Legislating for Violence: Issue Ownership and Occupational Heuristics in the Brazilian Congress

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Abstract

How does politicians signal to voters about their issue advantages in democracies with weak party labels? The answer to this question is crucial for understanding partisan politics on newly democratized societies. This article uses the case of law-and-order politicians in Brazil to show how a candidate's professional background works as a crucial informational shortcut that politicians rely upon to signal to voters about their policy priorities and competence. I argue that a candidate's professional experience acts as the main mechanism through which issue ownership advantages works on democracies with fragmented party systems. To provide evidence for my theory, I use computational text analysis to analyze a large corpus of more than one hundred thousand congressional speeches spanning almost twenty years of legislative activity in Brazil. Results provide robust evidence that House Members' prior professional history explains work as a superior device explaining who talks about public security in the House, and report contrasting differences on how law-and-order representatives frame the issue of public security in their speeches.

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Introduction

Political scientists have found ample evidence that voters use a variety of heuristics and cues to help them making political decisions. Among those traits, partisan identity has been long argued as the most crucial type of source cue voters rely upon (Zaller, 1992; Green et al., 2004). As a result, several studies show evidence for partisan identity affecting a wide range of voters' attitudes, such as how they evaluate candidates,their personal economic perceptions, support for democracy and authoritarianism, policy preferences, emotions and personal feelings towards those with a distinct partisan preference (Arceneaux, 2008; Druckman, 2001; Slothuus and De Vreese, 2010; Nicholson, 2012; Slothuus and De Vreese, 2010; Svolik, 2019; Evans and Andersen, 2006; Mason, 2018).

On the supply side of politics, partisan advantages on the voter side is commonly explained by a long-lineage of studies organized around the concept of party issue ownership (Petrocik, 1996; Kaplan et al., 2006; Adams et al., 2005; Budge and Farlie, 1983; Egan, 2013; Pardos-Prado and Sagarzazu, 2016). Partisans from distinct colors care about different issues. As a consequence, parties build across time a particular association with issues that cater strongly to their voters, building a certain reputation around these agendas. As a consequence, the electoral fate of these parties become strongly connected with the salience of these issue: parties win more, sometime crossing partisan lines, when a issue they own becomes more salient .

However, this is an expectation at odds to what we know about party labels and informational effects on democracies with weak partisan identities. In countries where partisan identities are more recent and relatively unstable, such as in Latin America (Samuels and Zucco, 2018; Lupu, 2017; Baker et al., 2016), our knowledge about what other types of information voters rely upon to make political decisions is somewhat limited. When party labels are too weak, recent studies have shown that voters rely on distinctive set of heuristics to make political decisions, such as gender, ethnicity, and race (Kristín Birnir, 2007; McDermott, 1998; Adida et al., 2017; Campbell and Cowley, 2014). A proper understanding of these different heuristics is crucial to the notion of who win and who loses when issues become more salient on fragmented democracies.

This articles uses the case of law-and-order candidates in Brazil to show how a candidate's professional background works as a crucial informational shortcut that politicians rely upon to signal to voters about their policy priorities and competence. I argue that a candidate's professional experience acts as the main mechanism through which issue ownership advantages works on democracies with fragmented party systems. For example, former police offices, members of the army, and other law and order candidates are able to use their personal history strategically to convince voters concerned with crime control about the credibility of their messages and the candidate's capacity and willingness to prioritize security while in office. I consider a law-and-order politician as actors who have previously held an occupation in police and/or military forces prior to entering in politics [1]

To provide evidence for my theory, I use computational text analysis to analyze a large corpus of more than one hundred thousand congressional speeches spanning almost twenty years of legislative activity in Brazil. Using structural topic models (Roberts et al., 2014a), I show the different ways that Federal Deputies talk about security in Congress, provide robust evidence that House Members' prior professional history explains more who talks about security in the House, and report contrasting differences on how law-and-order representatives frame the issue of public security in their speeches.

[1] The candidates and politicians' occupation is retrieved directly from electoral data available at official sources. See the appendix for the details in the classification employed here.

My work extends an emerging literature in political science examining political dynamics of law enforcement (Knox et al., 2020; Soss and Weaver, 2017; Magaloni et al., 2020). Brazil, the largest economy on the continent, is a interesting case to understand how law enforcement occupational heuristics may supersede partisan heuristics. In 2018, the populist leader Jair Bolsonaro, a former captain of the Brazilian Army, won in a landslide presidential election. Together with Bolsonaro, the public security caucus has become the largest in the Congress, and several candidates from police forces, the military, or other enforcement agencies have been elected to political positions. More important, while these candidates have become more frequent in the menu of politicians in Brazil, the traditional conservative parties have completely eroded . In a country where 57,358 people were violently murdered just in 2019 (Cerqueira et al., 2019), which puts Brazil as one of the most violent democracies in the world, having a military rank has become a crucial political asset.

The first contribution of this article is to explain how former law enforcement agents use their occupation as an political advantage when making politics. More importantly, I show how this process occurs in a context where violence has become a increasing concern on the voter side (Bonner, 2019; Holland, 2013; Dammert and Malone, 2006; Muggah and Tobón, 2018; Pérez, 2015), and how these politicians not only talk about security while in congress, but actually use their political positions to propagate more punitive views about security policies. Occupation heuristics in a fragmented environment, as the Brazilian system, has superseded at large traditional heuristics our theoretical expectation usually connects to party labels in developed democracies.

In this regard, a second contribution of this articles goes to the recent literature of behavioral changes driven by experiences of victimization on violent democracies. Recent scholarship on the intersection between criminal violence and political behavior 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), are less supportive of democratic attitudes (Fernandez and Kuenzi, 2010; Carreras, 2013; Bateson, 2012), and often develop a greater taste for iron-fist policies (Bateson, 2012; Visconti, 2019; Singer et al., 2020). By showing how occupational heuristics coming from law-and-order occupation matter, we provide a more credible explanation for how the greater salience of the crime issue, and in particular greater support for punitive security policies, is absorbed by the political system.

The rest of the paper is structured as follows: the next section introduces the hypothesis and positions the paper within the larger literature on behavioral heuristics, violence and law and order politics. 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.

Issue Ownership, Occupational Heuristics and Law-and-Order Politicians in Brazil

Arguments using issue ownership theory are deeply influential on studies on political behavior. Part of the appeal of this theoretical framework is its completeness: predictions from the issue ownership theory work both for the supply (politicians) and the demand (voter) side of politics.

On the supply side, issue ownership theory argues that some parties owns certain policy issues. For example, it is common knowledge in the the United States that Democrats are considered to own the issue of health care, while Republicans are more strongly associated with national security (Petrocik, 1996; Egan, 2013; Boldt, 2019). Otherwise, in some Western European countries, right-wing parties are believed to own the issues of immigration, socialist parties are perceived to own welfare politics, while and green parties are believed to own environmental issues (Budge et al., 2001). On the demand side, theory ownership theory assumes voters will perceive parties who "own" a particular issue as more competent and credible to legislate and act on this agenda (Calvo and Murillo, 2019; Adams et al., 2005; Budge and Farlie, 1983). When owning an issue, parties should argue to increase the salience of these topics among the voters, and voters will reciprocate these parties with voters.

Therefore, the observable implications of the model are straightforward. On the supply side, parties' best-strategy consists on working on issues that they own. Indeed, several empirical pieces have shown how parties use a variety of strategies, such as campaign ads (Kaplan et al., 2006), legislative speeches (Pardos-Prado and Sagarzazu, 2016), and even legislative committee meetings (Vallejo Vera, 2021), to increase the salience of their issues. On the demand side, voters are expected to cast their ballots on the parties that owns issues that are more salient in a particular context, as the literature has shown evidence (Bélanger and Meguid, 2008; Pardos-Prado and Sagarzazu, 2016; Boldt, 2019)

When considering the issue of crime and security, most of the literature argues in favor of a partisan advantage associated with conservative parties (Holland, 2013; Beckett, 1999; Beckett and Western, 2001; Cohen and Smith, 2016). This argument runs as follows. Because conservative voters possess a more substantial adherence to conformity and authority values (Gerber and Jackson, 2016; Cohen and Smith, 2016), they commonly rank security and crime issues as an higher priority. As a consequence, to cater to these voters, conservative parties work to historically build a reputation around the issue, therefore, talking more, and giving higher priority to crime control policies, and thus owning the issue of security. In her seminal piece about Law-and-Order politics in Salvador, Holland (2013) synthesizes this logic arguing that: "conservative parties have a comparative advantage in touting their security credentials. Crime can be viewed as a valence issue in which parties advertise their unique competence to achieve shared security [...] They can draw on language, figures, and founding myths from periods of authoritarian control to lend credibility to claims that they will provide security at all costs" (pp.52).

Issue ownership framework have substantially shaped our understanding of political behavior and party strategies on advanced democracies. Yet, quite little is known about how issue ownership really works on newly democratized countries. As a matter of fact, the expectation about the informational values of party labels, and the voter's ability to infer from labels the predictions of the issue ownership framework is mostly at odds with what we know about party labels and informational effects on cases where partisan identities are more fluid (Samuels and Zucco, 2018; Baker et al., 2016; Lupu, 2017).

Consider, for instance, the Brazilian example. Brazil adopts as unique open-list multi-district proportional system for House elections [2]. This institutional setting if often to blame critical features of the Brazilian political system. Incentives to fragmentation and partisan majoritarian bias (Calvo et al., 2015), progressive ambition in a context of candidate-centered incentives (Samuels, 2003), non-ideological formation of legislative coalitions in Congress (Amorim Neto et al., 2003; Zucco, 2009), extraordinary levels of party switching (Desposato, 2005), and the use of pork barrel towards candidates' electoral bases (Ames, 2001; Ventura, 2021) are some

[2] Brazil has a federal system organized at three levels: federal, state, and municipal. Elections in Brazil take place every four years. Local elections occur every two years after the national and state level elections. The Brazilian voter elects the chief of the executive on all the federal levels by direct voting in a plurality system with a run-off round when none of the candidates reach an absolute majority. The legislative representatives are elected by open-list proportional representation with the municipalities as districts for local councilors and the states for the House Representatives and state-level representatives.

of the main findings of the specialized literature about the party system in Brazil. This environment contributes to the common description of Brazil as having a fragment and weak party-system.

Occupational Heuristics and Issue Ownership

This paper presents a refinement on how predictions on the supply side of the issue ownership framework works on fragmented democracies. I argue that in an environment where partisan identity is an imperfect information shortcut, partisan advantages will hardly explain how parties build ownership around policy issues. Instead, in the absence of strong party labels, I argue that the candidates' personal characteristics are better predictors about a politician's behavior.

Among those traits, I argue that the politicians' occupation is a crucial heuristic explaining more which issues politicians focuses their agenda than parties labels. Occupational heuristic signals to voters and other political elites about the politicians' competence and knowledge of a particular issue. In addition, particularly on more technical policy areas, such as public security, *in-the-field* experience can be also used to show a candidates' credibility. A police officer, for instance, 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. Therefore, using the case of crime and public security issue, I expect that Law-and-Order politicians will own the issue in the Congress.

Hypothesis 1. *Law-and-Order Politicians will dedicate greater attention on their floor speeches to the issue of crime and public security.*

In addition, because positions in criminal justice agencies in Brazil are all public careers, with lifetime tenure under Brazilian law, such a declaration commonly represents an entire lifetime's training and experience in militarized institutions, which previous research has suggested encourages higher punitive preferences (Navajas et al., 2020). Indeed, in most developing countries, officials 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 more punitive policies (Bueno, 2012; Cano, 1997; Denyer Willis, 2015; Brinks, 2007; Caldeira, 2002). Therefore, these law-and-order heuristics should go beyond the simple "talk more" prediction from issue ownership theory (Kaplan et al., 2006; Petrocik, 1996), but also explains how these issues are framed in the Congress.

Hypothesis 2. *Law-and-Order Politicians will be associated with a stronger punitive framing on on their speeches about the issue of crime and public security.*

Police and Law-and-order Representative in the Brazilian Lower-Chamber

State-level authorities in Brazil have the legal delegation to most of the public security and policing responsibilities. The main Police Force are divided between a civil and military army. Although the police are not linked directly to the Brazilian Armed Forces, it is a "militarized" institution working under military principles of hierarchy, discipline, and ceremony. These rules governing the civil and military police in Brazil were all created during the military regime in Brazil (1964-1985) making the police's current institutional organization still largely a legacy from the country's authoritarian experience.

The country electoral and legal system imposes no restrictions on military members and police officers who decide to run for elected positions. Therefore, candidates with a professional experience on law-and-order agencies pay basically no costs to run for political positions. Only during the electoral campaign that these candidates are 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.

I start with some basic descriptive statistics about the presence of law-and-order politicians in the Brazilian Lower Chamber. Table 1 showcases an consistent upward trend on the number of elected House Members with candidates with a professional experience on security forces. From 2002 to 2018, Brazil saw the number of former law and order agents increase from 5 to 35 members in the House. If unified in a single party, these candidates would represent the third-largest party in the House. The large jump in 2018, representing the biggest presence of law-and-order politicians in legislative politics since the years of the military dictatorship in Brazil, also comes in the same context of the presidential election of law-and-order Jair Bolsonaro to the Presidency.

Furthermore, 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.

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 [3] Overall though, as expected, small conservative parties, with basically no strong

[3]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

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

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

party labels, have been the favorite choice of law-and-order candidates.

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

This paper framework is built upon the assumption that candidates from police and military forces occupation's supersedes weak partisans heuristics on fragmented democracies. To substantiate this argument, my empirical work shows how these law-and-order candidates, rather than traditional conservative parties, controls the agenda of public security over a span twenty years of legislative work in the Brazilian Congress.

To show evidence of my argument, the paper uses computational text analysis on a large corpus of data from from congressional speeches for House members. The speeches are publicly available and were collected through the Congress API [4]. I retrieved data from all the speeches made in the plenary floor, made between 2003-2019 resulting in a total of 147,584

PSB, PDT and PSOL, have succeeded in electing law-and-order officials to the House.

[4] The API is available here https://dadosabertos.camara.leg.br/

speeches. All my analysis are limited to the section called *Pequeno Expediente* which consists on five minutes speeches that occur before the beginning of a parliamentary session. By limiting the analysis to this section, I avoid discussing in the plenary related to voting justifications or other daily issues in congres, and focus mostly on House Members own decision to address issues of their interests and signal to voters about their policy priorities (Moreira, 2020) [5]

Congressional speeches constitute an unique source for measuring the attention candidates and parties give to a particular issue. Different than other types of data commonly employed for similar purposes, like expert surveys, news report, campaign ads, and party manifestos (Petrocik, 1996; Kaplan et al., 2006; Benoit, 2007; da Silva Tarouco, 2011; Power and Zucco Jr., 2012), congressional speeches "run" continuously over time and are less constrained by other pressures from electoral incentives. Similar data have been used to discuss a huge variety of issues in legislative politics, such as news methods for ideological scaling (Proksch and Slapin, 2010), how representatives communicate with their constituencies (Grimmer, 2010), the effects on speeches on voters' economic perceptions (Pardos-Prado and Sagarzazu, 2016), and gendered differences in legislative participation (Vallejo Vera and Gómez Vidal, 2021).

Modelling Strategy

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.

Structural Topic Models use probabilistic modeling in a non-supervised setting to maximize the co-occurrence of words in a particular corpus (**?**Grimmer, 2010). In simpler terms, these

[5] More information about the Data Collection and Processing steps in the data analysis are provided in the Appendix.

models look for words that frequently occur together across documents, and detect clusters of words. These clusters of words are defined as topics. Unlike other strategies, structural topic models maximize the co-occurrence of words while allowing topics to have a common correlation structure and covariates to be added in the priors of the likelihood function.

Before fitting the model, I adopt some standard pre-processing techniques in the corpus. I removed punctuation, capitalization, numbers, and symbols, and stop words in portuguese which are common and generally uninformative. Using this corpus, I fit a Structural Topic Model with 60 topics. I also 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.

Labelling the Topics

I present the most prevalent and the words with the highest frequency-exclusivity scoring (FREX) (Wallach et al., 2009; Roberts et al., 2014a) for each of the five topics in table 2. To label the topics related to the issue of public security, I adopted standard steps recommended by the literature in text analysis (Grimmer, 2010; Roberts et al., 2014a). First, I read the most frequent and FREX words for all the topics, then I read at least ten random speeches for each topic, and finally I analyze how some reference-politicians, who historically act on a particular policy issue, are associated with their expected topics. To provide to the reader more transparency about the topics, I add in the appendix some snippets of the congressional speeches for each of the five topics.

Five topics out of the sixty that address issues related to violence and security. 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

Table 2 Violence and Security on Congressional Speeches in the Brazilian House (2003-2020)

Topics	Most Likely Words	FREX Words
Topic 9: Police and Military	milit,seguranc,políc,polic,forc, policial,armad,públic,exércit,civil	polic,milit,armad,bombeir,policial, seguranc,exércit,civ,forc,políc
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))

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.

Validating the Security Topics

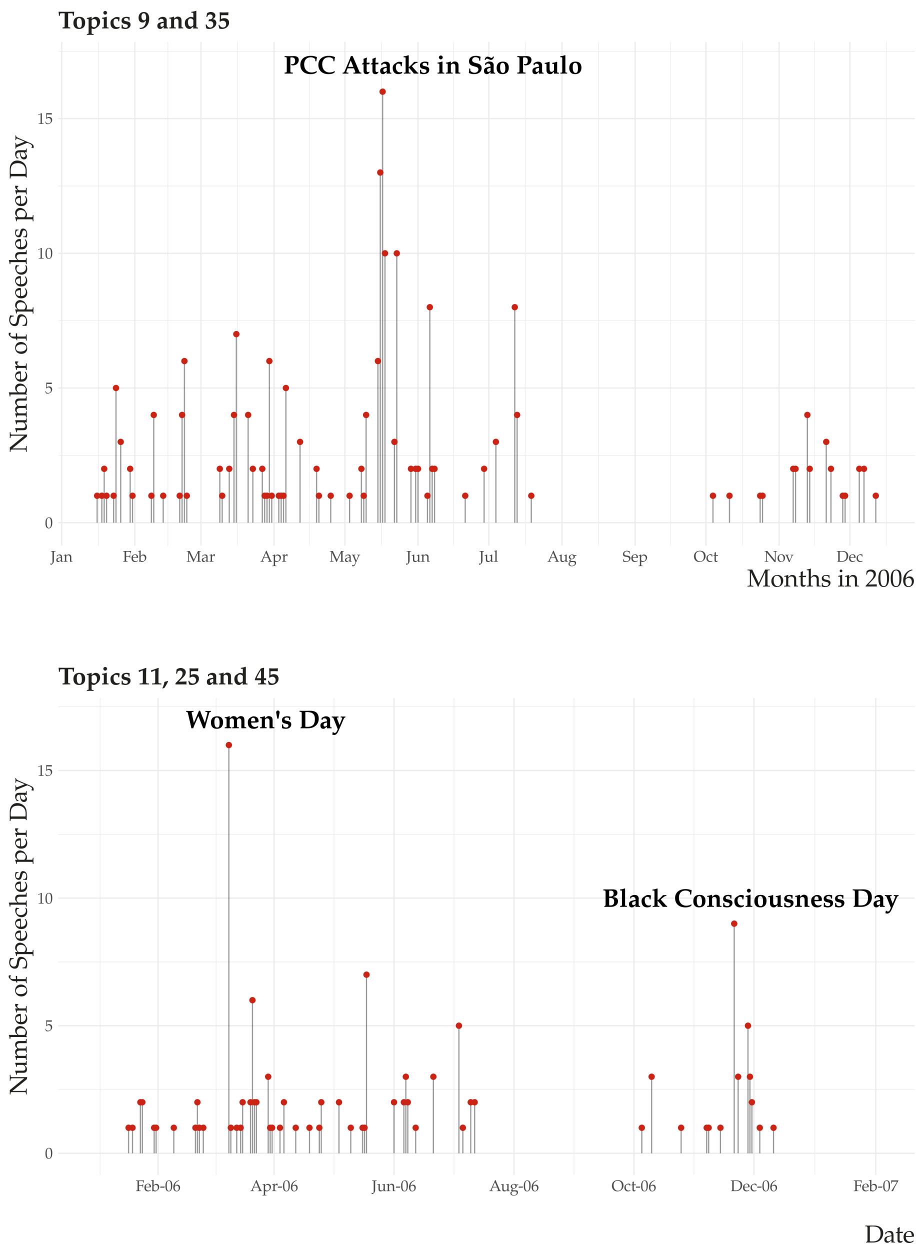
In any type of statistical modelling employed to identify latent dimensions on complex data structures, validation is key. Table 2 and the snippets in the appendix already provide some validation for the five topics labelled as public security. However, more is in order to validate my labelling decisions. Therefore, in this section, I provide one more piece of evidence for the substantive fir of the model. As in Grimmer (2010) and Quinn et al. (2010), I explore the daily number of speeches generated by each of the five topic about security, and map these distributions with certain nationally-relevant events to show that topics are substantively meaningful.

Figure 1 presents the results. I consider only congressional speeches from the year 2006. This is a crucial year in the history of security policies and criminal violence in Brazil. In May 2006, Brazil's *Primeiro Comando da Capital (PCC)*, the most powerful Drug-Trafficking Organization in the Country, launched a series of attacks on São Paulo city's while also organizing simultaneous riots in over 90 prisons across the Country. This series of attacks are often described as the largest and most organized attack of a criminal organization against state forces in Brazil (Feltran, 2018; Biondi, 2016; Willis, 2015).

Speeches classified on topics more related to public security and crime (9 and 35 as in table 2) see a huge spike in early May, as shown on the upper plot of figure 2. I keep the year constant to analyze the prevalence of the other three topics, which focus on violence and minorities. One can check how speeches on these issues increase in two special national events: International Women's Day in early March and Brazilian Black Consciousness Day in November. Grassroots organizations' protests often mark both commemorative dates and, as we detect, politicians bring these issues to Congress in their speeches. Indeed, these spikes in March and November appear on most of the years under analysis in this paper.

Taken together, the qualitative analysis of the words and documents together with Figure 1 demonstrate that the topic model is able to successfully retrieve a diversity of Congressional Speeches raising issues related to security and violence in Brazil.

Figure 1 Validation Checks for the Topics About Security and Violence.



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 logistical 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.

A critical issue in modelling this type of data is dealing with overdispersion in the number of speeches. In other words, the probability of a speech i_1 being about security is hardly independent from speech i_2 if they occur for example at the same legislature, or on representatives from the same electoral district. To deal with this challenge, 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). The statistical model is represented in the equation below:

$$\begin{aligned} y_{its} = \alpha_j + \beta_1 \text{law-and-order}_i + \beta_2 PT + \beta_3 PSDB + \beta_4 + DEM + \\ \beta_5 PMDB + \beta_6 PSL + \beta_7 PP + \beta_8 \text{Vote Share}_i + \sigma_t + \tau_i + \Sigma_s \end{aligned} \tag{1}$$

Results

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).

The effect of being a law-and-order House member is negative for speeches about violence against minorities and social inequalities. In other words, 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. This finding is substantively relevant because it shows how security, rather than a valence issue as most of the literature argue (Holland, 2013; Calvo and Murillo, 2019; Kaplan et al., 2006; Visconti, 2019), actually is rather divisive among Brazilian politicians. Those who "own" the issue of security focus on speeches catering for their corporation and usually calling for more punitive penal policies, while also being silent about other dimensions of violence, in particular, when targetting socio and ethnic minorities.

The 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. Therefore, these results show evidence for both hypothesis of the paper. Occupational heuristics at the candidate level are the main determinant explaining who owns the issue of security

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 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.

in the Brazilian Congress. Moreover, these former security officials also have a stronger association with a stronger punitive framing on their speeches about the issue of crime and public security.

Conclusion

Most of the previous work on issue ownership theory has failed to differentiate between party level and candidate level dynamics, as noted elsewhere (Kaplan et al., 2006; Kaufmann, 2004). The lack of attention to how candidates build and use their reputation on a issue is particularly concerning considering studies on political behavior on democracies with more fragmented party system. This paper is the first to show how occupational heuristics, for the case of security and violence issue, is a superior determinant of who "owns" an issue in the Brazilian Congress.

The results indicate that, rather than conservative parties, candidates with a professional experience in law-and-order, and who are spread among a variety of party labels in Brazil, own the issue of crime and security. Using novel methods in computational text-analysis, the paper depicts several robust results. I first show that law-and-order candidates dedicate greater attention in their speeches to public security. Then, I show that no more traditional conservative party, those that in other contexts have been described as owning the issue of security (Holland, 2013; Petrocik, 1996; Beckett, 1999; Beckett and Western, 2001), have a robust association with the issue of security in the Congress. To conclude, I explore distinct framing strategies among the speeches, and find that law-and-order candidates not only talk more about security, but these candidates are more likely to be associated with more punitive topics.

Connecting issue ownership theory and occupational heuristics for the case of public security provides a important substantive contribution to studies about quality of democracy in Latin America. As concerns about crime and violence have become a key social and political dilemma in most of Latin America countries (Pérez, 2015; Yashar, 2018; Arias and Goldstein, 2010), several countries have watched an array of law-and-order politicians becoming more and more competitive at the ballots. These politicians usually run on promises of being though on crime, and. when in power, frequently become a threat to individual civil and political rights, as the most recent case of Nayib Bukele in El Salvador rests assure.

This paper indicates a clear causal mechanism explaining this phenomenon. The emergence of populist, law-and-order politicians is not only a consequence of voters developing greater taste for iron-fist policies in a context of high violence (Visconti, 2019; Garcia-Ponce et al., 2019; Holland, 2013), but also result of changes in the supply-side of the political game. As voters become more concerned about crime, soon-to-be politicians, who are historically trained in delivering violence, see an opportunity to make their way intro politics, and use their occupational advantages to cater votes, throwing their traditional conservative contenders to knockout.

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Legislating 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 signals 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 portuguese words that refer to these professions. [6]

[6] 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 text documents, and have been used on a variety of data sources, 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.[7]

I use the Structural Topic Model (STM) developed by (Roberts et al., 2014b) in the paper. The STM 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), [8], draw a word from a multinomial distribution parametrized by $\beta_{d,k}$.

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

[8]$\beta_{d,k}$ 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.

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

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 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

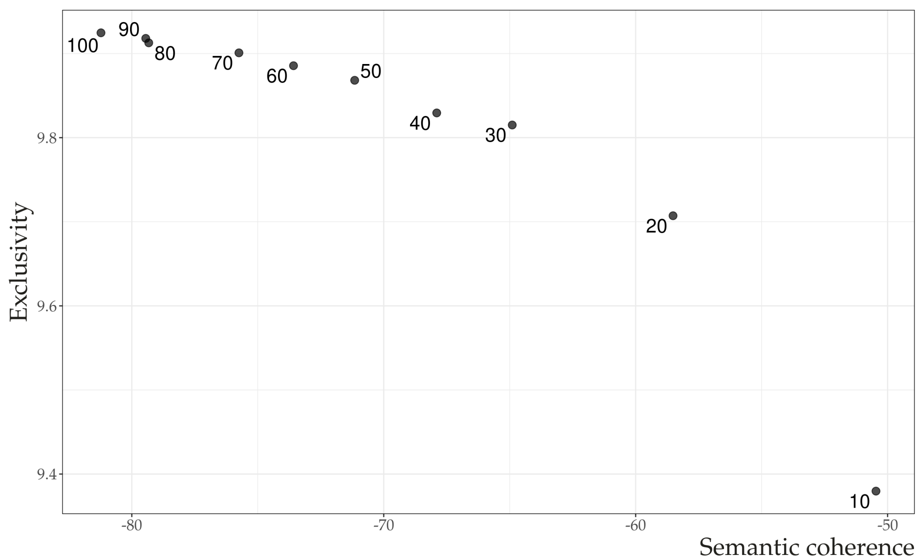
I first collected the Congressional Speeches using the Brazilian House API. I collected all the congressional speeches made between 2003 and 2020, resulting in a total of 147,584 speeches, and 252,038 different words. I limited the analysis to speeches on the *Pequeno Expediente* which consists on five 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(Mimno et al., 2011), and exclusivity measure how exclusive the words are to a given topic. Figure **??** provides the visual results. We 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 2 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

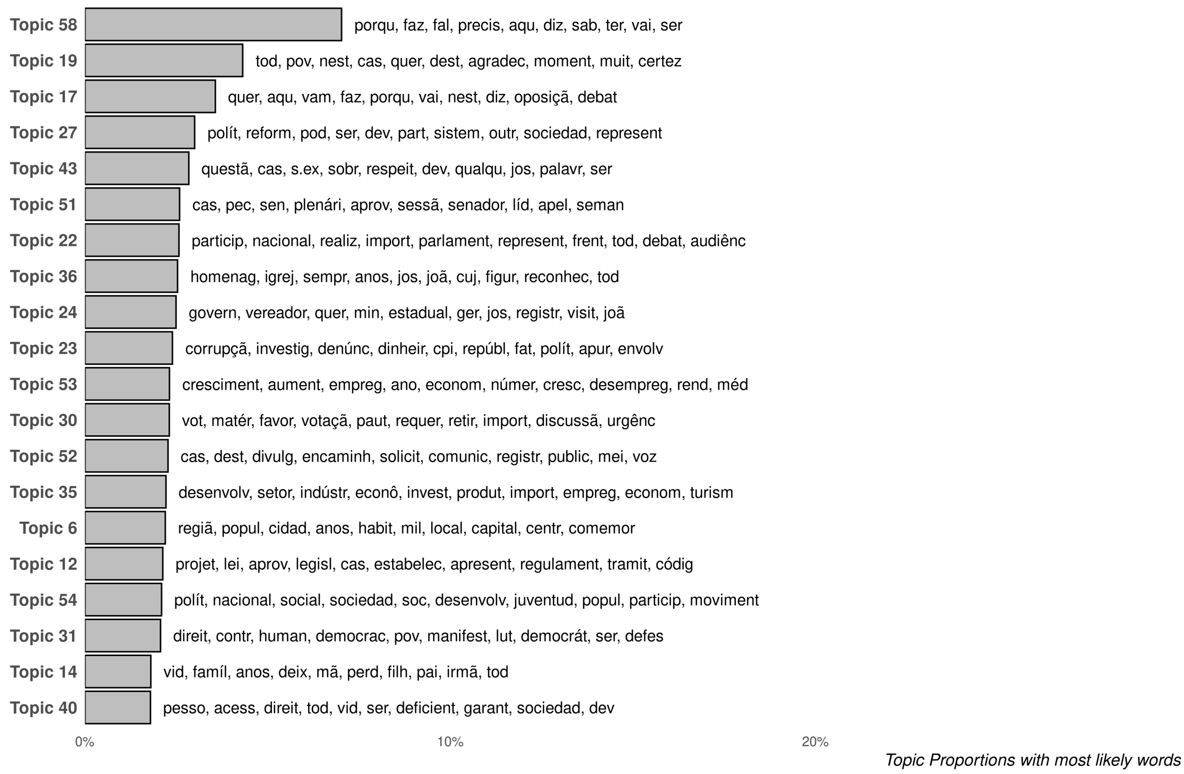
Additional Results

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 4 and 5 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. In addition, I present the overall distribution of topics across the corpus of congressional speeches. Figure 3 present the ten most prevalent topics with their respective most likely words as reported on tables 4 and 5.

Figure 3 Top Twenty Topics on Congressional Speeches



Note: The results are extracted from a Structural Topic Model fitted on a corpus of Congressional Speeches in the Brazilian House. The model if fitted with sixty topics

Table 4 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 5 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,polìc,brasíl,trânsit oper,veícul,feder,motor,rodoviár	distrit,trânsit,federal,brasíl,rodoviár veícul,motor,polìc,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 **??** 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, we use 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 6 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.