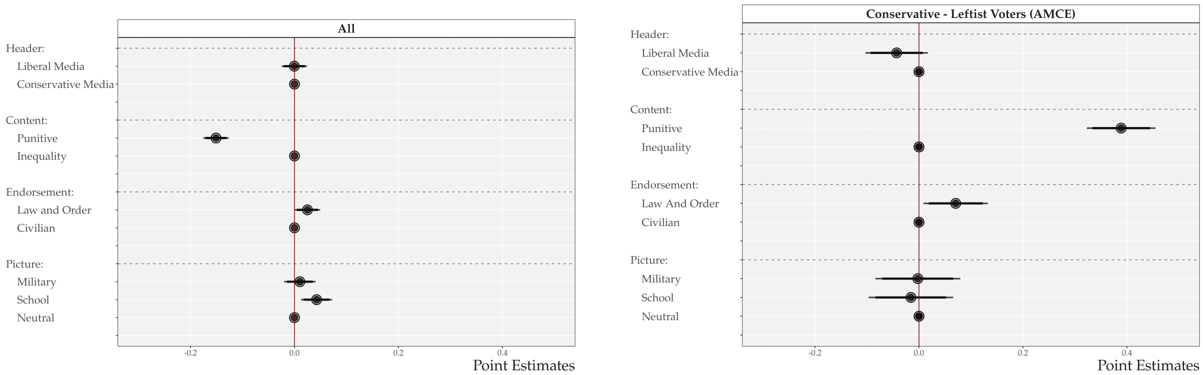
Results

In this section, I present the main results for the factorial experiment. All the quantities are estimated with OLS models regressing respondents' decision to share a tweet to indicator variables for each of the four components.[9] Figure 4 presents the average marginal component effects (AMCE) in the entire sample of respondents in the first plot (left plot); the right-plot estimates the same model, but filtering the data conditional on voters' voting preferences between the actual, law-and-order president Jair Bolsonaro and the 2018 candidate from the leftist party, the Workers' Party (PT), which won all the four previous presidential elections in Brazil. I present the differences between these two samples to highlight the partisan dynamic behind the support for punitive proposals and law and order candidates

[9]Standard Errors are not clustered because each respondent repeated only once the task

10

Figure 4 Average Marginal Component Effects of Tweets' Features on the Probability of Sharing the Message



Note: The left plot shows estimates of the randomly assigned attributes (Author, Content, Endorsement and Image) in the subject decision to share a edited tweet. The right plots shows differences in AMCE between Convervative and Leftists votes in Brazil. Estimates are based on the benchmark OLS model; we present point estimate with 95% and 90% confidence intervals. The points without bars represent the reference category for each attribute.

First, regarding the overall sample, I find a positive AMCE for the endorsement of a law-and-order politician. In other words, on average, across all the features of the experiment, reading a message about security coming from a politician using his military rank increases by 2.5% percentage points the support for the message. Although small in magnitude, the effect is statistically significant, using 95% confidence intervals, and appears in a setting using a low-dosage treatment, i.e., only adding the military rank at the name of the politician. In addition, I find on average respondents are more willing of sharing messages with more redistributive proposals to reduce crime than more punitive speeches: a punitive message is 15 percentage points less likely to be shared than a more redistributive one.

Beside, as in the electoral shocks models, more conservative voters in Brazil (supporters of the President Jair Bolsonaro) have a sizable difference compared to the entire sample in their support for more punitive tweets and messages endorsed by a law-and-order politician. These results provide strong support for the argument that conservative voters activate strongly the politicians' occupation as an heuristics shortcut; on average, Bolsonaro voters prefer to share content about public security policies sent by politicians with a military rank, than an otherwise, on average, equal politician without

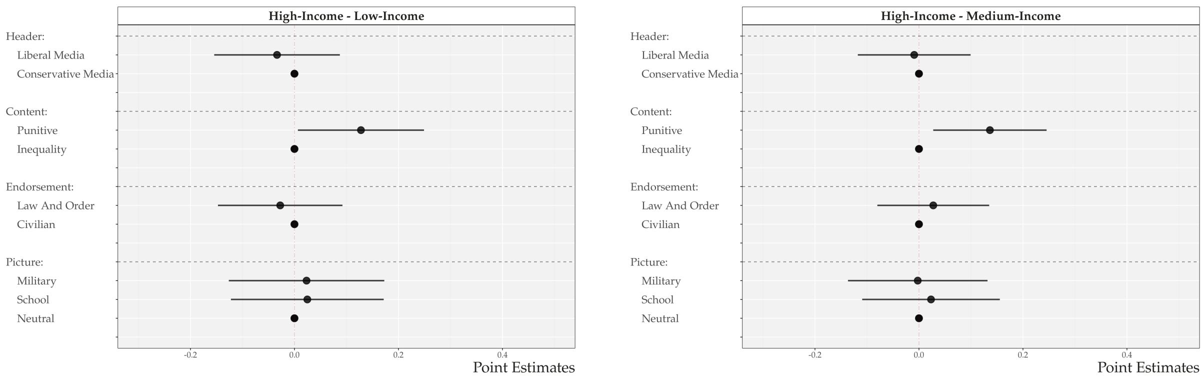
[10] We asked respondents to indicate whom they would vote for if in a runoff election to be held in the following week. We gave respondents the option to vote for the actual President Jair Bolsonaro, his contender from the Workers Party, Fernando Haddad, or to vote blank.

a military rank, and also proposing a more punitive approach.

Furthermore, I replicate with the experimental data the evidence discussed before about income dynamics explaining differences in support for punitive messages. Using pre-treatment variables asking respondents about their position in the countries income distribution, [11] I separate the data in three groups (low, middle, and high-income), and compare the AMCE for these groups.

Figure 5 presents the differences in AMCE between the different income groups [12]. Results replicate clearly the insurance dynamic detected with observation data. High-income respondents are more likely to support messages arguing in defense of more punitive measure when compared to both low and middle-level income.

Figure 5 Average Marginal Interactive Effects on the Probability of Sharing the Message with Income



Note: The plot shows marginal effects from linear interactive models between the factorial endorsement and individual level survey information about income. The figure presents differences in Interative Marginal Component Effects with 95% confidence intervals calculated from benchmark OLS model.

To conclude, I explore how more punitive voters, (a dynamic that as shown in figure 5 interacts with income and partisanship), strongly predicts the endorsement effects from the occupational heuristics in the experiment [13] Figure 6 presents the marginal effects for the quantities of interest extracted from the linear interactive models. Results indicate that respondents with stronger punitive preferences also show a positive and statistically significant likelihood of supporting a message endorsed by the law-and-

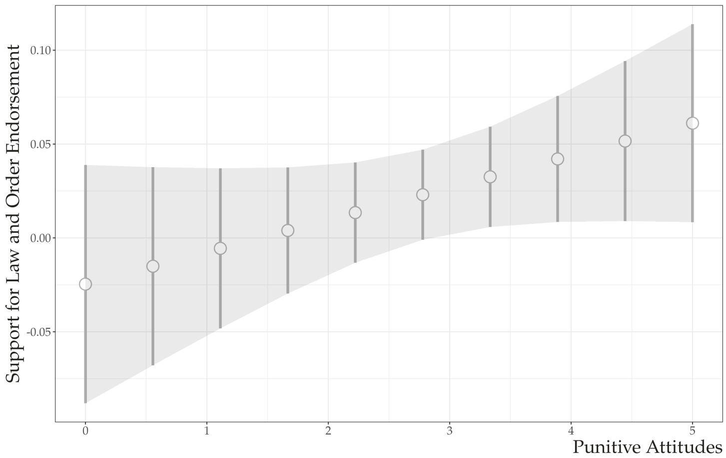
[11] The question asks: "Imagine a staircase with 10 steps. In the first step, people with lower income are located, and in step 10, people with higher income are located. Where would you be located". I split the data between three groups: low income (from 0-2), middle income (from 3-7), high-income (from 8-10)

[12] The numerical results are fully presented in the appendix

[13] To punitive preferences, I use a battery of five questions asking about support for punitive policies, such as gun control, militarization, use of violence by the police, the death penalty, and penal legal policy. I provide a full description of the questions and the distribution of answers in the appendix.

order politician. Taken together, these results show that, as my wedge theory predicts, conservative and wealthier voters show greater support to more for harsh approaches on crime, which therefore leads to a higher likelihood of supporting statements sent by law-and-order candidates using their occupational heuristics to attract voters attention.

Figure 6 Average Marginal Interactive Effects on the Probability of Sharing the Message



Note: The plot shows marginal effects from linear interactive models between the factorial endorsement and overt measures for punitive preferences. The figure presents marginal effects with 95% confidence intervals calculated from benchmark OLS model.

Conclusion

This study presents a novel theory to explain the recent wave of law-and-order politics in Brazil. I show that as violence increases, security concerns enters in the electoral arena as a wedge issue, as support for more punitive proposals overlaps with income differences and partisans identities. I provide evidence showing that: i) an exogenous shock on crime in the months right before the election substantively increases the vote share of law-and-order candidates in cities more afflicted by violence, ii) the shocks are particularly effective on conservative strongholds, and on polling-stations located at wealthier neighborhoods, iii) experimental results indicate that survey respondents more broadly support messages about public security endorsed by law-and-order candidates; iv) the endorsement is particularly attractive to more punitive voters.

This article presents three novel contributions for scholars interested in criminal violence and democratic politics. First, I contribute to the numerous recent studies on criminal violence and political behavior in Latin America (Krause, 2014; Malone, 2010; Carreras, 2013; Visconti, 2019; Garcia-Ponce et al., 2019; Ley, 2017). Although these studies reveal a wide-range of attitudes that are affected by personal victimization and contextual exposure to violence, what we know about how these changes entered in the electoral arena is still rather limited. Using the Brazilian case, I show how candidates' occupation and professional experience working in public security help to explain who wins and who loses when crime becomes a crucial concern, and how these heuristics work differently from explanations based on valence shocks and issue ownership at the party levels.

The article also makes a contribution to the recent literature on spillovers of crime in Latin America. Recent studies show negative effects of crime on educational outcomes in Rio de Janeiro (Monteiro and Rocha, 2017), on wages and women's labor force participation (Dell, 2015), and human capital (Cerqueira and Soares, 2016). This article shows similar spillovers in elections: a growth in criminal violence makes candidates from police and military forces more likely to win elections. The majority of these candidates have a historical commitment to the adoption of more punitive policies, and a great deal of work has found robust evidence that these policies are closely related to violations of human rights, mass incarceration, and racial bias in Brazil and elsewhere (Roberts et al., 2002; Davenport et al., 2011; Bueno, 2012; Brinks, 2007). More important, recent papers have provided robust causal evidence that law-and-order candidates and the adoption of *mano dura* policies have null effects on crime reduction, but render detectable increases on police abuses, and violence targeting social minorities (Novaes, 2018; Weintraub and Blair, 2020).

Years of growth on criminal violence combined with an weak, unstable partisan environment culminated on outsiders politicians advancing policy that makes the state more unequal and more repressive against certain socioeconomic and ethnic groups. Even more concerning, I show the existence of endogenous incentives, coming from the electoral arena and behavioral chances of crime victims, pushing law enforcement officers, with a future career goal in mind, to be more punitive, and build around them a reputation of being tough-on-crime in order to gain electoral support from better-off, punitive and more conservative voters. This endogenous dynamic is a risk to the Brazilian democracy as its consequences are the adoption of policies where the evidence of crime-reduction are at best mixed, but cases of abuse against social minorities are a given fact.

References

Ahnen, R. E. (2007). The Politics of Police Violence in Democratic Brazil. *Latin American Politics and Society*, 49(1):141–164.

Baker, A., Sokhey, A. E., Ames, B., and Renno, L. R. (2016). The dynamics of partisan identification when party brands change: the case of the workers party in brazil. *The Journal of Politics*, 78(1):197–213.

Bateson, R. (2012). Crime victimization and political participation. *American Political Science Review*, pages 570–587.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy*, 76(2):169–217.

Beckett, K. (1999). *Making crime pay: Law and order in contemporary American politics*. Oxford University Press.

Beckett, K. and Western, B. (2001). Governing social marginality: Welfare, incarceration, and the transformation of state policy. *Punishment & Society*, 3(1):43–59.

Berens, S. and Dallendörfer, M. (2019). Apathy or anger? how crime experience affects individual vote intention in latin america and the caribbean. *Political Studies*, 67(4):1010–1033.

Blei, D. M. (2012). Probabilistic topic models. *Commun. ACM*, 55(4):77–84.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research*, 3(Jan):993–1022.

Bonner, M. D. (2019). *Tough on crime: the rise of punitive populism in Latin America*. University of Pittsburgh Press.

Botero, S., Cornejo, R. C., Gamboa, L., Pavao, N., and Nickerson, D. W. (2015). Says who? an experiment on allegations of corruption and credibility of sources. *Political Research Quarterly*, 68(3):493–504.

Boyd-Graber, J., Hu, Y., and Mimno, D. (2017). Applications of Topic Models. *Foundations and Trends® in Information Retrieval*, 11(2-3):143–296.

Brinks, D. M. (2007). *The judicial response to police killings in Latin America: inequality and the rule of law.* Cambridge University Press.

Bueno, S. (2012). Letalidade Policial. In de Lima, R. S., Ratton, J. L., and de Azevedo, R. G., editors, *Crime, polícia e justiça no Brasil.* Editora Contexto.

Caldeira, T. P. (2002). The paradox of police violence in democratic brazil. *Ethnography*, 3(3):235–263.

Calvo, E. and Murillo, M. V. (2019). *Non-policy Politics: Richer Voters, Poorer Voters, and the Diversification of Electoral Strategies.* Cambridge University Press.

Cano, I. (1997). *Letalidade da ação policial no Rio de Janeiro.* Iser.

Carreras, M. (2013). The impact of criminal violence on regime legitimacy in Latin America. *Latin American Research Review*, pages 85–107.

Cerqueira, D., Bueno, S., Lima, R. S. d., Cristina, N., Helder, F., Paloma Palmieri, A., David, M., Reis, M., Cypriano, O., Sobral, I., et al. (2019). Atlas da violência 2019.

Cerqueira, D. and Soares, R. R. (2016). The welfare cost of homicides in brazil: accounting for heterogeneity in the willingness to pay for mortality reductions. *Health economics*, 25(3):259–276.

Cohen, M. J. and Smith, A. E. (2016). Do authoritarians vote for authoritarians? Evidence from Latin America. *Research & Politics*, 3(4):2053168016684066.

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

Davenport, C., Soule, S. A., and Armstrong, D. A. (2011). Protesting While Black?: The Differential Policing of American Activism, 1960 to 1990. *American Sociological Review*, 76(1):152–178.

Dell, M. (2015). Trafficking Networks and the Mexican Drug War. *The American Economic Review*, 105(6):1738–1779.

Denyer Willis, G. (2015). *The killing consensus : police, organized crime, and the regulation of life and death in urban Brazil.* University of California Press, Oakland, California.

Díaz-Cayeros, A. and Magaloni, B. (2009). Poverty, inequality, and democracy (ii): Aiding latin america's poor. *Journal of Democracy*, 20(4):36–49.

Dube, A., Dube, O., and García-Ponce, O. (2013). Cross-border spillover: Us gun laws and violence in mexico. *American Political Science Review*, pages 397–417.

Durán-Martínez, A. (2015). To kill and tell? state power, criminal competition, and drug violence. *Journal of Conflict Resolution*, 59(8):1377–1402.

Faganello, M. A. (2015). Bancada da bala: uma onda na maré conservadora. *Sebastiao Velasco e Cruz; Andre Kaysel; Gustavo Codas.(Org.). Direita, Volver*, pages 145–161.

Feltran, G. (2018). *Irmãos: uma história do PCC*. Editora Companhia das Letras.

Fernandez, K. E. and Kuenzi, M. (2010). Crime and Support for Democracy in Africa and Latin America. *Political Studies*, 58(3):450–471.

Ferraz, C. and Finan, F. (2008). Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electoral Outcomes. *The Quarterly Journal of Economics*, 123(2):703–745.

Flores-Macías, G. A. and Zarkin, J. (2019). The militarization of law enforcement: Evidence from latin america. *Perspectives on Politics*, pages 1–20.

Frantz, E. (2018). The legacy of military dictatorship: Explaining violent crime in democracies. *International Political Science Review*, page 0192512118769079.

Garcia-Ponce, O., Young, L., and Zeitzoff, T. (2019). Anger and Support for Punitive Justice in Mexico's Drug War. *Working Paper*.

Gelman, A. and Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press, Cambridge.

Gerber, M. M. and Jackson, J. (2016). Authority and punishment: On the ideological basis of punitive attitudes towards criminals. *Psychiatry, Psychology and Law*, 23(1):113–134.

Grimmer, J. (2010). A Bayesian hierarchical topic model for political texts: Measuring expressed agendas in Senate press releases. *Political Analysis*, 18(1):1–35.

Grimmer, J. and Stewart, B. M. (2013). Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts. *Political Analysis*, 21(3):267–297.

Haggard, S. and Kaufman, R. R. (2020). *Development, democracy, and welfare states*. Princeton University Press.

Hainmueller, J., Hopkins, D. J., and Yamamoto, T. (2014). Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments. *Political Analysis*, 22(1):1–30.

Holland, A. C. (2013). RIGHT ON CRIME? Conservative Party Politics and "Mano Dura" Policies in El Salvador. *Latin American Research Review*, 48(1):44–67.

Holland, A. C. (2018). Diminished expectations: Redistributive preferences in truncated welfare states. *World Politics*, 70(4):555–594.

Horiuchi, Y., Markovich, Z. D., and Yamamoto, T. (2018). Does conjoint analysis mitigate social desirability bias? *Unpublished paper,. https://www. cambridge. org/core/membership/services/aop-file-manager/file/5c2e26148d27516318ae9203/APMM-2019-Teppei-Yamamoto. pdf.*

Huff, C. and Kruszewska, D. (2016). Banners, barricades, and bombs: The tactical choices of social movements and public opinion. *Comparative Political Studies*, 49(13):1774–1808.

Kaplan, N., Park, D. K., and Ridout, T. N. (2006). Dialogue in American political campaigns? An examination of issue convergence in candidate television advertising. *American Journal of Political Science*, 50(3):724–736.

Knudsen, E. and Johannesson, M. P. (2019). Beyond the limits of survey experiments: How conjoint designs advance causal inference in political communication research. *Political Communication*, 36(2):259–271.

Krause, K. (2014). Supporting the Iron Fist: Crime News, Public Opinion, and Authoritarian Crime Control in Guatemala. *Latin American Politics and Society*, 56(1):98–119.

Lessing, B. (2017). *Making Peace in Drug Wars: Crackdowns and Cartels in Latin America.* Cambridge University Press.

Ley, S. (2017). To Vote or Not to Vote: How Criminal Violence Shapes Electoral Participation. *Journal of Conflict Resolution*, 62(9):1963–1990.

Lucas, C., Nielsen, R. A., Roberts, M. E., Stewart, B. M., Storer, A., and Tingley, D. (2015). Computer-assisted text analysis for comparative politics. *Political Analysis*, 23(2):254–277.

Lupia, A. (2002). Who can persuade whom? implications from the nexus of psychology and rational choice theory.

Lupu, N. (2017). *Party brands in crisis : partisanship, brand dilution, and the breakdown of political parties in Latin America.* Cambridge University Press.

Magaloni, B., Franco-Vivando, E., and Melo, V. (2020). Killing in the slums: Social order, criminal governance, and police violence in rio de janeiro. *American Political Science Review*, 114(2):552–572.

Malone, M. F. T. (2010). Does dirty harry have the answer? citizen support for the rule of law in central america. *Public Integrity*, 13(1):59–80.

Manning, C., Raghavan, P., and Schütze, H. (2010). Introduction to information retrieval. *Natural Language Engineering*, 16(1):100–103.

Marshall, J. (2019). Tuning in, voting out: News consumption cycles, homicides, and electoral accountability in mexico. Technical report, Working paper.

McDermott, M. L. (2005). Candidate occupations and voter information shortcuts. *The Journal of Politics*, 67(1):201–219.

Medeiros, É. and Fonseca, B. (2016). As bancadas da câmara. *Agencia pública*, 18.

Menezes, T., Silveira-Neto, R., Monteiro, C., and Ratton, J. L. (2013). Spatial correlation between homicide rates and inequality: Evidence from urban neighborhoods. *Economics Letters*, 120(1):97–99.

Merolla, J. L., Mezini, E., and Zechmeister, E. J. (2013). Crime, economic crisis, and support for democracy in mexico. *Politica y Gobierno*, pages 221–251.

Misse, M. (2011). Autos de Resistência: Uma análise dos homicídios cometidos por policiais na cidade do Rio de Janeiro (2001-2011). *Misse M, coordenador. Núcleo de Estudos da Cidadania, Conflito e Violência Urbana Rio de Janeiro: Universidade Federal do Rio de Janeiro*, pages 20–37.

Moene, K. and Wallerstein, M. (2001). Inequality, Social Insurance, and Redistribution. *American Political Science Review*, 95(4):859–874.

Moene, K. O. and Wallerstein, M. (2003). Earnings Inequality and Welfare Spending: A Disaggregated Analysis. *World Politics*, 55(04):485–516.

Monteiro, J. and Rocha, R. (2017). Drug battles and school achievement: Evidence from rio de janeiro's favelas. *The Review of Economics and Statistics*, 99(2):213–228.

Moreira, D. (2020). Com a palavra os nobres deputados: Ênfase temática dos discursos dos parlamentares brasileiros. *Dados*, 63(1).

Muggah, R. and Tobón, K. A. (2018). Citizen security in Latin America: Facts and Figures. *Strategic paper*, 33.

Mummolo, J. (2018). Militarization fails to enhance police safety or reduce crime but may harm police reputation. *Proceedings of the National Academy of Sciences*, 115(37):9181 LP – 9186.

Murray, J., Cerqueira, D. R. d. C., and Kahn, T. (2013). Crime and violence in Brazil: Systematic review of time trends, prevalence rates and risk factors. *Aggression and Violent Behavior*, 18(5):471–483.

Novaes, L. M. (2018). The Violence of Law and Order Politics The Case of Law Enforcement Candidates in Brazil. *Working paper.*

Pérez, O. J. (2015). The impact of crime on voter choice in Latin America. *The Latin American voter: Pursuing representation and accountability in challenging contexts*, pages 324–345.

Petrocik, J. R. (1996). Issue ownership in presidential elections, with a 1980 case study. *American journal of political science*, pages 825–850.

Quinn, K. M., Monroe, B. L., Colaresi, M., Crespin, M. H., and Radev, D. R. (2010). How to Analyze Political Attention with Minimal Assumptions and Costs. *American Journal of Political Science*, 54(1):209–228.

Roberts, J. V., Stalans, L. J., Indermaur, D., and Hough, M. (2002). *Penal populism and public opinion: Lessons from five countries.* Oxford University Press.

Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., and Rand, D. G. (2014a). Structural topic models for open-ended survey responses. *American Journal of Political Science*, 58(4):1064–1082.

Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., and Rand, D. G. (2014b). Structural Topic Models for Open-Ended Survey Responses. *American Journal of Political Science*, 58(4):1064–1082.

Rose, R. (2005). *The unpast: elite violence and social control in Brazil, 1954-2000*, volume 44. Ohio University Press.

Rueda, D. and Stegmueller, D. (2015). The Externalities of Inequality: Fear of Crime and Preferences for Redistribution in Western Europe. *American Journal of Political Science*, 60(2):472–489.

Samuels, D. J. and Zucco, C. (2018). *Partisans, Antipartisans, and Nonpartisans: Voting Behavior in Brazil.* Cambridge University Press, Cambridge.

Singer, A. J., Chouhy, C., Lehmann, P. S., Stevens, J. N., and Gertz, M. (2020). Economic anxieties, fear of crime, and punitive attitudes in latin america. *Punishment & Society*, 22(2):181–206.

Trejo, G., Albarracín, J., and Tiscornia, L. (2018). Breaking state impunity in post-authoritarian regimes: Why transitional justice processes deter criminal violence in new democracies. *Journal of Peace Research*, 55(6):787–809.

Trejo, G. and Ley, S. (2018). Why did drug cartels go to war in mexico? subnational party alternation, the breakdown of criminal protection, and the onset of large-scale violence. *Comparative Political Studies*, 51(7):900–937.

Trelles, A. and Carreras, M. (2012). Bullets and votes: Violence and electoral participation in Mexico. *Journal of Politics in Latin America*, 4(2):89–123.

Visconti, G. (2019). Policy preferences after crime victimization: panel and survey evidence from Latin America. *British Journal of Political Science*, pages 1–15.

Weintraub, M. and Blair, R. (2020). Fighting Crime with an Iron Fist: An Experimental Evaluation of Militarized Policing in Cali, Colombia. *Working paper*.

Zheng, T., Salganik, M. J., and Gelman, A. (2006). How many people do you know in prison? using overdispersion in count data to estimate social structure in networks. *Journal of the American Statistical Association*, 101(474):409–423.

Voting for Violence

Supporting Information Files (SIF)

Appendix A: Classification of Law and Order Candidates

To classify a law and order candidate, I use two main criteria. First, I define as a law and order all the candidates who reported as their main occupation being a member of police and military forces in Brazil. Together with their occupation, I use information from their ballot names to search for candidates whom send a explicit signal to voters about any type of previous occupational experience o law enforcement agencies.

To identify their occupation, I rely on two different data sources. Information for all the candidates is extracted directly from the Electoral Court data. This data includes detailed self-reported information for all the candidates to the House elections from 2002 to 2018. Using this huge dataset, I search for candidates who reported being members of the state-level military and civil police, members of any type federal police, military fire-fighters, and officers from the armed-forces (active-duty and reserved).

However, the occupation data from the electoral court have one crucial shortcoming. Candidates can change their self-reported occupation over time, which means, several candidates, in particular after being elected, report being a "politician" as their occupation . The case of the Brazilian President is emblematic on this regard. On his first two elections to the House, Jair Bolsonaro reported being a reserved military officer; however, in his last few elections, Bolsonaro changed his occupation to congressmen. Therefore, to remedy this limitation, I use information from the House API from 2002-2018 to search for elected members of the House who at some point of their career reported being a member of security forces. I merged both datasets, the electoral data and the House API using the candidates social security number (CPF). In this combine dataset, I use the same search criteria to identify candidates who reported in the House, after being elected, being a member of law enforcement agencies.

In the sequence, I search over the ballot names for all the candidates to identify explicit references to their occupation on security forces. In Brazil, it is common for candidates to change their ballot names to send a message to voters about their professional experience or policy priorities. For example, several candidates run with the labels "Professor", "Teacher", "Educator" as a prefix to their ballot names. For law and order candidates, I search for references to occupation on security forces using a common list of portugues words that refer to these professions. [14]

[14] See the list of word here: "soldado", "soldada", "inspetor", "inspetora", "soldada", "cabo" , "sargento", "sargenta", "sgt", "tenente", "major", "coronel","general", "comandante", "delegado", "delegada", "capitão", "capitã","capitao", "policial", "civil", "pc", "investigador", "investigadora","inspetor", "sub-tenente", "subtenente", "sub tenente","pm", "xerife", "sub-oficial", "suboficial", "sub oficial", "bombeiro", "detetive", "protetor", "comandante", "guarda", "insp", "policia"

Appendix B: Topic Models

In this appendix, I provide a in-depth discussion about the modelling choices for the computational text analysis performed on the legislative speeches. Results reported in the paper rely on unsupervised machine learning techniques to detect the association of words in the corpus of congressional speeches. Among this family of models, I use a probabilistic topic model. Topic models are used to uncover hidden dimensions in documents, such as academic publications, open-ended survey data, congressional documents, social media data, among others (Blei, 2012; Blei et al., 2003; Grimmer, 2010; Quinn et al., 2010; Huff and Kruszewska, 2016; Lucas et al., 2015). In the following paragraphs, I provide a succinct exposition of probabilistic topic models and some applications.

Topic models arise from a family of unsupervised machine learning algorithms. The output of the models - the topic - is estimated rather than assumed a priori. Hence, topic modeling does not require any input from the researcher about where, how, and for which words/sentences/tokens the algorithm should look for the topic (See Grimmer and Stewart (2013) for a review of machine learning methods for text data). The intuition behind topic models is that the text corpora comes from a data generating process in which each document emerges as a mixture over latent topics, where each topic is characterized by a set of words.

Consider a concrete example of the intuition behind topic models. Imagine a topic model for the collection of tweets sent by the President of the United States. The model estimates topics such as: immigration, economic issues, and attacks against the Democratic Party. For each of these topics, the model estimates the words that appear together most frequently. The model relies on the idea of co-occurrence to reveal the hidden dimensions of the generative model. For example, for the first topic, the model is likely to give us words such as *travelban, mexicans, crime, border*, while for the latter, one might expect to observe words like *pellosi, mueller, clinton, hoax*. While hypothetical, this exercise elucidates the use of the model. Most importantly, this example illustrates how the process of labeling the topics is a theoretically-driven enterprise.[15]

I use the Structural Topic Model (STM) developed by (Roberts et al., 2014b) in the paper. The STM

[15] We direct the reader to (Boyd-Graber et al., 2017) for a broader overview of different topic models.

has important theoretical and empirical advantages relative to other topic model. First, the STM allows the inclusion of covariates of substantive interest through a prior distribution of topics over the corpus (prevalence) and the association of words with topics (content). Second, by adjusting the priors of the generative model, the STM allows for joint estimation of the topics and the effects of covariates. Third, it allows for the topics to be correlated by adding a covariance matrix to the prior.

The data generation process of the STM model for each document works as follows:

1. Draw the document-level distribution of topics from a logistic-normal generalized linear model based on a vector of document covariates X_d and a covariance matrix Σ

   - $\theta_d \sim logisticnormal(X_d\gamma, \Sigma)$

2. For each word (n, Draw a topic based on the document-specific multinomial distribution over topics

   - $z_{d,n}|\theta_d \sim Multinomial(\theta_d)$

3. For each word, conditional on the topic chosen for $z_{d,n}$ and the probability distribution of the $v-th$ word for topic k in the vocabulary (β_k), [16], draw a word from a multinomial distribution parametrized by $\beta_{d,k}$.

   - $w_{d,n}|z_{d,n}, \beta_{d,k} \sim Multinomial(\beta_{d,k})$

Compared to the classic latent Dirichlet allocation model (LDA) developed by Blei (2012), the STM's central innovation is the addition of a separate prior over the distribution of topics; or making a reference to the label of the model, add more structure to the estimation of the topics. The new structure of the STM switches the global Latent Dirichlet non-informative prior for the distribution of topics employed on LDA models by a logistic normal prior distribution parameterized by a linear prediction of the covariates and a covariance matrix. The first explains changes in the parameter θ for the topic distribution per document due to covariates, the latter allows the topics to be correlated. Finally, model

[16] $\beta_{d,k}$ is drawn from a exponential distribution with covariates determining the topical content, or in other words, how covariates affect the use of words in each topic. In our case, we do not use covariates for topical content in the models we estimate; therefore, we omit the full description of this parameter.

estimation proceeds via the Expected-Maximization algorithm, using the spectral method for initialization, as suggested by Roberts et al. (2014b).

Preparing the data and choosing the number of topics

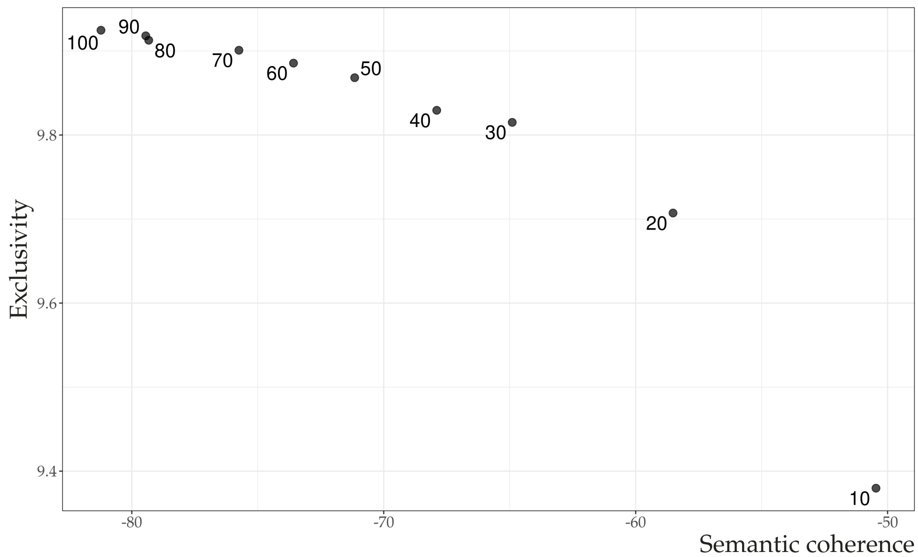
I first collected the Congressional Speeches using the Brazilian House API. I collected all the congressional speeches made between 2003 and 2020, resulting in a total of 147,584 speeches, and 252,038 different words. I limited the analysis to speeches on the *Pequeno Expediente* which consists on five minutes statements made by the Members of the House before the beginning of a parliamentary session. As described by Moreira (2020), Members of the House use these speeches to address a variety of policy issues going way beyond the legislative debates in each particular session. As a matter of fact, most of the representative use this opportunity to address issues of their interests and signal to voters about their policy priorities.

To pre-process the data, I first extract a set of functions words, such as names, legislative jargons, among others. Then, I adopt a set of procedures which are standard pre-processing steps in text analysis (Manning et al., 2010); I removed punctuation, capitalization, numbers, and symbols, and stop words in portuguese which are common and generally uninformative. Since topics models are unsupervised learning algorithms, beyond standard values for hyper-parameters for the statistical model, the number of topics - dimensions in the corpus - to be searched should be set by the researcher.

As suggested by Grimmer and Stewart (2013) and Roberts et al. (2014b), there is no "right answer" for the number of topics; each corpus, depending on the amount of information in each document, the size of the corpus, the granularity of the data, requires a different strategy. Therefore, I use a model with 60 topics, which in my view capture a reasonable balance between coherent and exclusive topics. More important, since my goal is only to identify speeches related to to public security, the total number of topics are less important as soon as these topics are clearly detected.

To provide a more quantifiable measure for the model fit, I estimate ten different STM models varying the number of topics from 10 to 100, and discuss the commonly used trade-off between the exclusivity and the semantic coherence for each model to corroborate the decision to work with 60 topic. Semantic Coherence is a measure that is maximized when the most probable words in a given topic frequently co-occur together, and it has been shown to correlated well with human annotated topics(**?**), and exclusivity measure how exclusive the words are to a given topic. Figure 7 provides the visual results. I conclude that gains on exclusivity are pretty much marginal on models with more than 60 topics, therefore, providing evidence that this number a good choice for the trade-off between these two measures.

Figure 7 Comparing Exclusivity and Semantic Coherence on STM Models



Note: The results are extracted from 10 distinct Structural Topic Model fitted on a corpus of Congressional Speeches in the Brazilian House. The models vary the number of topics from 10 to 100

Additional Results

The paper presents and discusses with greater attention the five out of the sixty topics that I classified as addressing issues related to the violence and security issue. Here, I present information for all the 60 topics estimated by the STM model.

Tables 6 and 7 presents the most likely words and the FREX words for all the topics. In blue, one can find the topics I label as being about violence and security. However, it is worth to explore the results a bit more in order to get a complete picture of the substantive performance of the model.

Let's see some examples. Topic 1 and Topic 30 are clearly about legislative proceedings, with the former more focused on constitutional changes and the latter on regular roll-call voting issue. Topic 18 has clear connection with native communities issues, particularly indigenous people in Brazil. On some other broader issue, Topic 20 relates to Health, Topic 23 is about corruption, Topic 16 talks about Energy Policy and Topic 21 on Oil, Topic 33 on Rural Policies and 34 on Welfare policies. Overall, the results indicate that fitting the model with 60 topics produce several topics with an interesting balance between substantive coherence and exclusivity, providing a substantive evidence about the performance of the STM model.

Table 6 Topics on Congressional Speeches in the Brazilian House (2002-2019)

Topics	Most Likely Words	FREX Words
Topic 1	emend,constitucional,constituiçã,parec,nacional execut,orçamentár,legisl,previst,pod	emend,orçamentár,constitucional,incis,resolu disposit,emit,previst,parec,constitucion
Topic 2	saúd,sistem,áre,agent,sus popul,comunitári,públic,plan,servic	saúd,comunitári,agent,sus,plan sistem,regulament,áre,básic,atençã
Topic 3	med,provisór,pod,relev,edit trat,cas,urgênc,dess,ser	med,provisór,edit,relev,urgênc extraordinári,urgent,ediçã,crédit,prorrog
Topic 4	salári,mínim,prevident,aposent,anos aposentador,reajust,reform,servidor,aument	aposent,prevident,salári,aposentador,mínim reajust,previdenciári,pension,inss,servidor
Topic 5	públic,administr,servidor,servic,gestã órgã,control,fiscaliz,cont,concurs	administr,públic,servidor,concurs,defensor gestã,fiscaliz,transparent,control,órgã
Topic 6	regiã,popul,cidad,anos,habit mil,local,capital,centr,comemor	habit,cidad,bairr,baian,regiã inaugur,local,morador,interior,emancip
Topic 7	trabalh,lut,sindicat,categor,grev condiçõ,hor,reivindic,sindical,jorn	sindicat,trabalh,grev,categor,sindical escrav,reivindic,hor,lut,jorn
Topic 8	univers,estud,curs,pesquis,ciênc tecnolog,federal,superior,técnic,institut	univers,curs,ciênc,pesquis,estud tecnológ,faculdad,tecnolog,prof,superior
Topic 9	milit,seguranc,políc,polic,forc policial,armad,públic,exércit,civil	polic,milit,armad,bombeir,policial seguranc,exércit,civ,forc,políc
Topic 10	ministr,ministéri,secret,port,pesc fazend,pescador,licenc,dess,past	ministr,pesc,ministéri,secret,pescador port,past,licenc,fazend,convêni
Topic 11	mulh,violênc,homens,contr,lut tod,feminin,direit,aind,gêner	mulh,homens,violênc,feminin,gêner igualdad,lut,comemor,internacional,contr
Topic 12	projet,lei,aprov,legisl,cas estabelec,apresent,regulament,tramit,códig	lei,projet,aprov,códig,regulament tramit,legisl,estabelec,decret,leis
Topic 13	comissã,constituiçã,especial,justic,membr instal,mist,analis,recorr,cidadan	comissã,constituiçã,membr,mist,recorr especial,analis,justic,instal,extern
Topic 14	vid,famíl,anos,deix,mã perd,filh,pai,irmã,tod	pai,falec,irmã,filh,mã vid,pes,amor,morr,perd
Topic 15	assoc,event,esport,entidad,realiz futebol,organiz,catarinens,club,jog	esport,futebol,event,assoc,club catarinens,prêmi,entidad,jog,torc
Topic 16	energ,consumidor,agênc,elétr,prec tarif,servic,telefon,usin,cust	energ,elétr,consumidor,tarif,agênc usin,telefon,prec,energét,regul
Topic 17	quer,aqu,vam,faz,porqu vai,nest,diz,oposiçã,debat	vam,oposiçã,aqu,quer,vai posiçã,porqu,debat,democrat,obstruçã
Topic 18	indígen,terr,áre,comun,índi pov,territóri,conflit,ocup,demarc	indígen,terr,índi,demarc,conflit territóri,regulariz,quilombol,comun,hect
Topic 19	tod,pov,nest,cas,quer dest,agradec,moment,muit,certez	agradec,pov,certez,parabéns,apart honr,mandat,nest,companheir,orgulh
Topic 20	médic,atend,hospital,saúd,hospit profission,servic,pacient,medicin,unidad	médic,hospital,hospit,atend,pacient medicin,profission,leit,clínic,unidad
Topic 21	petrobr,petról,dól,explor,gás pré-sal,refin,bilhõ,produçã,prec	petról,petrobr,refin,gás,pré-sal dól,óle,explor,miner,combust
Topic 22	particip,nacional,realiz,import,parlament represent,frent,tod,debat,audiênc	audiênc,particip,frent,parlament,reuniã seminári,debat,tem,convid,realiz
Topic 23	corrupçã,investig,denúnc,dinheir,cpi repúbl,fat,polít,apur,envolv	corrupçã,investig,cpi,denúnc,acus apur,desvi,escândal,denunc,dinheir
Topic 24	govern,vereador,quer,min,estadual ger,jos,registr,visit,joã	vereador,govern,min,estadual,visit espírit,joã,sexta-feir,vitór,jos
Topic 25	crianc,jovens,adolescent,anos,idad menin,sexual,infantil,explor,jov	crianc,adolescent,jovens,menin,sexual idad,infantil,infânc,jov,adult
Topic 26	empres,contrat,servic,privatiz,pequen funcionári,empreg,empresári,priv,terceiriz	empres,privatiz,contrat,terceiriz,funcionári empresári,licit,demit,negóci,concorrent
Topic 27	polít,reform,pod,ser,dev part,sistem,outr,sociedad,represent	reform,partidár,polít,list,part campanh,mudanc,individual,opiniã,mandat
Topic 28	jornal,imprens,inform,comunic,rádi internet,notíc,revist,televisã,glob	jornal,rádi,internet,imprens,televisã glob,reportag,emissor,s.paul,revist
Topic 29	águ,sec,regiã,problem,nordestin saneament,situaçã,abastec,integr,esgot	sec,águ,nordestin,esgot,transposiçã saneament,hídric,bac,abastec,irrig
Topic 30	vot,matér,favor,votaçã,paut requer,retir,import,discussã,urgênc	vot,matér,paut,votaçã,favor requer,retir,discussã,urgênc,mérit

Table 7 Topics on Congressional Speeches in the Brazilian House (2002-2019)

Topics	Most Likely Words	FREX Words
Topic 31	direit,contr,human,democrac,pov manifest,lut,democrát,ser,defes	democrac,ditadur,golp,democrát,tortur protest,direit,esquerd,human,desrespeit
Topic 32	doenc,drog,caus,tratament,cânc uso,problem,risc,pesso,acident	doenc,cânc,drog,tratament,medic prevençã,beb,acident,uso,risc
Topic 33	produtor,produçã,produt,agricultur,agrícol export,produz,cooper,tonel,setor	produtor,safr,agrícol,soj,tonel produçã,cooper,pecuár,produt,agronegóci
Topic 34	social,famíl,segur,idos,benefíci assistent,rend,anos,bols,morad	idos,segur,social,morad,assistent benefíci,bols,famíl,rend,beneficiári
Topic 35	desenvolv,setor,indústr,econô,invest produt,import,empreg,econom,turism	indústr,turism,industrial,comérci,desenvolv potencial,competit,setor,incent,empreend
Topic 36	homenag,igrej,sempr,anos,jos joã,cuj,figur,reconhec,tod	igrej,padr,cearens,dom,figur catól,homenag,ilustr,solen,trajetór
Topic 37	crim,violênc,pres,seguranc,crimin penal,organiz,armas,combat,públic	crim,crimin,armas,pres,penal criminal,homicídi,assassin,violênc,tráfic
Topic 38	rural,famili,camp,rur,agricultur aliment,reform,agricultor,assent,agrár	rural,rur,famili,agrár,camp assent,agricultor,aliment,agricultur,mst
Topic 39	federal,distrit,polic,brasíl,trânsit oper,veícul,feder,motor,rodoviár	distrit,trânsit,federal,brasíl,rodoviár veícul,motor,políc,deleg,oper
Topic 40	pesso,acess,direit,tod,vid ser,deficient,garant,sociedad,dev	acess,deficient,pesso,inclusã,físic cidadã,necess,cidadan,portador,assegur
Topic 41	ambient,amazôn,mei,ambiental,preserv sustent,desenvolv,áre,natur,regiã	ambient,ambiental,amazôn,desmat,preserv florest,sustent,natur,cerr,mei
Topic 42	recurs,municípi,estad,feder,uniã fund,federal,destin,tod,orçament	municípi,recurs,estad,uniã,royalti fund,feder,rep,pact,municip
Topic 43	questã,cas,s.ex,sobr,respeit dev,qualqu,jos,palavr,ser	questã,s.ex,regiment,esclarec,palavr chinagl,inocênci,intern,president,qualqu
Topic 44	banc,dív,econô,financeir,jur cris,crédit,financ,caix,tax	dív,jur,banc,caix,bndes financeir,cris,econô,crédit,bancári
Topic 45	pobr,negr,popul,fom,pobrez desigualdad,social,viv,ric,misér	negr,pobr,desigualdad,pobrez,misér fom,ric,branc,igualdad,rac
Topic 46	acord,relator,text,relatóri,apresent destaqu,entend,feit,parec,negoc	relator,relatóri,acord,text,destaqu original,entend,negoc,acat,apresent
Topic 47	educ,escol,professor,ensin,alun qualidad,médi,fundamental,básic,públic	educ,professor,escol,alun,ensin médi,educacional,aul,fundamental,qualidad
Topic 48	país,unid,estad,internacional,amér naçõ,europ,exterior,internacion,relaçõ	unid,europ,país,amér,latin chin,naçõ,norte-american,argentin,exterior
Topic 49	milhõ,rea,mil,invest,bilhõ ano,recurs,valor,orçament,aeroport	rea,milhõ,aeroport,mil,bilhõ invest,milhã,bilhã,pac,orçament
Topic 50	impost,tributár,receit,pag,fiscal sobr,arrecad,aument,gast,tribut	impost,tributár,receit,fiscal,arrecad tributári,tribut,cpmf,icms,alíquot
Topic 51	cas,pec,sen,plenári,aprov sessã,senador,líd,apel,seman	sessã,sen,líd,pec,plenári vet,senador,convoc,extraordinár,apel
Topic 52	cas,dest,divulg,encaminh,solicit comunic,registr,public,mei,voz	divulg,solicit,voz,public,encaminh document,comunic,ana,lid,registr
Topic 53	cresciment,aument,empreg,ano,econom númer,cresc,desempreg,rend,méd	cresciment,desempreg,cresc,méd,índic empreg,pib,econom,númer,domést
Topic 54	polít,nacional,social,sociedad,soc desenvolv,juventud,popul,particip,moviment	juventud,polít,desafi,fortalec,soc conferent,articul,constru,agend,consolid
Topic 55	mund,tod,mundial,cop,inteir ser,grand,viv,tud,mostr	mund,cop,mundial,inteir,planet prepar,tud,escolh,modern,grand
Topic 56	transport,obras,rodov,obra,quilôetr trech,estrad,construçã,ferrov,infraestrutur	rodov,transport,ferrov,obras,trech dnit,estrad,obra,duplic,quilôetr
Topic 57	cultur,histór,livr,cultural,conhec outr,sécul,anos,tod,ser	cultur,cultural,músic,livr,artist histór,bel,sécul,portugues,belez
Topic 58	porqu,faz,fal,precis,aqu diz,sab,ter,vai,ser	fal,cois,porqu,vou,sab nad,ninguém,vej,acontec,gent
Topic 59	justic,tribunal,federal,suprem,process decisã,judiciári,pod,advog,juiz	tribunal,suprem,judiciári,advog,juiz julgament,juíz,justic,julg,decisã
Topic 60	funcion,permanent,comissõ,cas,encerr inic,nest,pod,tod,determin	funcion,comissõ,permanent,encerr,inic determin,cas,iníci,acompanh,assunt

The main result in the paper presented on table 5 uses a multilevel logistic models to establish the effects of occupation heuristic on who "owns" the issue of security in the Brazilian Lower Chamber. Here, we estimate the same models however using the Linear Multilevel Models. Therefore, instead of using a binary classification for when each speech had one of the five security topics as its most prevalent theme, I use here the raw output from the STM model: the proportion of each security topic in the document. Results are robust using this new specification, and go on the same direction as the main result discussed in the paper.

Table 8 Regression Models: Issue Attention, Public Security, and Law-and-Order House Members

	Dependent variable:		
	(1)	(2)	(3)
Intercept	0.053***	0.027***	0.026***
	(0.002)	(0.002)	(0.001)
Law-and-Order Representative	0.062***	0.074***	−0.010***
	(0.005)	(0.003)	(0.003)
Vote Share	−0.053**	−0.020	−0.033**
	(0.021)	(0.015)	(0.013)
PT	0.005***	−0.001	0.007***
	(0.002)	(0.001)	(0.001)
PSL	−0.003	−0.013***	0.011***
	(0.004)	(0.003)	(0.002)
PSDB	−0.008***	−0.003**	−0.005***
	(0.002)	(0.001)	(0.001)
PFL-DEM	−0.004**	−0.004***	−0.001
	(0.002)	(0.001)	(0.001)
PMDB-MDB	0.001	0.002	−0.001
	(0.002)	(0.001)	(0.001)
PP	−0.008***	−0.006***	−0.001
	(0.003)	(0.002)	(0.002)
State Random Effects	yes	yes	yes
Representative Random Effects	yes	yes	yes
Legislature Random Effects	yes	yes	yes
Observations	131,125	131,125	131,125
Log Likelihood	148,286.700	190,306.900	207,278.400
Akaike Inf. Crit.	−296,547.400	−380,587.800	−414,530.700
Bayesian Inf. Crit.	−296,420.200	−380,460.600	−414,403.500

Notes: All the models use Linear Generalized Multilevel Models estimation. Model 1 uses all the speeches classified as addressing issues of violence, crime, and public security. Model 2 uses only the topics 2 (police and military) and 5 (crime), while the model 3 uses the other topics addressing issues of violence and social minorities. All the models uses random intercepts at the speaker, state, and legislature level.

Appendix C. Validity for the Pre-electoral Shocks

The statistical models showing an effect of crime on the support for law and order candidates rests in the identifying assumption that electoral shocks – an increase in the crime rates before/after the House elections - occurs endogenously. In other words, the variation in the crime rates over the months around the elections are idiosyncratic, and cannot be explain consistently by factors also correlated with the dependent variable in the models. This subsection presents validation tests about the plausibility of this identifying assumption.

First, as introduced in the paper, I find no consistent difference in the distribution of crime over time. I use a variety of placebos for the time cutoffs, and compare the density of these distributions over all the years and municipality with our target period (thre months before the election). The logic here is straightforward: if changes in the crime rate before the election were not exogenous, we would expect to find differences in their distributions when comparing our target distribution with some placebo examples. Figure plots the distribution of crime rates for all possible three months interval over the course of a year, including the pre-electoral period. If the timing of homicides comes from strategic manipulation of the local incumbent, or if criminal organizations manipulate the use of violence around the elections, we would observe detectable differences between these density distributions.

At a first sight, the average crime rate across ten distinct time periods all seem to emerge from a common distribution, reducing concerns of strategic manipulation of violence around the elections. I use Kolmogorov-Smirnov tests comparing the distribution of pre-electoral homicides, and all the other 3 months period, and fail to reject equality of distribution for every case.

I next show that pre-election homicide shocks are not systematically correlated with a wide variety of observable pre-treatment covariates. Table 9 presents results of a simple linear probability model regression the pre-electoral shock dummy on a set of municipal socio-demographics, and political variables. I also add state-level, and year fixed effects in the models. Only two, out of 45 parameters show a significant effect at the 5% level. Therefore, these results provide strong support for the validity of exogeneity assumption of the pre-electoral shocks. All the control variables are described in table 10

Table 9 Validity Checks: Examining Exogeneity of Crime Shocks

	Dependent variable:		
	(1)	(2)	(3)
Intercept	2.150***	2.084***	2.044***
	(0.308)	(0.346)	(0.348)
Gini	−0.063	−0.126	−0.131
	(0.148)	(0.163)	(0.162)
Income sm 1	0.134	0.127	0.100
	(0.108)	(0.126)	(0.126)
Income sm 20	−6.705	−6.308	−6.400
	(4.194)	(4.487)	(4.480)
Female	−1.398***	−1.256**	−1.241**
	(0.523)	(0.612)	(0.612)
Gdp pc	0.0004	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0004)
Ed lit	−0.080	−0.020	−0.007
	(0.145)	(0.170)	(0.169)
Rural	−0.040	−0.023	−0.031
	(0.043)	(0.047)	(0.047)
Income pc	−0.170	−0.186	−0.115
	(0.151)	(0.157)	(0.157)
Deaths Pre Campaing	0.0003	0.0004	0.0003
	(0.0003)	(0.0003)	(0.0003)
Income tax	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)
Tax Returns	0.00002	−0.001	−0.001
	(0.004)	(0.004)	(0.004)
Left President	0.019	0.074	0.176*
	(0.077)	(0.087)	(0.096)
Right President	0.219**	0.292***	0.243**
	(0.088)	(0.104)	(0.106)
Right House	−0.082	−0.051	−0.003
	(0.057)	(0.061)	(0.062)
State Fixed Effects	no	yes	yes
Time Fixed Effects	no	no	yes
Observations	7,069	7,069	7,069
Adjusted R^2	0.004	0.005	0.008
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10 Descriptive Information for the Control Variables

Label	Description
Gini	Gini Municipal
Income_sm_1	Share of Families Receiving one minimal wage
Income_sm_20	Share of Families Receiving 20 minimal wage
Female	Share of Female Population
Gdp_pc	GDP Per Capita
Ed_lit	Literacy Rates
Rural	Share of Rural Population
Deaths_Pre_Campaing	Deaths Before the Election
Income_pc	Income (Wages) Per Capita
Income_tax	Income (Tax Returns) Per Capita
Tax Returns	Share Population Who Declared Taxes
Left President	Vote Share Leftist Presidential Candidate
Right President	Vote Share Conservative Presidential Candidate (PSDB, PSDB, PSL)
Right House	Vote Share Conservative Party House (PSDB, PSDB, PSL)

Appendix D. Robustness Check: Law and Order versus Party Issue Ownership

To ensure robustness for the findings, in this appendix, I estimate models directly controlling for the alternative explanation positing that issue ownership explains how criminal violence makes some parties more competitive.

I modify the paper's main models using a distinct dependent variables that directly estimates the degree to which law and order candidates win more/less compared to the front runner conservative party for each electoral cycle. In these models, I use the log odds ratio between the vote share of law and order candidates and the House vote share of the front-runner conservative party and evaluate how electoral shocks and violence affect support for law and order. I use the PSDB for the years of 2010 and 2014, and the PSL for 2018. These parties had both the front-runners in the Presidential elections and won the most House seats among conservative parties for the each respective electoral cycle. Results go on the same direction as in the main paper.

Table 11 Regression Models: Robustness, Dependent Variable Ratio Vote Share Law and Order and Conservative Front Runner Party

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-8.189^{***}	-8.133^{***}	-5.519^{***}	-5.419^{***}	-539.632^{***}	-538.958^{***}
	(0.999)	(0.999)	(1.068)	(1.068)	(11.898)	(11.901)
Pre-Electoral Homicide Shock	0.059	-0.030	0.035	-0.075	0.004	-0.065
	(0.045)	(0.061)	(0.042)	(0.057)	(0.038)	(0.051)
Homicides Before Electoral Campaign (t_{-9} to t_{-4}	0.012^{***}	0.009^{***}	0.012^{***}	0.008^{***}	0.003^{**}	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Pre-Electoral Homicide Shock x Homicides Before Electoral Campaign		0.007^{**}		0.008^{***}		0.005^{**}
		(0.003)		(0.003)		(0.003)
Controls	yes	yes	yes	yes	yes	yes
State Fixed Effects	no	no	yes	yes	yes	yes
Time Fixed Effects	no	no	no	no	yes	yes
Observations	8,493	8,493	8,493	8,493	8,493	8,493
Adjusted R^2	0.019	0.019	0.146	0.147	0.311	0.311

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix E. Regression Tables for Partisan Effects of Heuristics Processing

Table 12 Regression Models: Partisan Models

	Dependent variable:					
	Conservative Strongholds			Leftist Strongholds		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-9.660^{***}	-8.712^{***}	-479.638^{***}	-6.915^{***}	-8.916^{***}	-407.701^{***}
	(1.022)	(1.064)	(10.443)	(1.060)	(1.097)	(12.110)
Pre-Electoral Homicide Shock	-0.122^{**}	-0.102^{*}	-0.074	0.050	0.007	-0.032
	(0.062)	(0.056)	(0.046)	(0.065)	(0.058)	(0.051)
Homicides Before Electoral Campaign (t_{-9} to t_{-4}	0.007^{***}	0.012^{***}	0.004^{**}	0.009^{***}	0.009^{***}	0.004^{*}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pre-Electoral Homicide Shock x Homicides Before Electoral Campaign	0.011^{***}	0.009^{***}	0.005^{**}	-0.002	-0.002	-0.0003
	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)
Controls	yes	yes	yes	yes	yes	yes
State Fixed Effects	no	yes	yes	no	yes	yes
Time Fixed Effects	no	no	yes	no	no	yes
Observations	4,419	4,419	4,419	3,815	3,815	3,815
Adjusted R^2	0.186	0.340	0.550	0.096	0.286	0.446

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix F. Factorial Experiment

In this section, I present an example of the instruments used in the Factorial experiment. The experiment was included in a national online survey in Brazil with 2.400 respondents. The survey was fielded by Netquest-Vanderbilt, with probabilistic samples drawn by the LAPOP team in Vanderbilt from users registered with Netquest.

The experiment randomly assign respondents to one set of 2 messages. Each respondent sees two built tweets side by side. The conjoint design consists on random rotation of four features for each tweet: the header, the text (a statement about security in Brazil), the author of the statement, and an image below the tweet. Table **??** presents the variation in the levels for each of the four features above described. After seeing the tweets, I ask the respondents which one they would share in their wall.

Table 13 Factorial Experiment: Support for Punitive Messages and Law and Order

Feature	Choices
Header	
	Liberal Media (*Folha de Sao Paulo*)
	Conservative Media (*O Antagonista*)
Content	
	Punitive Message (More Punishment to Criminals + Harsher Laws)
	Redistributive Message (More Investiment in Education and Opportunities for Youth)
Endorsement to the Message	
	Civil Federal Deputy
	Law and Order (with military Rank) Federal Deputy
Image	
	Neutral
	School
	Military Intervention
	Independent

Figure 8 provides an example of the conjoint task. This is just one of the 256 combinations between the four features that the factorial was rotating upon. The example below varies only the endorsement and the image of the tweet. The author and the message of the tweet, although not literally the same to avoid the respondent to read the same tweet, are the same.

Figure 8 Conjoint Experiment. In this example, the tweets have the same author, the same content for the text, an different endorsement by a politician, and a different image.

Numerical Results

The table below presents the numerical results for the models discussed on figures 4 e 6 in the main paper.

Table 14 Regression Estimates: Numerical Results of Factoral Experimental Design

	Dependent variable:			
	Model AMCE	Model AICE (Partisan)	Model AICE (High x Low Income)	Model AICE (High x Middle Income)
	(1)	(2)	(3)	(4)
Intercept	0.306***	0.492***	0.298***	0.325***
	(0.014)	(0.023)	(0.032)	(0.016)
Liberal Media	−0.0002	−0.010	0.006	−0.010
	(0.012)	(0.016)	(0.027)	(0.014)
Law and Order Endorsement	0.025**	−0.017	0.055**	0.010
	(0.012)	(0.024)	(0.027)	(0.014)
Punitive Content	−0.151***	−0.360***	−0.152***	−0.160***
	(0.012)	(0.024)	(0.031)	(0.015)
Image School	0.043***	0.004	0.041	0.037**
	(0.015)	(0.019)	(0.032)	(0.018)
Image Military	0.010	−0.005	−0.008	0.010
	(0.015)	(0.019)	(0.034)	(0.018)
Conservative Voter		−0.270***		
		(0.027)		
Law and Order Endorsement x Conservative Voter		0.071**		
		(0.031)		
Punitive Content x Conservative Voter		0.388***		
		(0.031)		
High Income vs Middle Income				−0.046
				(0.036)
High Income vs Low Income			−0.044	
			(0.042)	
Punitive Content x High Income vs Middle Income				0.140***
				(0.053)
Punitive Content x High Income vs Low Income			0.127**	
			(0.060)	
Observations	4,726	3,028	1,078	3,598
Adjusted R^2	0.031	0.073	0.021	0.031

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix E: Survey Human Objects

Human Subjects approval for the survey was granted by the IRB's University of Maryland, College Park, on February 17, 2020. The project approval is registered under the identification code [1552091-1]. Consent was requested at the beginning of the survey and a disclaimer provided respondents with information on how to contact the researchers or IRB if needed. Details of the application, recruitment, consent, and disclaimers follow:

Subject Selection

a. Recruitment: The survey respondents were recruited by Netquest for the on-line survey, from their panel of Brazilian and Mexican respondents.

b. Eligibility Criteria: Participants were at least 18 years old of age and nationals from Brazil or Mexico.

c. Enrollment Numbers: A total of 2,400 respondents. The number of participants met national representative samples for each country and enough statistical power for the different experimental treatments in the survey.

Risks

We anticipate only minimal discomfort associated with this procedure in case participants do not agree with social media messages, or the topics covered by it. We mitigate this risk by allowing respondents to skip questions they do not feel comfortable answering, as indicated in the consent form.

Confidentiality

The PI and team receive a de-identified respondent ID number. No private identifying information was stored in the servers of the PI or any other member of the team. Thus for the full survey we will be able to adequately ensure the anonymity of all survey respondents.

Consent Process

The informed consent procedure provides participants explicit consent to proceed and informs of their right to skip questions and to discontinue the survey.

The online consent was granted by IRB by waiving written consent, given the following criteria: 1. Our research involves no more than minimal risk to the subjects. As we have stated, the only potential risk is minimal discomfort due to the nature of the questions asked, and we mitigate this discomfort by allowing participants to skip questions. 2. The waiver will not adversely affect the rights and welfare of the subjects. All subjects in these pre-test and survey will be fully informed about their rights as participants and the nature of the study, and they will have access to the consent form online to save and print for their records. 3. This research could not practicably be carried out without the waiver because it is entirely performed online. Therefore, none of the co-PIs could gather written consent forms for all participants. 4. Whenever appropriate, the subjects will be provided with additional information after participation. Participants will have access to contact information for both co-PIs and IRB, allowing them to reach out in case they have any further questions.

IRB Approval letter

The official approval letter is available upon request.