Partisan Leaning *

Zuheir Desai[†] Anderson Frey[‡] Scott A. Tyson[§]

Abstract

Voters evaluate candidates along several dimensions, some ideological and others not. But a decisive or median voter's exact ideological position can be hard to predict, even for seasoned candidates. We develop a novel theory of ideological electoral competition where an electorate's *partisan leaning* serves as a signal of the median voter's ideological position and where extreme leanings are more informative about voters than centrist leanings. Our conceptualization of leaning leads to an endogenous sorting of districts into "extreme" and "centrist" categories, and an increase in the importance of candidate competence for voters increases polarization—but only in extreme districts. We evaluate our theory using data from mayoral elections in Brazil's 95 largest municipalities and exploit COVID-19 as a shock to the salience of candidate competence. We show that COVID-19 increases the salience of competence in these elections, leading to increased political polarization, which is concentrated in cities with extreme partisan leanings.

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[†]Assistant Professor, Department of Political Science, The Ohio State University. email: desai.596@osu.edu.

[‡]Assistant Professor, Department of Political Science and Research Associate, W. Allen Wallis Institute of Political Economy, University of Rochester. email: anderson.frey@rochester.edu.

[§]Associate Professor, Department of Political Science, University of Rochester, and Research Associate, W. Allen Wallis Institute of Political Economy, University of Rochester. email: styson2@ur.rochester.edu.

Voters assess candidates on ideological and non-ideological factors, yet predicting the precise ideological stance of the median voter proves challenging, even for the candidates themselves. The predictability of the decisive voter's ideological position often depends on the electoral district. For example, in the United States there is little (to no) uncertainty in any election cycle regarding whether the median voter in California district 12, which includes Berkeley and Oakland, prefers leftist policies. California district 12, represented by Democrat Barbara Lee, is the most heavily democratic district in the United States.[1] Indeed, Lee secured around 90% of the vote in 2022 (against Republican Stephen Slauson). Not all decisive voters are so predictable. Bury North in Greater Manchester is the most marginal constituency in the United Kingdom, where Conservative James Daly won by 105 votes in 2019. Bury North has consistently switched between Labour and Conservatives since the 1990s. Many constituencies around the world fall somewhere between these two extremes, and every democracy exhibits considerable variation regarding how well candidates know (or can predict) the ideological preferences of their decisive voter.

Electoral platforms often reflect what candidates know about their voters. Electorates that are known for being more ideologically extreme are typically the ones whose decisive voter is easier to identify (like Berkeley), compared to more moderate ones, whose median voter is harder to pin down (like Bury North). A district's *partisan leaning* provides a signal of the decisive voter's ideological position and can be thought of as a signal about where candidates "expect" their decisive voter to be, feeding into the electoral platforms of the candidates. Extreme leanings provide a more precise signal than centrist leanings—an overlooked feature of electoral politics (Dewan and Shepsle, 2011; Duggan, 2005).

In this article, we show that uncertainty about the ideological position of the decisive voter and the signal a district's leaning provides, are important for understanding electoral competition. We develop a novel theory of electoral competition between two policy-motivated candidates, one whose preferred policy is on the left while the other's is on the right. In our

[1]According to the Cook Partisan Voting Index, California 12 scores D+40, tied with Maryland 4 for the most heavily Democratic leaning district in the United States.

model, candidates choose their policy platforms while uncertain of two elements. First, voters learn about the competence gap between candidates over the course of the campaign.[2] Because of this, candidates are unsure who will enjoy a non-ideological advantage at the moment of choosing their campaign platforms. Second, candidates do not know their voters' exact ideological preferences. Instead, and novel to our model, candidates only know their district's *partisan leaning*, which serves as a signal of the voter's most preferred ideological position. The precision of that signal varies considerably with the district's leaning. The representative voter in our model cares both about ideology—or policy—as well as the competence of their representative, a quality independent from ideological concerns. We call the weight the voter places on competence (relative to ideology) the *salience of competence*.

We present three theoretical results about the ideological platforms candidates choose. Our first result shows that districts are divided endogenously into two categories which differ in what motivates campaign competition. Electoral competition in relatively "extreme" districts is primarily driven by how much voters will learn about the competence gap between candidates. In particular, because the voter's ideal point is relatively well-known in extreme districts, candidates' policy positions depend on potential competence differences. By contrast, in relatively centrist districts, electoral competition is primarily driven by uncertainty about the location of the representative voter.

Our main contribution is to show that partisan leaning and the salience of competence are important drivers of platform polarization, highlighted by two results.[3] First, we show that in centrist districts platform polarization strictly increases as the leaning becomes more centrist, whereas in extreme districts polarization is driven by the competence gap and is therefore constant in leaning. Second, increasing the salience of competence reduces the benefits of moderating in extreme districts, thus increasing polarization. At the same time, the salience

[2]Although there are many reasons this might be the case, most obviously is a shock that precedes the election, known in American politics as an "October Surprise."

[3]Platform polarization is important because it partially measures the extent to which candidates respond to voters' interests (Bernhardt, Duggan, and Squintani, 2009; Graham and Svolik, 2020; Matakos, Troumpounis, and Xefteris, 2016).

of competence also influences the categorization of districts, and an increase in the salience of competence increases polarization by driving up the share of districts that are extreme.

We take our theoretical results to data from the mayoral elections of 2012, 2016, and 2020 in the 95 largest Brazilian cities—an ideal setting to evaluate our theory for three reasons. First, the timing of the COVID-19 pandemic in relation to Brazil's electoral calendar created an exogenous shock to the salience of competence in these cities: the pre-scheduled mayoral elections of 2020 happened precisely between the first and second waves of infection. We use a combination of qualitative and quantitative evidence to first show that the competence of local candidates indeed became more salient to voters in that cycle.

Second, the ideological leaning of these large cities, measured by the national vote for the presidential candidate of the PT, is a reliable proxy for partisan leaning. The measure is extremely stable across elections and highly heterogeneous. Furthermore, when looking at voting data at the polling booth level, the variance of the vote distribution is higher in centrist municipalities than in extreme municipalities, as suggested by our theory.

Third, because all mayoral candidates in Brazil are required to disclose a document detailing their campaign platforms before the election, we can develop a measure of their policy positions. These campaign platforms are fairly heterogeneous, given that policy implementation in Brazil is highly decentralized, and mayors—-particularly in large cities—are in charge of services such as health care, education, transportation, infrastructure, and even (more recently) public security. We use several text-analysis techniques to transparently estimate platform polarization in these cities, combined with the *Finanças do Brasil*'s (FINBRA) dataset of local finances, which allows us to observe which policy areas concentrate most of the actual spending. In that, we add to a vast literature on empirical measures of ideological polarization, which has used measures based on a variety of sources such as court decisions (Clark, 2009), roll call voting (Poole and Rosenthal, 2000), campaign contributions (Bonica, 2013), candidate manifestos (Catalinac, 2018), and legislator speeches (Motolinia, 2021).

Our empirical findings are consistent with the theoretical results. We first present a robust empirical pattern: in elections with lower salience of competence (2012/2016), polarization is increasing in the city's centrism, and stable across elections. We then use the exogenous timing of COVID-19 and a differences-in-differences (DiD) design to estimate the shift in polarization in 2020. We show that a shock to the salience of competence leads to an increase in polarization that is concentrated in cities with more extreme partisan leanings. These effects are not restricted to one end of the spectrum, as they apply to *both* Left- and Right-leaning cities.

We conclude by showing that our empirical estimates are robust to alternative specifications; highly correlated with the actual COVID-19 incidence across cities; not exclusively driven by shifts in health-related proposals; and not driven by the contemporary Rightward-shift in the Brazilian electorate who elected Jair Bolsonaro president in 2018. We also consider two alternative models, one in which the informativeness of partisan leaning is reversed, i.e., it becomes more informative as it becomes more centrist, and one in which partisan leaning has no influence on the variance of the signal it provides. We show that in each of the alternatives the empirical implications about polarization do not match our empirical results. Our main model, where the precision of the signal partisan leaning provides becomes more precise as it becomes more extreme, is a better fit to the data.

Related Literature

Our article builds on the Empirical Implications of Theoretical Models tradition in political science. We explore both comparative static implications that follow from our model, which is fairly standard in applications, as well as what our model implies about the potential sample of cases (i.e., electoral districts). This allows us to consider more seriously the commensurability of our theoretical results with the empirical estimand from our design (Bueno de Mesquita and Tyson, 2020), and look for heterogeneity within the sample we study.

We build on models with policy-motivated candidates with aggregate uncertainty (Calvert, 1985; Wittman, 1983; Roemer, 1997), a setting where one *expects* platform polarization.[4] Contrary to spatial models of electoral competition with probabilistic voting that exclusively incorporate electoral uncertainty as either purely about the location of the decisive voter (Buisseret and Van Weelden, 2021; Sasso and Judd, 2022) or as a valence shock (Desai, 2024; Invernizzi, 2021), our model includes both. The substantive importance of modeling uncertainty about voters in these two different ways has been highlighted by Ashworth and Bueno de Mesquita (2009), who show how results can change markedly depending on the modeling choice.

The theoretical literature on polarization in political platforms has established that while beneficial in moderation, extreme polarization drives voter welfare down (Bernhardt, Duggan, and Squintani, 2009). Others have identified mechanisms influencing platform polarization, such as economic development (Desai, 2024), electoral rule disproportionality (Matakos, Troumpounis, and Xefteris, 2016), foreign manipulation (Antràs and i Miquel, 2011), and motivated reasoning in a dynamic setting (Callander and Carbajal, 2022). Focusing on valence, in a multidimensional setting with office-motivated candidates, a large enough valence advantage is sufficient for the existence of an equilibrium (Ansolabehere and Snyder Jr, 2000), and in a setting with policy-motivated candidates and electoral uncertainty, a small valence advantage leads the advantaged candidate to moderate and the disadvantaged candidate to polarize (Groseclose, 2001). Disentangling valence considerations from ideological considerations, however, remains a relatively understudied topic. Exceptions are Bernhardt, Câmara, and Squintani (2011), who show that dynamic considerations are key to understanding the tradeoff high-valence incumbents face between using their advantage to become more extreme and compromise to hold onto office for longer, and Tolvanen, Tremewan, and Wagner (2022), who show that candidates may run on ambiguous platforms to capture extremists on both sides of the ideological spectrum. Closer to our model, Desai and Tyson (2024) study how perceived competence advantages can drive polarization directly and indirectly. Our contribution is the

[4] Other ways to ensure platform polarization is to assume that candidates possess platform-motivated preferences (Callander and Wilkie, 2007; Kartik and McAfee, 2007), or that office-motivated candidates have asymmetric information regarding voter preferences (Bernhardt, Duggan, and Squintani, 2007).

introduction of *partisan leaning*, which provides a signal of voters' ideological preferences to candidates, and is more precise as it becomes more extreme.

Finally, our findings also contribute to an empirical literature on the relationship between polarization and the COVID-19 pandemic. This work primarily focuses on the impact of pre-existing levels of polarization, or electoral incentives, on pandemic-related policies, both in Brazil (Ajzenman, Cavalcanti, and Da Mata, 2022; Bruce et al., 2022; Chauvin and Tricaud, 2022) and abroad (Milosh et al., 2021; Pulejo and Querubín, 2021). Our analysis departs from this literature in two significant ways. We are interested in polarization as an *outcome* of the COVID-19 crisis, and not as the *moderator* of government responses. Also, both our empirical and theoretical results apply to polarization that affects policy dimensions other than COVID-19 responses, such as spending in education or public security.

THE MODEL

We develop a model where electoral competition within a district (municipality, etc.) depends on the skill or competence of candidates as well as their ideological positions. In each district, j, there is an election between two candidates, indexed by $i \in \{L, R\}$, whose ideological policy preferences are represented by party ideal points, y_i.[5] In the first stage of the game, each candidate chooses an ideological platform, denoted by π_i^j. Candidate i's payoff from policy π is given by $-|y_i - \pi|$, and we can write i's expected payoff as

$$-P(L^j \text{ wins} \mid \pi_L^j, \pi_R^j) \cdot |y_i - \pi_L^j| - (1 - P(L^j \text{ wins} \mid \pi_L^j, \pi_R^j)) \cdot |y_i - \pi_R^j|. \tag{1}$$

Candidates are also evaluated by their performance on non-ideological issues, which is captured by political competence, and denoted by c_i^j. Denote the *competence gap* in district j

[5] That candidates across districts have the same ideal points is not consequential in our analysis.

by $\gamma^j \equiv c_L^j - c_R^j$, which is drawn from

$$\gamma^j \sim U[-\psi, \psi],$$

where ψ gives the variance of the competence gap.

The electorate of district j is represented by a single representative voter (e.g., the district median voter) whose ideological preferences are characterized by an ideal point z^j. In the second stage of our game, the district's representative voter sees both candidates' platforms, (π_L^j, π_R^j), her ideal point, z^j, and the competence gap, γ^j, and chooses between candidates. The importance of competence (relative to ideology) is captured by $\alpha \in [0,1]$, which we refer to as the *salience of competence*. The voter's payoff in district j, when candidate i is elected, is

$$-(1-\alpha)|z^j - \pi_i^j| + \alpha c_i^j. \tag{2}$$

The first term represents the voter's ideological payoff, which is the distance between her ideal point, z^j, and the policy platform of candidate i, π_i^j. The second term represents the competence of candidate i, c_i^j, weighed by the salience of competence, α.

What matters for candidates' platform choice is what they know about their districts decisive voter at the time they must choose their platform. Novel to our model, uncertainty about the voter's ideal point is not the same across districts. Each district is characterized by its *partisan leaning*, $\zeta^j \in [-1,1]$, which can be thought of as where candidates "expect" the voter to be ideologically. There is a unit mass of districts, with leanings distributed uniformly on the $[-1,1]$ interval. Within each district, there is uncertainty about the ideal point of the district's representative voter, and district leaning acts as a signal of the voter's true position. Specifically, for $\delta > 0$, when the district's leaning is ζ^j, its representative voter's ideal point, z^j, is drawn from a uniform distribution

$$z^j \sim U[\zeta^j - (1-|\zeta^j|)\delta, \zeta^j + (1-|\zeta^j|)\delta].$$

Table 1: Summary of Model

Object	Interpretation	Range
ζ^j	Partisan Leaning	$[-1,1]$
z^j	Ideal point of decisive voter	$[-1-\delta, 1+\delta]$
y_i	Ideal point of candidate i	$\mathbb{R}$
α	Salience of competence	$[0,1]$
γ	Competence gap	$[-\psi, \psi]$
δ	Baseline variance of leaning signal	$(0, +\infty)$
ψ	Variance of competence gap	$(0, +\infty)$
π_i	Platform for candidate i	$\mathbb{R}$

Partisan leaning provides a (non-strategic) signal of the ideological position of the decisive voter, and the parameter δ indexes the baseline variance of that signal. Several factors influence this variance including differences between the policy dimension and the leaning dimension, differential turnout rates between L and R supporters, and changes in voter preferences over time.

Partisan leaning also determines the precision of the signal it provides about ideology. In centrist districts, i.e., those where $\zeta^j \approx 0$, candidates face the most uncertainty about the ideological preferences of their district, and in extreme partisan districts, i.e., those with $\zeta^j \approx -1$ or 1, candidates face the least uncertainty about the ideological preferences of their district.

To summarize, the timing is as follows: (i) candidates in district j select their policy proposals π_L^j and π_R^j; (ii) the location of the decisive voter, z^j, and the competence gap, γ^j, are realized; (iii) the voter votes and the winning candidate's platform is implemented.[6] We restrict attention to party ideological preferences that are more extreme than those of representative voters, i.e., where $y_L < -1-\delta$ and $y_R > 1+\delta$, which precludes corner solutions and simplifies

[6]As is standard in spatial models of electoral competition, candidates in our model are committed to implementing their platforms. In Figure D.6 (appendix), we show evidence that mayors in Brazil indeed adhere closely to their campaign platforms.

the analysis. Moreover, we restrict to cases where uncertainty about the competence gap (for candidates) is not so large that it swamps out concerns about the location of the representative voter in some districts, which corresponds formally to $\delta > \psi$. Table 1 summarizes our model parameters.

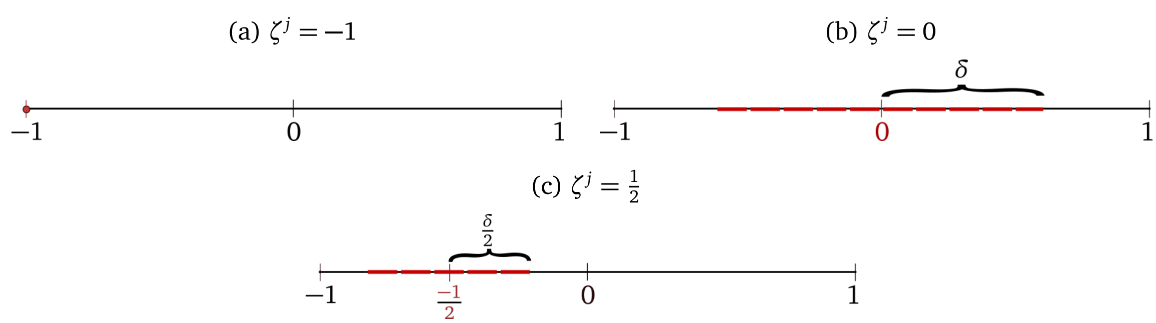
Comments on the Model

Partisan leanings are a (non-strategic) signal of the ideological preferences of voters, where the leaning of an electoral district, ζ^j, determines both the ideological preferences of the decisive voter and the precision of the signal leaning provides about the median voter's ideal point, z^j. The variance of the signal leaning provides of the voter's ideal point in district j is

$$Var(z^j) = (1 - |\zeta^j|)^2 \cdot \frac{\delta^2}{3}. \tag{3}$$

The role of partisan leanings is illustrated in Figure 1 for $\zeta = -1$, $\zeta = \frac{1}{2}$, and $\zeta = 0$ respectively, showing how there is relatively less uncertainty in a district where the voter is expected to be extreme, compared to a centrist district where the voter could be moderate or extreme. We examine different versions of our model below where we alter the relationship between leaning and the precision of the signal they provide about the decisive voter's ideal point.

Figure 1: Support of z^j for different leanings



In our model, the competence gap isn't perfectly known by candidates when they choose their platforms, which in Brazil is about a month before the election. Our formulation of competence uncertainty reflects the idea that a voter's perception of the competence gap between two candidates is not known precisely at the moment candidates choose electoral platforms, and it can fluctuate over the course of the campaign. There are at least two reasons why the competence gap is learned over the course an electoral campaign, rather than being known ex-ante and fixed throughout the course of the electoral campaign. First, events such as gaffes or scandals often effect voters' perceptions of candidates (Di Lonardo, 2017). Second, aspects of candidates, especially challengers, are revealed through the course of a campaign, and thus influence what aspects of competence are relevant to voters on election day. Take for example, João Dória, who was elected mayor of São Paulo in 2016. Early on in the campaign period in late August, only 7% of the electorate declared their intentions to vote for him. But during the campaign period, his career as a businessman burnished a reputation for being a competent manager, with him eventually winning the race in early October.

We assume that neither L nor R enjoy a competence advantage on average to ensure that our results come from the interaction of uncertainty about competence advantages, which resemble valence, and uncertainty about local ideological preferences that vary across districts, which is novel to our setup. Large competence advantages, relative to the general pool of challengers, tend to create a scare-off effect among potential challengers (e.g., Cox and Katz, 1996), implying that in contested elections there may be reason to believe that challengers are not systematically disadvantaged at the entry stage (Alexander, 2021). Our assumption would be a problem in our empirical specification if partisan leaning were correlated with factors that might indicate an early insurmountable competence advantage.[7]

Finally, our model presents a stylized election where candidates are evaluated by a single representative voter along two dimensions, ideology and competence. Our model isolates the role of the district's leaning as a signal of the voter's ideological preferences. We intentionally omit a number of other features of elections that, although important, are not critical to the

[7]One potential and intuitive empirical proxy of ex ante competence advantage, incumbency, is uncorrelated with leaning (p-value=0.7), which further suggests that potential competence advantages do not seem to be driving our empirical results.

mechanism here. We do this to focus our theory on the role of district leaning in isolation, as though we are holding such other factors fixed, as one might do in an experiment (Paine and Tyson, 2020).

Platforms and Polarization

We start with the representative voter (in the second stage) who knows her ideal point, z, the competence gap, γ, and candidates' platforms, (π_L, π_R). From (2), the voter chooses L if and only if,

$$-(1-\alpha)|z-\pi_L| + \alpha\, c_L \geq -(1-\alpha)|z-\pi_R| + \alpha\, c_R,$$

and chooses R otherwise. Rearranging, the voter's decision rule is a cutoff,

$$\gamma^*(\pi_L, \pi_R; z) = \frac{1-\alpha}{\alpha}(|z-\pi_L| - |z-\pi_R|),$$

where the representative voter votes for L if and only if $\gamma \geq \gamma^*(\pi_L, \pi_R; z)$ and votes for R otherwise. The cutoff rule, $\gamma^*(\pi_L, \pi_R; z)$, determines the level of the competence gap, γ, for which the voter prefers L to R, and its value depends on candidates' platform choices, π_L and π_R, as well as the voter's true ideal point, z^j.

Moving backward to the candidates, when they choose their ideological platforms, they do not know the voter's ideal point, z, nor the competence gap, γ. Consequently, candidates do not know the voter's decision rule, $\gamma^*(\pi_L, \pi_R; z)$. Thus, the probability that L wins the election is $P(\gamma \geq \gamma^*(\pi_L, \pi_R; z))$, and the probability R wins is $P(\gamma < \gamma^*(\pi_L, \pi_R; z))$, and the problem for candidate $i \in \{L, R\}$ is

$$\max_{\pi_i} \; -P(\gamma \geq \gamma^*(\pi_L, \pi_R; z) \mid \zeta)|y_i - \pi_L| - (1 - P(\gamma \geq \gamma^*(\pi_L, \pi_R; z) \mid \zeta))|y_i - \pi_R|. \tag{4}$$

A pair of ideological platforms (π_L, π_R) that simultaneously solve (4) for L and R, along with $\gamma^*(\pi_L, \pi_R; z)$ from above, together constitute a subgame perfect Nash equilibrium to our game.

We characterize the equilibrium platforms in the following Proposition.

Proposition 1. *There exists a unique symmetric subgame perfect Nash equilibrium where for an extreme-left (extreme-right) district, i.e., for all $\zeta < \bar{\zeta}_L$ ($\zeta > \bar{\zeta}_R$),*

$$\pi_L^* = \zeta - \frac{\alpha\psi}{2(1-\alpha)} \quad \textit{and} \quad \pi_R^* = \zeta + \frac{\alpha\psi}{2(1-\alpha)}; \tag{5}$$

for all centrist districts, i.e., $\bar{\zeta}_L \leq \zeta \leq \bar{\zeta}_R$,

$$\pi_L^\dagger = \zeta - (1-|\zeta|)\delta \quad \textit{and} \quad \pi_R^\dagger = \zeta + (1-|\zeta|)\delta; \tag{6}$$

and where

$$\bar{\zeta}_L = \min\left\{\frac{\alpha\psi}{2(1-\alpha)\delta} - 1, 0\right\} \quad \textit{and} \quad \bar{\zeta}_R = \max\left\{1 - \frac{\alpha\psi}{2(1-\alpha)\delta}, 0\right\}. \tag{7}$$

Proposition 1 shows that there are two qualitatively different kinds of equilibria, depending on a district's leaning. At the time candidates choose platforms, their choices are motivated by uncertainty about the ideal point of the representative voter, z, the magnitude of which depends on the district's leaning, $|\zeta|$, and uncertainty about the competence gap, γ, which is substantively more important in districts that have more extreme leanings because the voter's ideal point is relatively certain. Whichever kind of uncertainty is most salient determines the platform choices of candidates, and consequently, the equilibrium level of polarization.

Both candidates chase the expected decisive voter, ζ, and polarize away from ζ based on the competence gap in extreme districts, and the leaning signal in centrist districts. From (5), the equilibrium platforms in extreme districts are equidistant from the leaning ζ, and what drives differences in platforms between L and R is uncertainty about the competence gap.[8] For

[8]Note if $\alpha \to 0$, removing the importance of competence to the voter, then platforms converge to each other when $\zeta = -1$, in line with median voter theorem style results.

such districts, polarization is

$$\pi_R^* - \pi_L^* = \frac{\alpha\psi}{1-\alpha},$$

which is strictly increasing in the salience of competence, α. As a district becomes more centrist-leaning, i.e., as $-|\zeta|$ increases, then uncertainty about the voter's ideal point becomes more important, and eventually drives candidate platform choices. In centrist districts, from (6), polarization is

$$\pi_R^\dagger - \pi_L^\dagger = 2(1-|\zeta|)\delta,$$

which is independent of the salience of competence, α.

We now unpack our equilibrium characterizations in terms of the relationship between polarization and leaning and the relationship between the salience of competence and polarization.

Proposition 2. *Platform polarization in centrist districts is strictly decreasing in the ideological centrism of the leaning, measured by $-|\zeta|$, whereas there is no relationship between platform polarization and district leaning in extreme districts.*

Platforms move parallel to each other in ζ as long as the district is extreme enough, and that platforms move further away from each other in ζ as the district leans more to the center. There is a positive relationship between district leaning and platform polarization—but only in centrist districts. In extreme districts, where information regarding the ideological preferences of the voter is more precise, there is no relationship between polarization and leaning, because electoral competition is driven by voters' perceptions of competence, rather than the location of the decisive voter.

Proposition 2 contrasts platform polarization in a single district, as that district's leaning is changed (all-else-equal). While we would like to directly assess Proposition 2, which is at the district level, to achieve the counterfactual comparison it outlines we would need to observe (or identify separately) the extensive margin as well as different leanings for the that district. To assess how our model speaks to the data, it is important that we understand how changes in the salience of competence, α, influence polarization, $\pi_R - \pi_L$, when averaged across all districts. We focus on the *average level of polarization* across districts,

$$P(\zeta < \bar{\zeta}_L \text{ or } \zeta > \bar{\zeta}_R)(\pi_R^* - \pi_L^*) + P(\bar{\zeta}_L \leq \zeta \leq \bar{\zeta}_R)(\pi_R^\dagger - \pi_L^\dagger), \tag{8}$$

because any empirical estimand will measure such a quantity. The first term is the level of polarization in extreme districts, and the second term is the level of polarization in centrist districts, both weighted by the prevalence of the type of district in the population.

Proposition 3. *The average level of polarization across districts is strictly increasing in the salience of competence, α. In particular, the level of polarization in extreme districts, $\pi_R^* - \pi_L^*$ is strictly increasing in α, whereas the level of polarization in centrist districts, $\pi_R^\dagger - \pi_L^\dagger$, is constant in α. Moreover, the share of centrist districts decreases in α.*

This result is about how the salience of competence influences polarization. In centrist districts, an increase in α has no effect on candidate platforms, and hence, no direct effect on polarization. In extreme districts, uncertainty about the competence gap influences the level of polarization, which is strictly increasing in the salience of competence, α. These two effects, which differ depending on a district's leaning, capture the *intensive margin* by which the salience of competence influences the average level of polarization. The magnitude of this intensive margin is

$$\left| \frac{d\pi_R^* - \pi_L^*}{d\alpha} \right| = \frac{\psi}{2(1-\alpha)^2} > 0, \tag{9}$$

in extreme districts and

$$\left| \frac{d\pi_R^\dagger - \pi_L^\dagger}{d\alpha} \right| = 0, \tag{10}$$

in centrist districts. Combining (9) with (10) shows that changes in polarization due to changes in the salience of competence are driven by extreme districts.

Since a shock to the salience of competence influences polarization only in extreme districts, and because whether a district is extreme is endogenous, we must also consider what determines whether a district is centrist. This amounts to analyzing, from Proposition 1, the cutoffs $\bar{\zeta}_L$ and $\bar{\zeta}_R$ which determine the share of extreme districts, and are themselves dependent on the salience of competence, α. In particular, using that district leanings are uniformly distributed, we can rewrite (8) as

$$\left(\frac{2+\bar{\zeta}_L-\bar{\zeta}_R}{2}\right)\cdot\left(\frac{\alpha\psi}{1-\alpha}\right)+(\bar{\zeta}_R-\bar{\zeta}_L)(1+\zeta^j)\delta.$$

This expression highlights that the salience of competence, α, also influences the share of districts where polarization depends on the salience of competence, identifying the *extensive margin* by which the salience of competence influences polarization. In particular, $\bar{\zeta}_L$ is strictly increasing in α, while $\bar{\zeta}_R$ is strictly decreasing in α, establishing that an increase in the salience of competence reduces the number of centrist districts, by a magnitude of

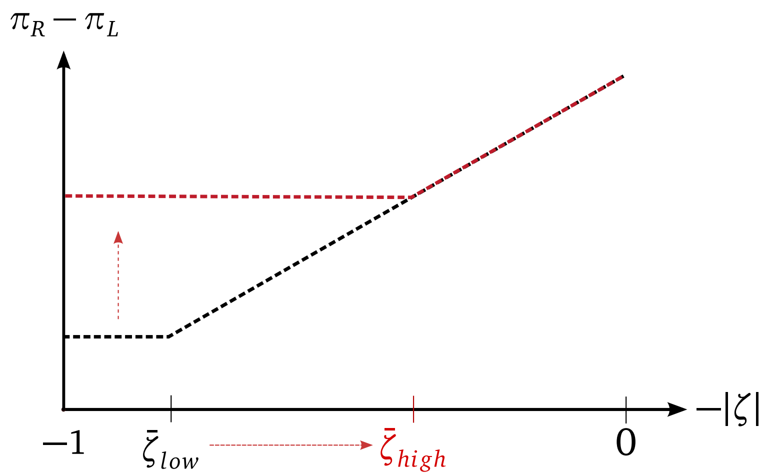
$$\left|\frac{d\bar{\zeta}_i}{d\alpha}\right|=\frac{\psi}{2(1-\alpha)^2\delta}.$$

This latter effect further increases the observed level of polarization when averaging over districts because an increase in α implies that more districts are extreme.

The overall effect of the salience of competence, α, on the average level of polarization can be decomposed into two reinforcing channels, characterized by intensive and extensive margins, that together increase polarization with increases in the salience of competence.

Finally, while partisan leaning and its heterogeneous informativeness are our primary contributions, partisan leaning interacts with uncertainty regarding the competence gap, especially for the result in Proposition 3. To see this more clearly, consider taking $\psi\to 0$. In extreme districts both candidates' platforms converge to the district leaning, eliminating platform polarization—a "median voter theorem"-style logic. Additionally, the cutoffs $\bar{\zeta}_L$ and $\bar{\zeta}_R$ approach the endpoints of the space of partisan leanings, -1 and 1 respectively, and as a consequence, removing uncertainty about the competence gap makes all districts 'centrist' districts where polarization does not depend on the salience of competence. More precisely, if there is

Figure 2: District centrism and equilibrium polarization



This figure illustrates the two theoretical implications we take to the data. $\bar{\zeta}_{low}$ and $\bar{\zeta}_{high}$ denote the cutoffs that determine whether a district is extreme or centrist when α is low or high respectively. When α is low, there is a strong positive relationship between the centrism of the district, $-|\zeta|$, and polarization. As α becomes high, the share of extreme districts increases, the positive relationship between polarization and $-|\zeta|$ attenuates, and average polarization increases, with the increase concentrated in extreme districts.

no uncertainty regarding the competence gap, then α has no effect on platforms.

Before proceeding to the empirical application we briefly summarize the two main theoretical results from Propositions 2 and 3 we take to the data, which are also illustrated in Figure 2. First, Proposition 2 shows that if the salience of competence (α) is low enough, polarization is always **increasing in *centrism*** across districts (municipalities). When α is low enough, there is a strong positive relationship between polarization and centrism, measured by $-|\zeta|$. Second, Proposition 3 establishes that an increase in the salience of competence **attenuates the leaning-polarization relationship** across municipalities. The increase in average polarization therefore stems from districts that are extreme.

A Case Study in Brazilian Municipalities

We first provide a brief background on features of Brazilian politics that are relevant to our empirical application. We then provide details on how we measure—in Brazilian cities—

-the following empirical quantities that are pertinent to our theory: local partisan leaning, platform polarization, and the shock to the salience of competence in mayoral elections. We then proceed to the empirical estimation and discussion of the results.

Two main features of the Brazilian party system that make it a suitable empirical application for our theory. Our model is set in a political environment where leaning in the Left-Right dimension is relevant for electoral competition, widely recognized by voters and politicians, stable over time, and interpretable on similar scale across districts. While Brazil has a fragmented party system, with 30+ active parties, the coarse Left-Right party divide is highly salient (Power and Zucco, 2009, 2012). Party positioning on this divide is consistent across surveys with legislators, experts, and voters (Desai and Frey, 2021), and even with roll call votes in congress.[9] At least for the period of our empirical analysis, Left-Right positioning is also aligned with preferences for redistribution for both politicians (Power and Zucco, 2012) and voters (Hunter and Power, 2007; Lupu, 2016). More importantly, the divide has defined the presidential vote since the democratization with PT (Worker's party) on the Left, and on the right, PSDB in 1994-2014 and Jair Bolsonaro (PSL) in 2018. This is partly due to PT's institutional stability, which anchors both the ideological space from the Left and the competition with the more decentralized Right (Samuels and Zucco, 2018).

Our model also assumes that candidates adapt policies to the preferences of the decisive voter in each city. In other words, we need Right-wing parties to be able to credibly move local policies Left, and vice-versa. Here, both the ideological flexibility and regional fragmentation of Brazilian parties help us immensely in bringing the theory to the data. Despite the well established Left-Right cleavage described above, it is much harder to ideologically differentiate parties within the same broad group. Particularly for some large center-Right parties, they are often better described by their *modus operandi* (e.g., clientelism) or rent-seeking behavior (e.g., some consistently engage in alliances with Leftist incumbents) rather than ideological coherence (Power and Rodrigues-Silveira, 2019). Also, parties struggle to control individual

[9] See news in Portuguese: https://bit.ly/4aC6ixw.

politicians (Desposato, 2006; Klašnja and Titiunik, 2017), and local candidates have ample flexibility to tailor their platforms to local electorates. For example, Rightist mayors often prioritize redistribution in poor areas (Desai and Frey, 2021), and even PT's governor of Bahia recently became tough on crime.[10] Altogether, the solidity of the nationally recognized Left-Right cleavage anchored around PT, combined with the flexibility for local candidates coming from the party fragmentation, makes Brazil a suitable environment to study our theory.

Our application focuses on mayoral elections in the 95 largest Brazilian cities—those that have a runoff system—in 2012, 2016 and 2020.[11] These races constitute the ideal group for our analysis, for two reasons. First, voters are more exposed to the campaign platforms of the top candidates in large Brazilian municipalities, both in time and intensity. Not only does the potential runoff often extend campaign times for the top candidates, but they also have subsidized, mandatory, prime-time TV campaigns on all the over-the-air channels.[12] Second, given the highly decentralized structure of public spending, mayors of large cities spend the budget on a broad portfolio of policy areas such as health care, education, social assistance, transportation, and even public security.[13]

A Proxy for Ideological Leaning at the Municipal Level

Our empirical proxy for partisan leaning is based (without loss of generality) on the share of the municipal vote for the Left (e.g., Workers Party, PT) in the final round of the last pre-treatment presidential election in Brazil (2010), which we denote by L_j in municipality j.

[10]See the news in Portuguese: https://bit.ly/3THjwlH).

[11]The runoff round happens unless the lead candidate in the first round achieves more than 50% of the votes. By law, the group of eligible cities consists of all municipalities with more than 200,000 voters. The 95 cities that met this condition in 2020 are our potential sample for the entire period of analysis.

[12]TSE's resolution 23457 from Dec, 2015. The top two candidates receive the exact same TV time in the second round. In the first round, time is given to parties according based on their share of seats in the national congress. In 2012-2016, the top two candidates received on average 3/4 of all votes in the first round.

[13]The spending portfolio of mayors in small towns is less diversified, as many invest little to nothing in areas such as public security, transportation, and even sanitation.

Specifically, in municipality j leaning is given by

$$lng_j = 1/2 - |L_j - 1/2|.$$

Leaning is defined in the interval $[0, 1/2]$, and that more extreme cities—either to the Left or Right—have lower values.

The rationale behind our choice is threefold. First, Brazilian presidential races are historically highly polarized in the Left-Right dimension: all elections since democratization were dominated by one Left- and one Right-wing party.[14] Second, the share of Left-wing presidential votes in each municipality is persistent across elections, and highly heterogeneous across municipalities. The average PT vote share in 2010 was 53%, with values ranging from 24% to 84%. Figure D.1 (appendix) also shows that the 2010 vote shares are highly correlated—across municipalities—with the shares in the subsequent presidential races of 2014 and 2018.

Third, at the core of our theory is the idea that the uncertainty about the ideological preference of the decisive voter is positively correlated with district centrality. Figure 3 below shows that this relationship holds for our leaning measure. For each city in the sample, we calculate the variance of PT's vote share in 2010, based on voting data at the ballot box level (e.g., São Paulo has 90,446 ballot boxes, with slightly more than 300 votes each, on average). We then compare these municipality-level variances to the leaning measure. The plot shows that the variance is lower in extreme cities, and higher in more centrist locations.[15]

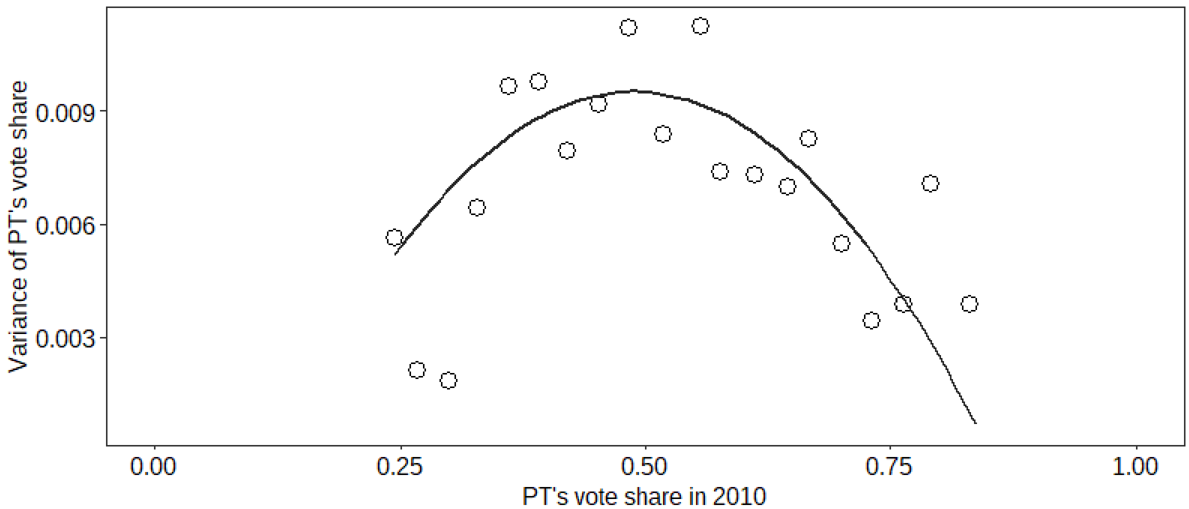
Measuring Platform Polarization

We measure platform polarization using data about the policy proposals of mayoral candidates in the 95 largest Brazilian cities. Since 2009, all candidates for executive offices are

[14] PT for the Left in all elections. For the Right: PRN (1989), PSDB (1994, 1998, 2002, 2006, 2010, and 2014), PSL (2018), and PL (2022).

[15] In the appendix (Figure D.8), we also show that our measure of leaning is correlated with the partisanship of the past winning mayoral candidates in our sample, i.e., in more extreme cities to the Left (Right), mayoral candidates from Left-wing (Right-wing) parties also perform better.

Figure 3: Variance of PT's Vote Share in 2010, at the Ballot Box Level



The 95 cities in the sample are aggregated in 20 bins along the x-axis. The values in the y-axis have the average variance for each bin. Variances are calculated for each city with PT's vote share in 2010 at the ballot box level. The line shows a quadratic fit.

required by the federal electoral court (TSE) to disclose a document with their campaign platforms and priorities. These documents typically have extended discussions on the candidates' proposals for different areas of the local administration, and are published in the TSE's website around a month before the election. They are also extensively scrutinized by the local press.[16]

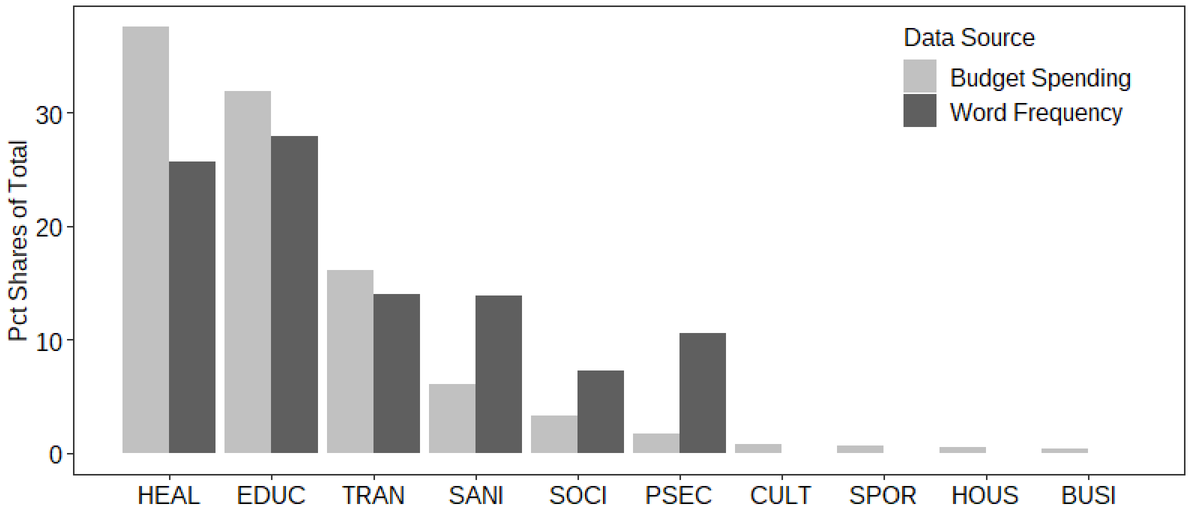
We use the TSE documents to identify and measure the policy priorities, in 6 different areas, of the two top contenders in each election. The relevance of policy areas is based on the classification of the actual budget expenses of Brazilian cities, obtained from the FINBRA database maintained by the National Treasury. Figure 4 shows the main spending categories in these 95 cities, according to this classification. Note that, although these 10 categories account for 99% of all policy-related expenditures,[17] only 6 of them—health care, education, transportation/urbanization, sanitation/the environment, social assistance, and public security—individually account for more than 1% of local budgets. We show in the appendix (Table C.4)

[16] Examples of press reports in Portuguese: https://bit.ly/45Ky35n and https://bit.ly/3OYUmOL.

[17] Policy-related spending excludes expenditures with the local council, local courts, overhead (administrative spending), retirement benefits, debt service, and energy.

that our results are robust to the inclusion of the other 4 minor categories.

Figure 4: Spending Categories in Large Brazilian Cities



Spending is from 2017-2020. For correspondence, the word frequency shown here only includes the proposals in the same electoral cycle (2016). The light gray columns show the average share of each category (99% of total expenses). The dark gray columns show the share of policy-related words in candidates' platforms that belong to each of the 6 main categories – using the first 2 words shown in Table 2, for each category.
HEAL: Health care; EDUC: Education; TRAN: Transportation & Urbanization; SANI: Sanitation & the Environment; SOCI: Social Assistance; PSEC: Public Security; CULT: Culture; SPOR: Sports & Leisure; HOUS: Housing; and BUSI: Businesses and Tourism.

Our primary measure of polarization is built using the frequency of words that are uniquely and directly related to each policy area. More precisely, we first find the 2 most frequent policy-words for each category in all documents. We then calculate the *score* of each policy category as: the count of its policy words as a share of the total frequency of all policy words in the document. We use these scores to calculate the polarization level in each city-year, which is the 6-dimensional Euclidean distance between the proposals of the top two candidates.

The most common policy-related terms in each category are shown in Table 2, and the full list of the 200 most frequent words in the sample is shown in Table B.1 (appendix). Figure 4 has the relative frequencies of these categories in the candidates' platforms (dark gray columns), and how they are largely consistent with the actual budget implementation. In the appendix, we show that the results are robust to several different choices in the number of words used to define the categories. Table C.6 shows the estimates for measures built with the 3 and 4 most frequent words for each category; respectively. Table C.7 has estimates for measures that use all policy words in each category that are among the 200 or 300 most frequent words in the sample; respectively. Table B.3 (appendix) details which words are used in each specification.

Table 2: Main Words in Each Budget Category

Category	Words counted
Health	Saúde (*health*), Hospital (*hospital*), Médico (*doctor*)
Education	Educação (*education*), Escola (*school*), Ensino (*teaching*)
Transportation and Urbanization	Transporte (*transportation*), Mobilidade (*mobility*), Trânsito (*traffic*)
Public Security	Segurança (*security*), Violência (*violence*), Guarda (*guard*)
Social Assistance	Assistência social (*social assistance*), Deficiência (*disability*), Creche (*creche*)
Saniation and the Environment	Ambiental (*environmental*), Meio Ambiente (*natural environment*), Água (*water*)

Table B.1 has the list of the 200 most frequent words in the sample (appendix).

As an illustration, consider the city of Cariacica (ES), where the 2020 race was a runoff between candidates from DEM (Right-wing) and PT (Left-wing). DEM's candidate emphasized his proposals for public security, highlighting that the area would be "one of the priorities of this administration."[18] The document explains in detail the several action points for this area such as arming the municipal guard, hiring officers, and increasing neighborhood patrols. Overall, the share of policy terms in the document that were dedicated to security measures was 29%. The same share for the proposal of PT's candidate was only 9%. Not only did the Left-wing's document fail to single out security as a priority, but it also had a shorter discussion on the topic that was primarily focused on investing in education and leisure for youth populations.[19]

Our primary metric has a number of advantages for our empirical exercise. First, sim-

[18]In Portuguese: "segurança pública estará dentro das prioridades do nosso governo" (page 12).
[19]The proposals can be found at: https://bit.ly/43LOqxY (PT) and https://bit.ly/4aqJiC6 (DEM).

ple metrics are highly intuitive (Eggers and Spirling, 2018), easy to interpret, and also have the virtue of ensuring "transparency and replicability" (Wilkerson and Casas, 2017). Another important advantage is that simple metrics can be explicitly linked to theoretical objects or out-of-sample topic categorizations such as the structure of local budgets that we use here.

Our simple metric, however, raises two main concerns. The first is that, by relying on the frequency of a few selected terms, it might fail to capture polarization that comes from the remaining words in the document. Second, a metric that is free from assumptions about the ideology of parties and/or policies might not be substantively related to our empirical proxy for partisan leaning described above. To address such concerns, we first show that cities with similar leaning have, on average, candidates that propose similar policies (Figure D.3, appendix). This suggests that leaning is highly correlated with the content of the average campaign platforms across cities, and that it does so without additional assumptions about the ideological content of specific policy categories.

We also replicate our analysis using the well-known scaling approach based on **Wordscores** (Laver, Benoit, and Garry, 2003), which has been previously used to study the Brazilian proposals data (Pennec, 2022; Pereira, 2021). Here, we follow Desai and Frey (2021) and categorize the largest parties in 2012 as either Left- or Right-wing. We then use the proposals of their 2012 mayoral candidates to train the algorithm that classifies the whole set of documents on a Left-Right scale,[20] and use the absolute distance between the scores of the top 2 candidates as a measure of polarization.

Including the results based on the Wordscores metric side-by-side with our main specification provides a few advantages. First, this alternative metric uses assumptions on the ideological leaning of parties, but it does not rely on assumptions about the relevance of policy

[20]Brazil has a multiparty system where sometimes subtle programmatic differences between parties are not salient, particularly among the center-right group. We prefer a conservative binary categorization, as "there is a widely accepted consensus by experts, voters, and candidates alike on what constitutes the broader Left-Right divide in Brazil" (Desai and Frey, 2021). We use the most extreme parties to train our main specification (PT, PSB, and PCdoB for the Left, and PL, PP, PSD, and DEM for the Right). In the appendix (Table C.8) we show that the results are robust to also using the most centrist parties from each group (PMDB, PSDB, and PTB to the Right, and PPS and PDT to the Left), or all parties with candidates in 2012.

categories in local budgets. In doing so, it provides evidence that our main findings are not an artifact of our polarization metric. They are also more naturally interpretable in the same dimension as our leaning variable. The striking similarity between leaning and polarization across these two metrics (as later shown in Table 3) provides additional evidence that our primary policy-based metric has substantive meaning in the Left-Right dimension of leaning.

Finally, the party based metric produces scores for each proposal that are based on the frequency of all words in the documents, rather than policy words only, which addresses the concerns with the simplicity of our measure.

In the appendix, we show results estimated with an additional alternative measure of polarization that is built using the seeded sequential topic-model by Watanabe and Baturo (2024). This is a semi-supervised approach that has the computational advantages of traditional topic models, with the use of seed words as a weak form of supervision on the definition of topics. In a nutshell, regular LDA-based topic models split documents in a pre-specified number of topics based on the relative clustering of words in the documents. This approach re-weights the clusters of words based on their relationship with seed words provided by the researcher, and by doing so creates topics that are more likely to be substantively related to the (seed) themes defined by the researcher. We fit 6 topics on the data using the words in Table 2 as seed. In Appendix B we provide additional details on the construction of these databases, which also include details on the standard pre-processing steps.

COVID-19: A Shock to the Salience of Competence

In a context where voters value both ideology and competence, we are interested in the impact of the "shock" introduced by the unprecedented and quick spread of COVID-19 in 2020. We argue that one of the most prominent impacts of the pandemic is that it altered the importance voters place on non-ideological aspects of politicians, especially competence. In our model, the parameter α captures the salience to voters of such a shock. In the data, the (pre-scheduled) timing of the 2020 local elections in Brazil, combined with the country's decentralized system of public health spending, created an ideal context that helps us study the relationship between the salience of competence and platform polarization.

The country-wide mayoral elections happened nearly 8 months into the pandemic, between the first and second waves of infection. This event increased the salience of the mayor's managerial ability not only due to its timing, but also because municipal administrations in Brazil bear the bulk of the responsibility of delivering health care services through the universal system (SUS). Health care services are the largest budget category in municipalities, and also the highest priority for voters: in a 2020 survey, 87% of the 2,002 respondents considered health care as a top priority for the elected mayor in 2020, the highest among all choices (CNT, 2020).

In 2020, mayors were also granted autonomy by the Supreme Court to decide whether or not to implement measures to contain the spread of the virus, even at odds with federal or state governments (Bruce et al., 2022; Chauvin and Tricaud, 2022). Not surprisingly, a survey with 3,235 municipal administrations showed that 97% of mayors implemented stay-at-home measures, 52% created blockades to limit inter-municipality movements, and 73% formally approved state of emergency in the municipality (Albert et al., 2020). Accordingly, both the press as well as local experts anticipated that the pandemic would play a significant role in the 2020 election by increasing the salience of the mayor's managerial ability.[21]

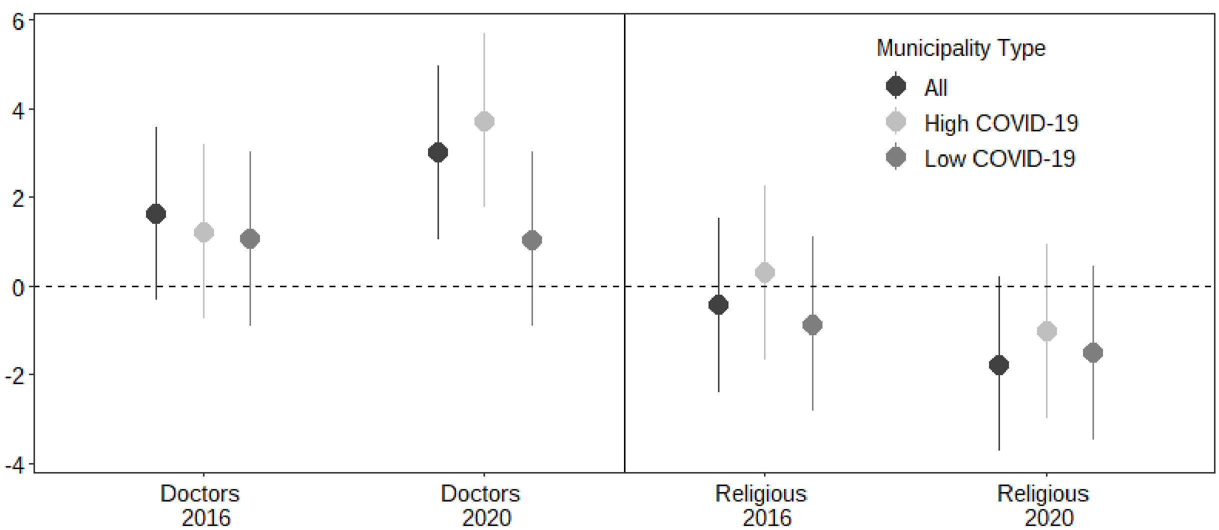
We also rely on Boas (2014) to provide suggestive evidence of a COVID-related increase in the salience of competence for local candidates. Brazilian candidates are allowed to use "electoral" names on the ballot, instead of their birth names. As a consequence, they often use their ballot names to convey positive signals to voters. Common choices are names that refer to their occupation, such as "Dr. Maria," or religious affiliation, such as "Pastor Pedro." Boas (2014) uses an original survey to examine the effect of religious and occupational heuristics conveyed via such titles—specifically the commonly used "pastor" and "doctor". Boas (2014) finds that title of doctor has "a positive effect on vote intention that appears to be mediated by the positive stereotypes, such as intelligence and competence," which is not observed for the

[21]For example: https://bit.ly/37mjlo3 and https://glo.bo/3rVR3dy, in Portuguese.

religious title.

In this context, we examine the use of these occupational heuristics by candidates in 2012, 2016, and 2020 in the 95 cities we consider in our empirical analysis. In the previous three mayoral elections, 1,633 doctors and 565 religious leaders ran for either mayor or local councilor (most of them for council). Figure 5 shows how their use of a title in the ballot name changes over time. For both groups, there are no changes in this heuristic between 2012 and 2016. However, during the 2020 COVID-19 crisis, doctor-candidates became significantly more likely to use the title, particularly in the cities that were more severely affected by the first wave. These effects are not observed for religious leaders.[22]

Figure 5: The Salience of COVID-19 in 2020 Local Campaigns



95% confidence intervals for errors clustered by municipality. The x-axis has the normalized effects in units of standard deviation. The dependent variable is a dummy that indicates whether or not the candidate used a ballot name with the occupational heuristic. Baseline: in 2012, 76% of doctor candidates and 64% of religious leaders used the ballot box name heuristic. Coefficients are the effect in relation to the 2012 baseline, and come from the following regressions: (1) $H_{cjt} = YEAR_t + \lambda_j + \epsilon_{cjt}$, used for all municipalities; and (2) $H_{cjt} = YEAR_t * Covid_j + \lambda_j + \epsilon_{cjt}$, used for the separate effects by COVID incidence. For candidate c, in municipality j, and election t, H_{cjt} is the dependent variable. $YEAR_t$ are year fixed-effects, λ_j are municipality fixed-effects, and $Covid_j$ is a dummy that indicates whether municipality j was more affected than the median by the first wave of COVID-19 in 2020 (pre-election). See Table C.14 in the appendix for the full results.

Finally, we emphasize that this exercise is only illustrative of one dimension that reflects

[22]Why would a doctor candidate *not* always use the title? The most likely reason is that doctors may want to avoid appearing elitist and would drop the title to appeal to voters in poor areas (Desai and Frey, 2021).

the increase in the salience of competence in the 2020 campaign. In fact, being a doctor is not the only possible signal of competence in this context, and not necessarily the most effective one. Mayoral candidates have used their past as political incumbents, law enforcement officials, CEOs, and entrepreneurs as a signal of managerial competence. We also do not use the the presence of doctors in mayoral races to measure the competence gap. Besides being inconsistent with our theory, competence is not a quality that an outside analyst can systematically observe, even if they had more details on the pre-existing characteristics of candidates.

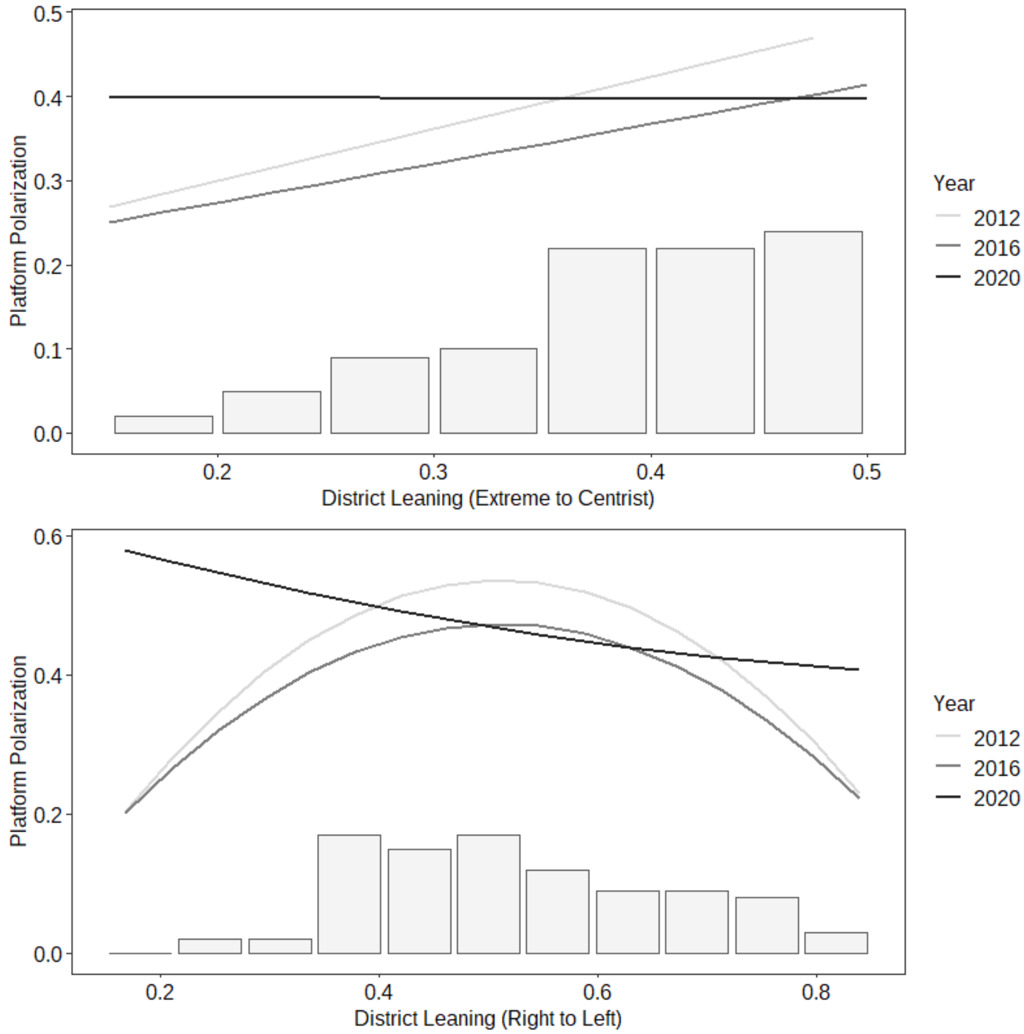
Empirical Strategy and Results

We use the data above to illustrate two key implications of the model. For this, we take advantage of the pandemic's timing, which makes it an unexpected and highly salient competence shock for mayoral races. We start by showing the relationship between platform polarization and leaning for each election in Figure 6. The first plot shows how polarization changes with the local values of leaning on our scale that moves from more extreme (0), either very Left or very Right, to more centrist (0.5). The second plot shows how polarization changes along the district leaning on a Right (0) to Left (1) scale. Here we fit a quadratic function on polarization to more explicitly show the symmetry in polarization across the center.

Our theory suggests that, in the absence of a competence shock, polarization should be positively correlated with centrism (Proposition 2), which is evident in both plots of Figure 6 for both pre-pandemic elections (2012 and 2016), and for both sides of the ideological scale. The most important implication of our model is that a shock to the salience of competence—such as the one generated by COVID-19—increases campaign polarization in areas with more extreme partisan leanings (Proposition 3). Consequently, a shock to the salience of competence should dampen the relationship between polarization and centrism. Although this pattern is already visible in Figure 6,[23] we further examine it using a differences-in-differences design with contin-

[23]The slope of the polarization-leaning relationship in 2020 (the dark line in the plot, or $\beta_2 + \beta_3$ in Table 3), although negative for most specifications, has highly volatile magnitude across estimates; it is often near zero; and consistently fails to achieve statistical significance. Nevertheless, in the context of our theory, the most natural

Figure 6: Platform Polarization and Leaning in Brazil



All variables are described in the text. The columns represent the sample distribution along the x-axis. The outcome is (*Platform Polarization*), and the slopes show the specification from column 6 in Table 3. The lines represent the linear (1st plot) or quadratic (2nd plot) fits of the outcome for each year.

uous treatment. Accordingly, for municipality j in period t, we estimate the following equation:

$$pol_{jt} = \beta_0 + \beta_1 tre_t + \beta_2 lng_j + \beta_3 tre_t \cdot lng_j + \epsilon_{jt} \tag{11}$$

explanation for a negative slope in 2020 could be that shocks to the salience of competence are different across municipalities. In Proposition 3, which averages over cities, the change in the salience of competence is the same, and this implies that the 2020 slope should be nearly flat if α is high enough. Now, if α also varied across cities, this could lead to an average slope that is negative.

where pol_{jt} is polarization. The cross-section variation in leaning (lng_j), on a scale of extreme to centrist, is measured in 2010 (pre-treatment) according to the methodology described on page 18, and it is fixed in time.[24] Finally, tre_t is the treatment dummy that assumes value one when the election happens during the pandemic (i.e., 2020), and 0 otherwise, for all cities.

The coefficient β_3 identifies how the COVID-19 pandemic changes the slope of the polarization-leaning relationship. Following Proposition 3, we expect $\beta_3 < 0$. Table 3 shows the estimates of β_3 for several different specifications that include covariates and various fixed effects.[25]

The estimate of β_3 is negative, statistically significant, and stable across specifications and metrics.[26] The appendix shows that β_3 remains robust (and even higher in magnitude) after changes in the number of policy words used in the analysis (Table C.6 and C.7); the use of 10 policy categories (Table C.4); or a change in the parties used to train the Wordscores model (Table C.8); or with the use of a seeded topic model to measure polarization (Table C.9).[27]

We also highlight that the intercept β_1 measures the increase in polarization in 2020 for the most extreme case possible. Even though this coefficient is not as well identified as the DiD coefficient β_3, the positive estimate is also consistent with the prediction in Proposition 3 that polarization increases, but only in extreme districts. Nevertheless, the average increase in polarization for the entire sample in 2020 is relatively modest (7.4%), given that polarization did not change significantly in centrist districts.

Identification assumptions. The identification of effects in this empirical design relies on

[24]Figure D.1 (appendix, second plot) shows that the municipal PT vote is stable across elections in 2010-2018.

[25] For each city-election: Document covariates are time-variant, and include the total number of words in the two documents, and the absolute difference between them, both logged. Election covariates are time-variant, binary variables that indicate whether or not (i) each top 2 party is Left-wing; (ii) one of the top 2 parties was PT or PSDB; (iii) the incumbent party was among the top 2 in the race; and (iv) the incumbent mayor was running for reelection (and top 2); and (v) the incumbent mayor was a doctor. The Left-wing parties are CIDADANIA, PCB, PCdoB, PCO, PDT, PMN, PSB, PSOL, PSTU, PT, and UP. The other city-level, time-invariant covariates are listed in the footnote in page 37. The inclusion of covariates and fixed effects is not necessary for the identification of treatment effects in this design, it is typically used to reduce the variance in the estimation.

[26]The convergence in the magnitude of the estimates across different polarization metrics highlights that our primary approach, based on the frequency of a few policy words, is able to capture similar levels of polarization in the documents when compared to the Wordscores approach that use the frequencies of all words in the documents. This suggests that the relative simplicity of our primary metric is not consequential to the analysis .

[27]Table C.12 (appendix) also shows that the polarization shift is weaker for the subsample of city-year observations where one of the top 2 candidates was a sitting mayor running for reelection. It is likely that these incumbents are less able to shift their platforms in reelection races than newcomers.

Table 3: Polarization of Mayoral Campaigns During the Pandemic

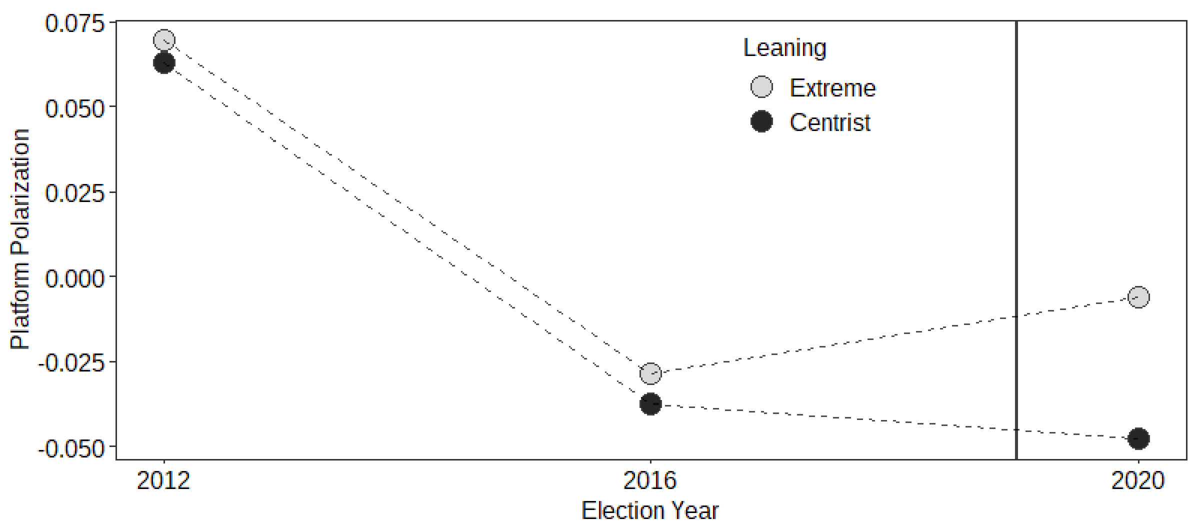
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Platform Polarization based on Policy Words								
β_1	0.144	0.233*	0.245*	0.246*	0.244*	0.241*	0.259*	
	(0.095)	(0.092)	(0.090)	(0.092)	(0.094)	(0.099)	(0.090)	
β_2	0.145	0.390*	0.401*	0.332+	0.313+	0.550*		
	(0.159)	(0.156)	(0.158)	(0.183)	(0.184)	(0.254)		
β_3	-0.475*	-0.564*	-0.582*	-0.578*	-0.574*	-0.567*	-0.596*	-0.565*
	(0.221)	(0.214)	(0.208)	(0.213)	(0.216)	(0.228)	(0.209)	(0.206)
$\beta_2 + \beta_3$	-0.329+	-0.174	-0.181	-0.247	-0.261	-0.017		
	(0.186)	(0.171)	(0.164)	(0.185)	(0.186)	(0.275)		
OUTCOME: Platform Polarization based on Wordscores								
β_1	0.153	0.210+	0.231+	0.238+	0.242+	0.249+	0.279*	
	(0.110)	(0.117)	(0.122)	(0.124)	(0.127)	(0.135)	(0.129)	
β_2	0.410*	0.555*	0.511*	0.560*	0.633*	0.475+		
	(0.179)	(0.179)	(0.181)	(0.205)	(0.200)	(0.259)		
β_3	-0.544*	-0.605*	-0.631*	-0.643*	-0.656*	-0.678*	-0.727*	-0.638*
	(0.269)	(0.282)	(0.295)	(0.297)	(0.302)	(0.321)	(0.311)	(0.314)
$\beta_2 + \beta_3$	-0.133	-0.050	-0.120	-0.083	-0.023	-0.203		
	(0.200)	(0.220)	(0.232)	(0.254)	(0.266)	(0.319)		
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. 256 Observations in all regressions. The coefficients come from equation (11). The outcomes were normalized to values between zero and one for better comparison between metrics. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with Municipality fixed-effects. The same happens to β_2 and β_1 (with year FEs). The full regression coefficients are shown in Tables C.1 (policy words) and Table C.2 (Wordscores).

a few assumptions. First, that the timing of the pandemic was exogenous. In practice, this means that COVID-19 was not itself caused by other idiosyncratic factors that could have had an impact on the Brazilian electoral cycle—a very benign assumption in our context.

Second, on the assumption that the relationship between polarization and leaning would have remained positive and unaltered in 2020, in the absence of COVID-19 (parallel trends assumption). Given that our data has only two pre-treatment periods, we are limited in our ability to conduct a more extensive pre-trends test to support this assumption. Nevertheless, Table C.11 (appendix) shows that our estimates of β_3 are statistically insignificant for placebo regressions with data from 2012 and 2016 only, and $tre_t = 1$ in 2016 (i.e., consistent with the lines already shown in Figure 6). We further illustrate this in Figure 7, which shows the average polarization in 2012-2020 for two groups of cities, with centrist leaning above or below the median. The ratio of the polarization between the groups shifts only in 2020.

Figure 7: Polarization Trends for Different Levels of Leaning



All variables are described in the text. The outcome (*Platform Polarization*) was regressed on the total number of words in both documents and on year-specific trends, and normalized to values between zero and one for better visualization. The dots represent the average normalized outcome for both groups.

Third, the standard DiD compares two groups—treatment and control—in periods before and after treatment, and the binary treatment variable only assumes a value of one for the treatment group in the "second" period. While our design also compares units before and after treatment, the exposure is based on a continuous variable (leaning). In this case, β_3 only has a causal interpretation under a stronger form of the parallel trends assumption, namely, that "the path of outcomes for lower-dose units must reflect how higher-dose units' outcomes would have changed had they instead experienced the lower dose." Callaway, Goodman-Bacon, and SantAnna (2024, pg. 13). In other words, that low-leaning cities would have experienced the same polarization change as high-leaning ones, if they were high-leaning in the first place. While this assumption is untestable in the context of our data, we try to do a second best. Specifically, the stronger parallel trends assumption might be violated if there are city-level unobservables that affect both treatment intensity and treatment effects (DHaultfuille, Hoderlein, and Sasaki, 2023, pg. 665). While we cannot measure unobservables, in Figure D.4 (appendix) we show that the strong magnitude of our β_3 estimate is not driven by heterogeneity generated by several city-level observable characteristics. We do so by including an interaction term between tre_t and the election and city covariates used in Table 3, and region fixed effects, which adjusts β_3 for any effect heterogeneity by leaning that would have been generated by these variables. The adjusted β_3 estimates remain significant and are slightly stronger in magnitude than our main specification, which suggests that potential violations of the stronger parallel trends assumption might not be a major concern in our context.

Finally, while specifications like ours are usually estimated with two-way fixed-effects (TWFE)—city and year in column 8 of Table 3—this model aggregates unit-level effects using weights that might hinder the causal interpretation of β_3. We address this concern following Callaway, Goodman-Bacon, and SantAnna (2024), and estimating a β_3 equivalent that is free from these weighting issues. The alternative estimate is shown in Figure D.5 (appendix), where we also explain the regression we run. The estimate is very similar to the ones obtained with our main specifications, being slightly stronger in magnitude.

Is all polarization health-care related? Our model suggests that the shifts in the platform contents should not be confined to the proposals that are directly and uniquely related to the administration's response to COVID-19. On the contrary, it predicts that candidates would also polarize in areas that are seemingly unrelated to the pandemic. We take a closer look at this issue in Table C.5 (appendix). The top panel shows that the results remain robust to the inclusion of pandemic related words in the construction of our measure.[28] In the second panel, the measure excludes all mentions of health-care from the proposals. Overall, both have statistically significant estimates of β_3. The fact that the coefficient is stronger in the top panel suggests that at least part of the 2020 polarization shift in extreme districts came from health care-related issues. However, this result also stresses that the increased polarization in 2020 was also a more general political phenomenon that affected other policy areas.

Alternative Measures and Explanations

The key feature of our model is that district leaning provides a signal of the decisive voter's ideal point which becomes more precise as leaning becomes more extreme. We now consider two alternative modeling choices for the relationship between district leaning and the precision of the signal provided by leaning. First, we consider the case where there is no relationship between district leaning and how much candidates know about their voter. Second, we reverse (relative to the main model) how district leaning influences what candidates know about their district's representative voter. In each case, we show that the formulation of district leaning in our main model is necessary for congruence with the empirical findings. We then consider whether our main effect is concentrated in districts most effected by COVID-19 incidence, and whether the rise of the far-right in Brazil could account for our results.

[28]The words pandemic and covid (or coronavirus) did not appear in the sample in 2012 or 2016, and vaccine was only the 2,891rd most frequent word. In 2020, they were the 177th, 258th, and 2,151rd most frequent words. We included these three words.

Alternative Models of Leaning

Alternative Model 1. We consider the case where the ideological location of a district's representative voter is drawn from a uniform distribution centered at the district's leaning, but where leaning does not otherwise influence the voter's ideal point. While all other aspects of our theoretical model remain the same, we suppose that

$$z^j \sim U[\zeta^j - \delta, \zeta^j + \delta].$$

That is, the variance of the signal the leaning provides is $\frac{\delta^2}{3}$ for all $\zeta \in [-1, 1]$, as compared to (3), where extreme leanings provided more precise information to candidates relative to centrist leanings.

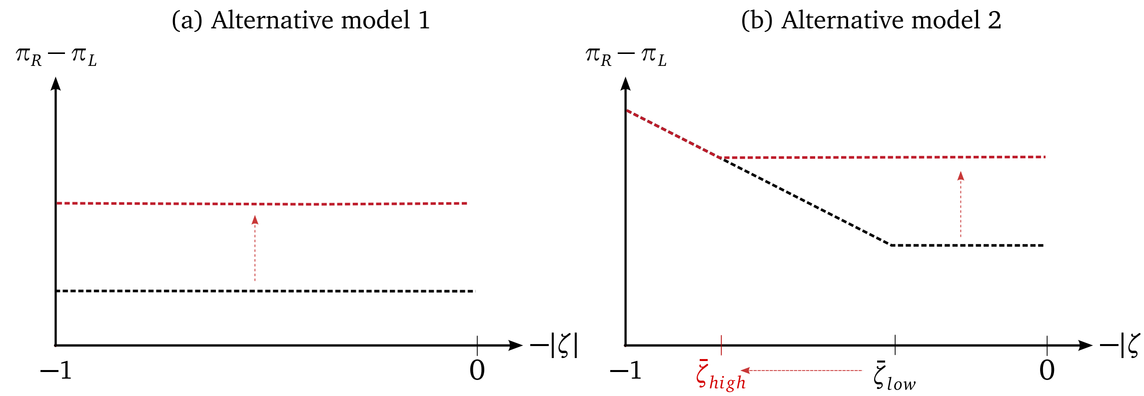
Proposition A.1 in the supplemental appendix characterizes the unique symmetric equilibrium which we summarize with:

Remark 1. *When variance is independent of leaning, then average polarization is increasing in the salience of competence only if α is high enough and there are no heterogeneous effects in leaning.*

We illustrate the results in Figure 8a, which should be contrasted with Figure 2 reflecting our main model. If the variance of the leaning signal is constant across different leanings, then there is no discernible relationship between leaning and polarization. Furthermore, increasing the salience of competence increases polarization only if α is high enough to begin with, and if α increases polarization it does so homogeneously for all districts. In terms of our main specification in (11), if variance was constant in centrism, we would expect $\beta_1 \geq 0$ and $\beta_2 = \beta_3 = 0$.

Alternative Model 2. We now reverse the relationship between leaning and the precision of its signal so that leaning provides a less precise signal of the decisive voter's ideal point as leaning becomes more extreme. Specifically, while all other aspects of our theoretical model remain

Figure 8: Polarization, Centrism, and the Salience of Competence in alternative models



Panel (a) illustrates the results of Alternative Model 1, where variance of the leaning signal is constant. As α increases, polarization weakly increases uniformly for all leanings only if α is high enough. Panel (b) illustrates the results of Alternative Model 2. $\bar{\zeta}_{low}$ and $\bar{\zeta}_{high}$ denote the cutoffs that determine whether a district is extreme or centrist when α is low or high respectively. When α is low, there is a strong negative relationship between the centrism of the district, $-|\zeta|$, and polarization. As α becomes high, the share of centrists districts increases, the negative relationship between polarization and $-|\zeta|$ attenuates, and average polarization increases, with the increase concentrated in centrist districts.

the same, we suppose that

$$z^j \sim U[\zeta^j - (1+|\zeta^j|)\delta, \zeta^j + (1+|\zeta^j|)\delta.$$

Proposition A.2 in the supplemental appendix characterizes the unique symmetric equilibrium which we summarize below:

Remark 2. *When variance decreases in centrism, polarization is weakly decreasing in centrism and average polarization across districts strictly increases in the salience of competence, α, concentrated in centrist districts.*

The empirical implications of the model where centrist leanings are more informative than extreme leanings are illustrated in Figure 8b. In contrast to Figure 2, Figure 8b indicates that if the variance of the signal provided by leaning decreased in centrism, then we would expect there to be a weakly negative relationship between leaning and polarization. An increase in the salience of competence would lead to an increase in average polarization, concentrated in centrist districts. In terms of our main empirical specification in (11), if variance decreased in centrism, we would expect $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 > 0$.

Table 4: Empirical implications of alternative models

Model	β_1	β_2	β_3
Main	$> \mathbf{0}$	$> \mathbf{0}$	$< \mathbf{0}$
Alternative 1	≥ 0	$= 0$	$= 0$
Alternative 2	> 0	< 0	> 0

The first row corresponds to the empirical implications of our main model in the context of equation (11), and the second and third rows correspond to those of the alternative models considered in this section.

We summarize the results in Table 4 and compare them to those of our main model. The first row indicates the implications for the coefficients in (11) stemming from our main model, and the other rows indicate those from the two alternative conceptualizations considered here. As is evident, only the implications of the model where extreme leanings are more informative than centrist leanings are consistent with our empirical findings in Table 3, and we can in fact reject the other two at conventional levels of statistical significance.

Local incidence of COVID-19 and the polarization shift

As further evidence of our argument, we show that the change in the relationship between leaning and polarization is correlated with the incidence of COVID-19 cases across Brazilian cities in 2020, i.e., our effects are concentrated in places that were more affected by the pandemic in the period preceding the electoral campaigns. For this, we now re-estimate equation (11) using a continuous variable tre_{jt} instead of the binary tre_t. As before, tre_{jt} is zero for all municipalities in both 2012 and 2016. However, in 2020, it takes the value of the per capita COVID-19 cases in each municipality before the campaign platforms were released. This means that $\beta_3 < 0$ only if the municipalities more affected by the pandemic were also the ones driving the change in the slope of the polarization-leaning relationship.[29] The left-side plot of Figure

[29] It is straightforward to see that β_3 will be positive if polarization mostly increases in the least affected cities.

9 shows that the estimates of β_3 are negative, and robust to different specifications.

We are aware that, although the timing of COVID-19 was exogenous, its spatial incidence was not. The number of cases in each city is likely correlated with other pre-existing characteristics, which could ultimately be the factors responsible for this heterogeneity. To alleviate this concern, we also re-estimate β_3 using only the residual variation in COVID-19 cases as our tre_{jt} variable. In practice, we control by a series of (pre-2020) observed traits of the municipalities that were likely correlated with the incidence of COVID-19, and their interaction with both the leaning variable and an indicator for the 2020 election.[30] The right-side plot of Figure 9 shows that the estimate of β_3 remains significant and negative after this adjustment (label COVID-19 in the last row). In addition, we show that the interaction of leaning with these individual covariates is not statistically significant for any of them, which suggests that the heterogeneity in the results is *not* driven by one of these factors.

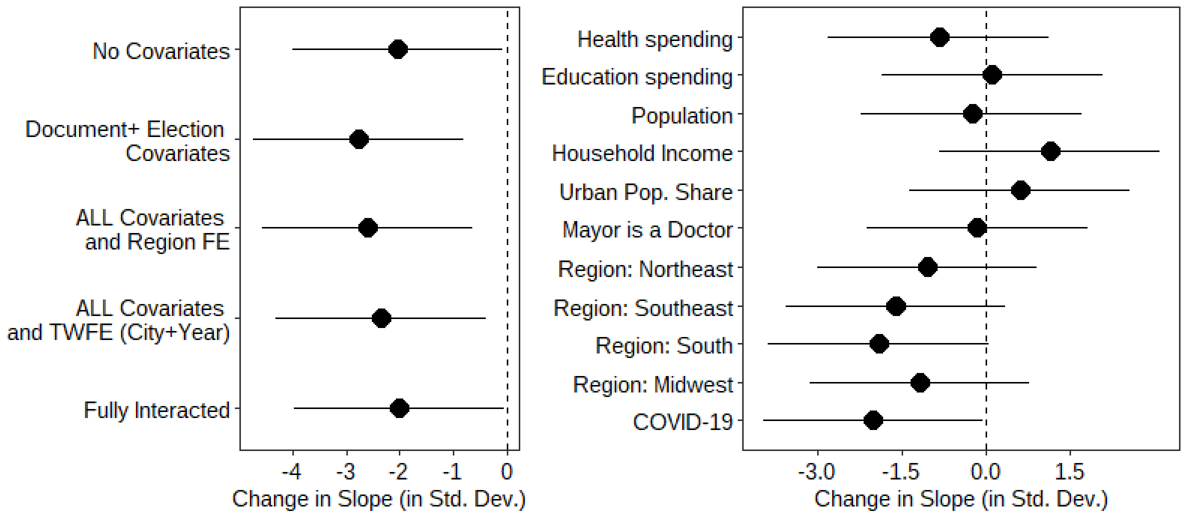
Alternative Explanation: The Rise of the Extreme-Right?

One potential explanation for the patterns in the results is that the level of polarization in Brazil might have increased after (and with) the victory of extreme-right Presidential candidate Jair Bolsonaro in 2018, which marked the end of the longstanding polarization between PT and PSDB in national politics. Fortunately, our data allows us to rule out the impact of this narrative on our findings. We create a variable that measures the change in the presidential Right-wing vote between 2014 and 2018 for each city, and use it as a city-level proxy for this Right-shift in Brazilian politics. Accordingly, we first show in Figure D.2 (appendix) that this variable is uncorrelated with the changes in polarization between 2020 and 2016 across our cities. Second, we estimate equation (11) including this variable as a control,[31] and show that β_3 remains negative and statistically significant (Table C.10, appendix).

[30] The variables are: population, share of urban population, and household income (all from the 2010 Census); share of the local budget spent in health care and education in the 4 years preceding each election; and a dummy that indicates whether or not the incumbent was a medical doctor; and region dummies.

[31] The variable assumes the value of zero for 2012 and 2016.

Figure 9: COVID-19 Drives the Change in the Polarization-Leaning Relationship



For both plots: 95% CIs clustered at the city level. Both are based on regressions with 256 observations where the dependent variable is **Polarization**. All coefficients are normalized by the standard deviation.
The left-side plot shows the estimates of β_3 from equation 11. It uses the COVID-19 measure described in the text (tre_{jt}), which is also normalized to be between zero and one. Fully interacted means that the covariates shown in the right-side plot are interacted with both leaning and the 2020 election dummy. It also includes all other covariates and TWFE (Table C.3 in the appendix shows the full regression results).
The right-side plot focuses on the Fully interacted specification. The dots show the coefficient for the triple interaction between each control variable, the leaning variable, and the 2020 election dummy.

Conclusion

We develop a model of electoral competition where candidates choose their ideological platforms while uncertain about voters' preferences. Candidates are distinguished both in terms of their ideological platforms and their non-ideological competence. We introduce the *partisan leaning* of an electoral district, which provides a signal of its voters' ideological preferences, and moreover, the precision of that signal increases as the leaning becomes more extreme. We focus our theoretical and empirical analysis on understanding how partisan leaning, and the salience of competence, act as drivers of platform polarization. Specifically, we show that partisan leaning leads to an endogenous sorting between "centrist" and "extreme" districts. We further show that increasing the salience of competence leads to increased polarization through two different, but reinforcing, channels. First, we show that increasing the salience of competence leads to greater polarization, but only in extreme districts. Second, we show that increasing the salience of competence also increases the share of electoral districts that are extreme where competence, and not district leaning, drives polarization.

We take these theoretical results to the data in the context of the mayoral elections of 2012, 2016, and 2020 in the 95 largest Brazilian cities. We first present a robust empirical regularity: in elections with lower salience of competence (e.g., 2012, 2016), platform polarization is increasing in the municipality's centrism, and stable across elections. We then take advantage of the exogenous timing of COVID-19 to estimate the shift in polarization between 2020 and the previous races to show that a shock to the salience of competence leads to increased polarization, but mostly in cities with more extreme electorates.

Although our empirical application is focused on elections in Brazil, we expect that similar findings would arise in other countries where ideological polarization is an important aspect of democratic competition. Put differently, we expect our mechanism has external validity and would produce similar results (Slough and Tyson, 2023), provided one looks at similar comparisons across the salience of competence and measured polarization similarly, i.e., using the text of campaign platforms. In particular, we expect our theory to apply to contexts such as the US, where the L-R competition in national politics comes very naturally and because US mayors in large cities have a lot of flexibility to offer platforms that might be less consistent with the national party line (a good example is NYC, where Democrat mayor Eric Adams has a tough on crime platform.) Finally, we highlight that our framework might be particularly attractive to explain polarization patterns in political environments where the vast majority of districts are ideological extreme, and increases in the salience of competence might lead to very significant shocks to the average, country-wide polarization.

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Partisan Leaning

Supplemental Materials

Table of Contents

A Model Appendix

We suppress notation regarding districts in the following whenever possible to simplify exposition.

A.1 Proofs

Proof of Proposition 1. First, note that at any equilibrium, $\pi_L \leq \pi_R$. If not, both candidates have a profitable deviation to their opponent's position since candidates are purely policy-motivated. The probability that L wins the election is $\Pr(u_z(\pi_L) \geq u_z(\pi_R))$ and, by the law of total probability, this is given by

$$\begin{aligned}
& \Pr\left(\alpha\gamma \geq (1-\alpha)\left(|z-\pi_L| - |z-\pi_R|\right)\right) \\
= \quad & \Pr(z < \pi_L)\Pr\left(\gamma \geq \left(\frac{1-\alpha}{\alpha}\right)(\pi_L - \pi_R)\right) + \Pr(z > \pi_R)\Pr\left(\gamma \geq \left(\frac{1-\alpha}{\alpha}\right)(\pi_R - \pi_L)\right) \\
& + \Pr\left(\gamma - 2\left(\frac{1-\alpha}{\alpha}\right)z \geq -\left(\frac{1-\alpha}{\alpha}\right)(\pi_L + \pi_R) \mid z \in [\pi_L, \pi_R]\right)
\end{aligned}$$

Let $\xi(z; \pi_L, \pi_R) \equiv \left(\frac{1-\alpha}{\alpha}\right)(-(\pi_L + \pi_R) + 2z)$, and let $\underline{\beta} = \zeta - (1-|\zeta|)\delta$ and $\bar{\beta} = \zeta + (1-|\zeta|)\delta$, so that z is distributed uniformly between $\underline{\beta}$ and $\bar{\beta}$. Furthermore, let

$$g(\gamma) = \begin{cases} \dfrac{1}{2\psi} & \text{if } \gamma \in [-\psi, \psi] \\ 0 & \text{otherwise} \end{cases} \quad \text{and} \quad h(z) = \begin{cases} \dfrac{1}{2(1-|\zeta|)\delta} & \text{if } z \in [\underline{\beta}, \bar{\beta}] \\ 0 & \text{otherwise} \end{cases}$$

as the probability density functions of γ and z respectively, with associated CDFs given by $G(\cdot)$ and $H(\cdot)$. The probability L wins can now be written as

$$\begin{aligned}
F(\pi_L, \pi_R) \quad \equiv \quad & \int_{\pi_L}^{\pi_R} \int_{\xi(0;\pi_L,\pi_R)}^{\psi - 2\left(\frac{1-\alpha}{\alpha}\right)z} g\left(\gamma + 2\left(\frac{1-\alpha}{\alpha}\right)z\right) h(z)\, \mathrm{d}\gamma\, \mathrm{d}z \\
& + \Big(1 - G\big(\xi(\pi_L; \pi_L, \pi_R)\big)\Big) H(\pi_L) + \Big(1 - G\big(\xi(\pi_R; \pi_L, \pi_R)\big)\Big)\big(1 - H(\pi_R)\big),
\end{aligned} \tag{A.1}$$

where $1-F(\pi_L,\pi_R)$ is the probability that R wins.

Since candidates are policy-motivated, candidate i's expected payoff is

$$V_i(\pi_L,\pi_R) \quad = \quad -F(\pi_L,\pi_R)\,|y_i-\pi_L| - (1-F(\pi_L,\pi_R))\,|y_i-\pi_R|.$$

We first focus on L, whose interior best-response is characterized by the first-order condition:

$$\frac{\partial F}{\partial \pi_L}(\pi_R-\pi_L) \quad = \quad F(\pi_L,\pi_R). \tag{A.2}$$

Since F is differentiable almost everywhere, using the Leibniz integral rule, the first derivative of the probability that L wins the election with respect to π_L is given by

$$\begin{aligned}\frac{\partial F}{\partial \pi_L} = \quad & h(\pi_L)\Big(1-G\big(\xi(\pi_L;\pi)\big)\Big) - \left(\frac{1-\alpha}{\alpha}\right) g(\xi(\pi_L;\pi))H(\pi_L) + \left(\frac{1-\alpha}{\alpha}\right)(1-H(\pi_R))g(\xi(\pi_R;\pi)) \\ & + \int_{\pi_L}^{\pi_R}\left(\frac{1-\alpha}{\alpha}\right) g(\xi(z;\pi))\,h(z)\,\mathrm{d}z - \int_{\xi(0;\pi_L,\pi_R)}^{\psi-2\left(\frac{1-\alpha}{\alpha}\right)\pi_L} g\left(\gamma+2\left(\frac{1-\alpha}{\alpha}\right)\pi_L\right) h(\pi_L)\,\mathrm{d}\gamma\end{aligned}$$

which because

$$\int_{\xi(0;\pi_L,\pi_R)}^{\psi-2\left(\frac{1-\alpha}{\alpha}\right)\pi_L} g\left(\gamma+2\left(\frac{1-\alpha}{\alpha}\right)\pi_L\right) h(\pi_L)\,\mathrm{d}\gamma \quad = \quad h(\pi_L)\Big(1-G\big(\xi(\pi_L;\pi)\big)\Big),$$

reduces to

$$\left(\frac{1-\alpha}{\alpha}\right)\left[(1-H(\pi_R))g(\xi(\pi_R;\pi)) + \int_{\pi_L}^{\pi_R} g(\xi(z;\pi))\,h(z)\,\mathrm{d}z - g(\xi(\pi_L;\pi))H(\pi_L)\right]. \tag{A.3}$$

Similarly, the first-order condition for R is

$$\frac{\partial F}{\partial \pi_R}(\pi_R-\pi_L) \quad = \quad 1-F(\pi_L,\pi_R), \tag{A.4}$$

and the derivative of the probability L wins with respect to π_R is

$$\frac{\partial F}{\partial \pi_R} = -h(\pi_R)\Big(1-G\big(\xi(\pi_R;\pi)\big)\Big) + \left(\frac{1-\alpha}{\alpha}\right) g(\xi(\pi_L;\pi))H(\pi_L) - \left(\frac{1-\alpha}{\alpha}\right)(1-H(\pi_R))g(\xi(\pi_R;\pi))$$
$$+ \int_{\pi_L}^{\pi_R} \left(\frac{1-\alpha}{\alpha}\right) g(\xi(z;\pi))\, h(z)\,\mathrm{d}z - \int_{\xi(0;\pi_L,\pi_R)}^{\psi-2\left(\frac{1-\alpha}{\alpha}\right)\pi_L} g\left(\gamma + 2\left(\frac{1-\alpha}{\alpha}\right)\pi_L\right) h(\pi_L)\,\mathrm{d}\gamma$$

which, through a similar calculation as for L, reduces to

$$\left(\frac{1-\alpha}{\alpha}\right)\left[-(1-H(\pi_R))g(\xi(\pi_R;\pi)) + \int_{\pi_L}^{\pi_R} g(\xi(z;\pi))\, h(z)\,\mathrm{d}z + g(\xi(\pi_L;\pi))H(\pi_L)\right]. \quad \text{(A.5)}$$

Any pair of platforms (π_L, π_R), that simultaneously satisfy (A.2) and (A.4), along with $\gamma^*(\pi_L, \pi_R; z)$, characterize an interior equilibrium.

To solve explicitly for equilibrium platforms, we consider equilibria which are symmetric around ζ. Therefore, we let $\pi_L = \zeta - x$ and $\pi_R = \zeta + x$, for some $x \geq 0$. Using the expression in (A.1), we first establish that the probability that L wins is equal to $\frac{1}{2}$ in any equilibrium symmetric around ζ. There are two cases.

Case 1. When $x \geq (1-|\zeta|)\delta$, the probability L wins is

$$\int_{\underline{\beta}}^{\bar{\beta}} \int_{-2\left(\frac{1-\alpha}{\alpha}\right)\zeta}^{\psi-2\left(\frac{1-\alpha}{\alpha}\right)z} g\left(\gamma + 2\left(\frac{1-\alpha}{\alpha}\right)z\right) h(z)\,\mathrm{d}\gamma\,\mathrm{d}z.$$

The bounds on the outer integral depend on whether $2\left(\frac{1-\alpha}{\alpha}\right)(z-\zeta) \in [-\psi, \psi]$, which reduces to $z \in \left[\zeta - \frac{\alpha\psi}{2(1-\alpha)}, \zeta + \frac{\alpha\psi}{2(1-\alpha)}\right]$. Thus, the above expression simplifies to

$$\frac{1}{2}\left(H\left(\zeta + \frac{\alpha\psi}{2(1-\alpha)}\right) - H\left(\zeta - \frac{\alpha\psi}{2(1-\alpha)}\right)\right) + H\left(\zeta - \frac{\alpha\psi}{2(1-\alpha)}\right),$$

which is $\frac{1}{2}$ since H is uniform and centered at ζ.

Case 2. When $x < (1-|\zeta|)\delta$, the probability that L wins is

$$\int_{\zeta-x}^{\zeta+x}\int_{-2\left(\frac{1-\alpha}{\alpha}\right)}^{\psi-2\left(\frac{1-\alpha}{\alpha}\right)z} g\left(\gamma+2\left(\frac{1-\alpha}{\alpha}\right)z\right)h(z)\,\mathrm{d}\gamma\,\mathrm{d}z+\left(1-G\left(-2\left(\frac{1-\alpha}{\alpha}\right)x\right)\right)$$
$$\times H\left(\zeta-\frac{\alpha\psi}{2(1-\alpha)}\right)+\left(1-G\left(2\left(\frac{1-\alpha}{\alpha}\right)x\right)\right)H\left(\zeta+\frac{\alpha\psi}{2(1-\alpha)}\right).$$

If $x \geq \frac{\alpha\psi}{2(1-\alpha)}$, then the last two terms in the above expression reduce to 0, and through similar calculations as for the first case, the probability L wins is $\frac{1}{2}$. If $x < \frac{\alpha\psi}{2(1-\alpha)}$, then the above expression reduces to

$$\frac{1}{2}\left(H(\zeta+x)-H(\zeta-x)\right)+\left(\frac{\psi+2\left(\frac{1-\alpha}{\alpha}\right)x}{2\psi}\right)H(\zeta-x)+\left(\frac{\psi-2\left(\frac{1-\alpha}{\alpha}\right)x}{2\psi}\right)(1-H(\zeta+x)),$$

which simplifies to $\frac{1}{2}$ because $H(\zeta-x)=1-H(\zeta+x)$.

Finally, in any symmetric equilibrium, because H is symmetric around ζ, and because

$$\xi(z;\zeta-x,\zeta+x)\in\left[-\frac{1}{2\psi},\frac{1}{2\psi}\right]\iff z\in\left[\zeta-\frac{\alpha\psi}{2(1-\alpha)},\zeta+\frac{\alpha\psi}{2(1-\alpha)}\right],$$

the derivatives in equations (A.3) and (A.5) reduce to

$$\left(\frac{1-\alpha}{2\alpha\psi}\right)\left(\min\left\{1,\frac{\frac{\alpha\psi}{2(1-\alpha)}+(1-|\zeta|)\delta}{2(1-|\zeta|)\delta}\right\}-\max\left\{0,\frac{(1-|\zeta|)\delta-\frac{\alpha\psi}{2(1-\alpha)}}{2(1-|\zeta|)\delta}\right\}\right).\tag{A.6}$$

Thus, the first-order conditions for any symmetric equilibrium $(\zeta-x,\zeta+x)$ are

$$x=\frac{1}{4\frac{\partial F}{\partial\pi_L}}=\frac{1}{4\frac{\partial F}{\partial\pi_R}}.\tag{A.7}$$

Using these equations we show that there exists a unique symmetric equilibrium.

First, consider a symmetric equilibrium with $x > (1-|\zeta|)\delta$. There are two cases to consider.

Case 1. When $(1-|\zeta|)\delta > \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.6) reduces to

$$\left(\frac{1-\alpha}{2\alpha\psi}\right)\left(\frac{\frac{\alpha\psi}{2(1-\alpha)}+(1-|\zeta|)\delta}{2(1-|\zeta|)\delta}-\frac{(1-|\zeta|)\delta-\frac{\alpha\psi}{2(1-\alpha)}}{2(1-|\zeta|)\delta}\right)=\left(\frac{1}{4(1-|\zeta|)\delta}\right).$$

Plugging it back into (A.7), we get that $x=(1-|\zeta|)\delta$, which is a contradiction.
Case 2. When $(1-|\zeta|)\delta \leq \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.6) is $\left(\frac{1-\alpha}{2\alpha\psi}\right)$. Therefore, by equation (A.7), $x=\frac{\alpha\psi}{2(1-\alpha)}$. Therefore we conclude that a symmetric equilibrium where $x>(1-|\zeta|)\delta$ exists if and only if $(1-|\zeta|)\delta \leq \frac{\alpha\psi}{2(1-\alpha)}$ which is equivalent to $\zeta \leq \min\left\{\frac{\alpha\psi}{2(1-\alpha)\delta}-1,0\right\} \equiv \bar{\zeta}_L$ and $\zeta \geq \max\left\{1-\frac{\alpha\psi}{2(1-\alpha)\delta},0\right\} \equiv \bar{\zeta}_R$, and that $\pi_L^*=\zeta-\frac{\alpha\psi}{2(1-\alpha)}$ and $\pi_R^*=\zeta+\frac{\alpha\psi}{2(1-\alpha)}$ constitute this equilibrium.

Now, consider an equilibrium where $x \leq (1-|\zeta|)\delta$. As before, we consider two cases
Case 1. When $(1-|\zeta|)\delta < \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.6) is $\left(\frac{1-\alpha}{2\alpha\psi}\right)$, and by equation (A.7), $x=\frac{\alpha\psi}{2(1-\alpha)}$, which implies that $x \leq (1-|\zeta|)\delta < \frac{\alpha\psi}{2(1-\alpha)}=x$, a contradiction.
Case 2. When $(1-|\zeta|)\delta \geq \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.6) reduces to $\frac{1}{4(1-|\zeta|)\delta}$, and by equation (A.7), $x=(1-|\zeta|)\delta$. Therefore we conclude that a symmetric equilibrium where $x \leq (1-|\zeta|)\delta$ exists if and only if $(1-|\zeta|)\delta \leq \frac{\alpha\psi}{2(1-\alpha)}$ which is equivalent to $\zeta \in [\bar{\zeta}_L,\bar{\zeta}_R]$, and that $\pi_L^\dagger = \zeta-(1-|\zeta|)\delta$ and $\pi_R^\dagger=\zeta+(1-|\zeta|)\delta$ constitute an equilibrium.

Note that when $\zeta=\bar{\zeta}_L$ or $\zeta=\bar{\zeta}_R$, both (π_L^*,π_R^*) and $(\pi_L^\dagger,\pi_R^\dagger)$ coincide. Thus, for all ζ there exists a unique symmetric equilibrium. □

Proof of Proposition 2. The proof follows from the expressions in equations (5) and (6). □

Proof of Proposition 3. When $\zeta<\bar{\zeta}_L$ (and when $\zeta>\bar{\zeta}_R$)), the first derivative of $\pi_R^*-\pi_L^*=\frac{\alpha\psi}{1-\alpha}$ with respect to α is

$$\left.\frac{\partial(\pi_R^*-\pi_L^*)}{\partial\alpha}\right|_{\zeta<\bar{\zeta}_L}=\frac{\psi}{(1-\alpha)^2}>0. \tag{A.8}$$

When $\bar{\zeta}_L<\zeta<\bar{\zeta}_R$, equilibrium polarization is $\pi_R^\dagger-\pi_L^\dagger=2(1-|\zeta|)\delta$, which does not depend on α.

Now, differentiate the expression in $\bar{\zeta}_L$ to get

$$\frac{d\bar{\zeta}_L}{d\alpha} = \frac{\psi}{2(1-\alpha)^2\delta} > 0. \tag{A.9}$$

Thus, whenever interior to $[-1,0]$, $\bar{\zeta}_L$ is strictly increasing in α, and when it hits 0, it remains constant in α. By symmetry, $\bar{\zeta}_R$ is decreasing in α whenever interior, and remains 0 thereafter.

Average polarization is given by

$$\left(\frac{1}{2}\right)\left[\int_{-1}^{\bar{\zeta}_L}\left(\frac{\alpha\psi}{1-\alpha}\right)\,\mathrm{d}j + \int_{\bar{\zeta}_R}^{1}\left(\frac{\alpha\psi}{1-\alpha}\right)\,\mathrm{d}j + \int_{\bar{\zeta}_L}^{\bar{\zeta}_R} 2(1+\zeta^j)\delta\,\mathrm{d}j\right],$$

which simplifies to

$$\left(\frac{2+\bar{\zeta}_L-\bar{\zeta}_R}{2}\right)\cdot\left(\frac{\alpha\psi}{1-\alpha}\right)+(\bar{\zeta}_R-\bar{\zeta}_L)(1+\zeta^j)\delta.$$

Combining (A.8) and (A.9), this expression is strictly increasing in α. □

A.2 Model Extensions

A important and novel feature of our model is the relationship between district leaning and what candidates know about their decisive voter. Specifically, as a district's leaning becomes more ideologically extreme candidates face less uncertainty about the location of their district's representative voter. In this supplement we consider two alternative modeling choices for how district leaning influences uncertainty about a district's representative voter. First, we consider when the precision of the signal provided by a district's leaning does not vary with the leaning. Second, we reverse (relative to the main model) how district leaning influences what candidates know about their district's representative voter. In each case we show that the formulation of district leaning in our main model is necessary for congruence with the empirical findings.

A.2.1 Alternative Model 1: Variance Independent of Leaning

In this section we consider the case where the ideological location of a district's representative voter is drawn from a uniform distribution centered at the district's leaning, but where leaning does not otherwise influence the voter's ideal point. That is, suppose

$$z^j \sim U[\zeta^j - \delta, \zeta^j + \delta],$$

where all other aspects of the model are identical to the main model.

Proposition A.1. *In the unique symmetric equilibrium,*

$$\begin{aligned} \pi_L^* &= \zeta - \max\left\{\frac{\alpha\psi}{2(1-\alpha)}, \delta\right\} \\ \pi_R^* &= \zeta + \max\left\{\frac{\alpha\psi}{2(1-\alpha)}, \delta\right\}, \end{aligned} \tag{A.10}$$

there is an intensive margin if and only if $\alpha \geq \frac{2\delta}{2\delta+\psi}$, and there is no extensive margin, i.e.,

$$\bar{\zeta}_L = \begin{cases} -1 & \text{if } \alpha \leq \frac{2\delta}{2\delta+\psi} \\ 0 & \text{if } \alpha \geq \frac{2\delta}{2\delta+\psi} \end{cases}, \tag{A.11}$$

and $\bar{\zeta}_R = -\bar{\zeta}_L$.

Proof. The expression for the probability of victory remains similar to equation (A.1), with the only difference being that $h(z) = \frac{1}{2\delta}$ for $z \in [\zeta - \delta, \zeta + \delta]$.

Because of the symmetry in the model, at any symmetric equilibrium the probability either candidate wins is $\frac{1}{2}$. The first derivatives in equations (A.3) and (A.5) similarly reduce to

$$\frac{\partial F}{\partial \pi_L} = \frac{\partial F}{\partial \pi_R} = \left(\frac{1-\alpha}{2\alpha\psi}\right)\left(\min\left\{1, \frac{\frac{\alpha\psi}{2(1-\alpha)} + \delta}{2\delta}\right\} - \max\left\{0, \frac{\delta - \frac{\alpha\psi}{2(1-\alpha)}}{2\delta}\right\}\right). \tag{A.12}$$

and the FOC's at any symmetric equilibrium $(\zeta - x, \zeta + x)$ are the same as in (A.7).

First, suppose there exists a symmetric equilibrium where $x > \delta$. Mirroring the proof in Proposition 1, we consider two cases.

Case 1. When $\delta > \frac{\alpha\psi}{2(1-\alpha)}$, the first derivative of the probability of winning function, F, with respect to both π_L and π_R, reduce to

$$\left(\frac{1-\alpha}{2\alpha\psi}\right)\left(\frac{\frac{\alpha\psi}{2(1-\alpha)}+\delta}{2\delta}-\frac{\delta-\frac{\alpha\psi}{2(1-\alpha)}}{2\delta}\right)=\left(\frac{1}{4\delta}\right).$$

Plugging it back into (A.7), we get that $x=\delta$, which is a contradiction.

Case 2. When $\delta \leq \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.12) is $\left(\frac{1-\alpha}{2\alpha\psi}\right)$. Therefore, by equation (A.7), $x=\frac{\alpha\psi}{2(1-\alpha)}$. Therefore we conclude that a symmetric equilibrium where $x > \delta$ exists if and only if $\delta \leq \frac{\alpha\psi}{2(1-\alpha)}$ which is equivalent to $\alpha \geq \frac{2\delta}{2\delta+\psi}$, and that $\pi_L^* = \zeta - \frac{\alpha\psi}{2(1-\alpha)}$ and $\pi_R^* = \zeta + \frac{\alpha\psi}{2(1-\alpha)}$ constitute this equilibrium.

Now, consider an equilibrium where $x \leq \delta$. As before, we consider two cases

Case 1. When $\delta < \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.12) is $\left(\frac{1-\alpha}{2\alpha\psi}\right)$, and by equation (A.7), $x=\frac{\alpha\psi}{2(1-\alpha)}$, which implies that $x \leq \delta < \frac{\alpha\psi}{2(1-\alpha)} = x$, a contradiction.

Case 2. When $\delta \geq \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.12) reduces to $\frac{1}{4\delta}$, and by equation (A.7), $x=\delta$. Therefore we conclude that a symmetric equilibrium where $x \leq \delta$ exists if and only if $\delta \geq \frac{\alpha\psi}{2(1-\alpha)}$ which is equivalent to $\alpha \leq \frac{2\delta}{2\delta+\psi}$, and that $\pi_L^* = \zeta - \delta$ and $\pi_R^* = \zeta + \delta$ constitute an equilibrium.

Taken together, the electoral equilibrium is expressed by $\pi_L^* = \zeta - \max\left\{\frac{\alpha\psi}{2(1-\alpha)}, \delta\right\}$ and $\pi_R^* = \zeta + \max\left\{\frac{\alpha\psi}{2(1-\alpha)}, \delta\right\}$. Two things become apparent. First, there is an intensive margin if and only if $\alpha \geq \frac{2\delta}{2\delta+\psi}$ because α affects polarization only in this case. And second, there is no extensive margin. That is,

$$\bar{\zeta}_L = \begin{cases} -1 & \text{if } \alpha \leq \frac{2\delta}{2\delta+\psi} \\ 0 & \text{if } \alpha \geq \frac{2\delta}{2\delta+\psi} \end{cases}, \tag{A.13}$$

and $\bar{\zeta}_R = -\bar{\zeta}_L$. □

This establishes that when a district's leaning does not influence the quality of candidates' knowledge about their voters, then the average level of platform polarization is

$$\max\left\{\frac{\alpha\psi}{(1-\alpha)}, 2\delta\right\},$$

which, by inspection, weakly increases in the salience of competence. Contrary to our main model, the salience of competence here affects the average level of platform polarization only along the intensive margin, and only when α is high enough. If this alternative model extension were a better representation of the relationship between platform polarization and district leaning, then we should have found null results in the data. On the contrary, our empirical results demonstrate robust evidence for a relationship between the average level of platform polarization and district leaning.

A.2.2 Alternative Model 2: Variance Decreases in Centrism

In our main model, as a district's leaning becomes more extreme, the signal it provides about the location of the district's representative voter becomes more precise. In this section we reverse this feature of our model and suppose that as a district's leaning becomes *less* extreme the precision of the signal it provides about the location of the district's representative voter becomes *more* precise. Specifically, we suppose that

$$z^j \sim U[\zeta^j - (1+|\zeta^j|)\delta, \zeta^j + (1+|\zeta^j|)\delta,$$

and where all other aspects of the model are identical to the main model.

Proposition A.2. *In the unique symmetric equilibrium, for all centrists districts, i.e.* $\bar{\zeta}_L \leq \zeta \leq \bar{\zeta}_R$,

$$\begin{aligned} \pi_L^* =& \zeta - \frac{\alpha\psi}{2(1-\alpha)} \\ \pi_R^* =& \zeta + \frac{\alpha\psi}{2(1-\alpha)}; \end{aligned} \tag{A.14}$$

and for an extreme-left (extreme-right) district, i.e., for all $\zeta < \bar{\zeta}_L$ ($\zeta > \bar{\zeta}_R$),

$$\begin{aligned} \pi_L^\dagger =& \zeta - (1+|\zeta|)\delta \\ \pi_R^\dagger =& \zeta + (1+|\zeta|)\delta; \end{aligned} \tag{A.15}$$

and where

$$\bar{\zeta}_L = \min\left\{1 - \frac{\alpha\psi}{2(1-\alpha)\delta}, 0\right\} \quad \textit{and} \quad \bar{\zeta}_R = \max\left\{\frac{\alpha\psi}{2(1-\alpha)\delta} - 1, 0\right\}. \tag{A.16}$$

Proof. Because of the symmetry in the model, at any symmetric equilibrium the probability either candidate wins is $\frac{1}{2}$. The first derivatives in equations (A.3) and (A.5) similarly reduce to

$$\left(\frac{1-\alpha}{2\alpha\psi}\right)\left(\min\left\{1, \frac{\frac{\alpha\psi}{2(1-\alpha)} + (1+|\zeta|)\delta}{2(1+|\zeta|)\delta}\right\} - \max\left\{0, \frac{(1+|\zeta|)\delta - \frac{\alpha\psi}{2(1-\alpha)}}{2(1+|\zeta|)\delta}\right\}\right). \tag{A.17}$$

The first-order conditions for any symmetric equilibrium $(\zeta - x, \zeta + x)$ remain as in (A.7). Our proof now follows that for Proposition 1.

First, consider a symmetric equilibrium with $x > (1+|\zeta|)\delta$. There are two cases to consider. *Case 1.* When $(1+|\zeta|)\delta > \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.17) reduces to

$$\left(\frac{1-\alpha}{2\alpha\psi}\right)\left(\frac{\frac{\alpha\psi}{2(1-\alpha)} + (1+|\zeta|)\delta}{2(1+|\zeta|)\delta} - \frac{(1+|\zeta|)\delta - \frac{\alpha\psi}{2(1-\alpha)}}{2(1+|\zeta|)\delta}\right) = \left(\frac{1}{4(1+|\zeta|)\delta}\right).$$

Plugging it back into (A.7), we get that $x = (1+|\zeta|)\delta$, which is a contradiction.
Case 2. When $(1+|\zeta|)\delta \le \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.17) is $\left(\frac{1-\alpha}{2\alpha\psi}\right)$. Therefore, by equation (A.7), $x = \frac{\alpha\psi}{2(1-\alpha)}$. Therefore we conclude that a symmetric equilibrium where $x > (1+\zeta)\delta$ exists if and only if $(1+|\zeta|)\delta \le \frac{\alpha\psi}{2(1-\alpha)}$ which is equivalent to $\zeta \ge \min\left\{1 - \frac{\alpha\psi}{2(1-\alpha)\delta}, 0\right\} \equiv \bar{\zeta}_L$ and $\zeta \le \max\left\{\frac{\alpha\psi}{2(1-\alpha)\delta} - 1, 0\right\} \equiv \bar{\zeta}_R$, and that $\pi_L^* = \zeta - \frac{\alpha\psi}{2(1-\alpha)}$ and $\pi_R^* = \zeta + \frac{\alpha\psi}{2(1-\alpha)}$ constitute this equilibrium.

Now, consider an equilibrium where $x \leq (1+|\zeta|)\delta$. As before, we consider two cases

Case 1. When $(1+|\zeta|)\delta < \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.6) is $\left(\frac{1-\alpha}{2\alpha\psi}\right)$, and by equation (A.7), $x = \frac{\alpha\psi}{2(1-\alpha)}$, which implies that $x \leq (1+|\zeta|)\delta < \frac{\alpha\psi}{2(1-\alpha)} = x$, a contradiction.

Case 2. When $(1+|\zeta|)\delta \geq \frac{\alpha\psi}{2(1-\alpha)}$, the RHS of equation (A.6) reduces to $\frac{1}{4(1+|\zeta|)\delta}$, and by equation (A.7), $x = (1+|\zeta|)\delta$. Therefore we conclude that a symmetric equilibrium where $x \leq (1+\zeta)\delta$ exists if and only if $(1+|\zeta|)\delta \leq \frac{\alpha\psi}{2(1-\alpha)}$ which is equivalent to $\zeta \leq \bar{\zeta}_L$ and $\zeta \geq \bar{\zeta}_R$, and that $\pi_L^\dagger = \zeta - (1+|\zeta|)\delta$ and $\pi_R^\dagger = \zeta + (1+|\zeta|)\delta$ constitute an equilibrium.

Note that when $\zeta = \bar{\zeta}_L$ or $\zeta = \bar{\zeta}_R$, both (π_L^*, π_R^*) and $(\pi_L^\dagger, \pi_R^\dagger)$ coincide. Thus, for all ζ there exists a unique symmetric equilibrium. □

To connect this characterization with the empirical implications of this model we have

Proposition A.3. *(i) Platform polarization in centrist districts is strictly decreasing in the ideological leaning of the district, i.e., $-|\zeta|$, whereas there is no relationship between platform polarization and district leaning in extreme districts.*

(ii) The average level of polarization across districts is strictly increasing in the salience of competence, α. In particular, the level of polarization in centrist districts, $\pi_R^* - \pi_L^*$, is strictly increasing in α, whereas the level of polarization in extreme districts, $\pi_R^\dagger - \pi_L^\dagger$, is constant in α. Moreover, the share of centrist districts increases in α.

Proof. The first claim follows through the expression in (A.14) and (A.15).

For the second, the expression in (A.15) implies that the intensive margin is the same as in the model in the main text. The extensive margin serves to increase the share of "centrist districts" where competition is driven by competence uncertainty. As opposed to Proposition 3, in this version of the model, this increase in average polarization is concentrated in centrist districts. □

The alternative models we develop in this section, and their empirical implications from the main text, are important because they show the importance of how we model district leaning in our main model in producing our empirical results. In particular, they show that the only model of leaning that is consistent with the data is that which is based on the intutive assumption that leaning becomes more infomrative, i.e., provides a more precise signal of a district's representative voter, as it becomes more extreme.

B Building the Campaign Proposals Dataset

The campaign proposals for each candidate are available for the mayoral elections of 2012, 2016, and 2020 at the following website: *https://divulgacandcontas.tse.jus.br/divulga/*. For the top two candidates in our 95 large cities in these three elections, we had a potential of 570 proposals, which implies a maximum of 285 municipality-year observations for the polarization measure in our data. Given that a few candidates failed to produce the document, our effective sample has 256 observations.

The downloaded documents in PDF were first converted to text and then incorporated into a corpus. As usual, we removed *stopwords*, symbols, separators, punctuation, numbers, and accents; converted all characters to lower-case; converted plural words to singular; de-gendered the words (e.g., *publico* and *publica* became the same word); and kept only words with two or more letters.

We also made sure that our methodology counted the words that directly refer to the names of the budget categories present in the FINBRA database of local finances. Accordingly, we manually converted the following pairs of words to a single term: *Meio Ambiente* (Natural Enviroment) and *Assistência Social* (Social Assistence). None of the other names of budget categories were compound words.

As it is usual, we also removed words that were too common or uncommon. More precisely, we only kept words that appear in at least 10% of the documents, and no more than 90% of documents. This gave us a total of 2,861 words for the analysis. We emphasize that all policy words from our list were kept in the dataset whether or not they satisfy these conditions.

With this data, we calculate the frequency of each policy word as a share of total frequency of policy words in each document. We use these frequencies to calculate the polarization level in each city-year, which is the 6-dimensional Euclidean distance between the proposals of the top two candidates. For the *Wordscores* methodology we train the algorithm on the 2012 proposals of the most relevant Brazilian parties on each end of the Left-Right spectrum in 2012,[1] which are classified as either left (score of -1) or right (score of 1). Based on this, each proposal receives a score, and the polarization level in each city-year is the absolute difference between the scores of the top two candidates. Finally, for the seeded-topic model the algorithm generated 6-topics with our seed words, and for every document, it attributed the weight related to each topic. This allowed us to again build a city-year polarization score based on the 6-dimensional Euclidean distance between the topic-weights of the top two candidates.

[1] PT, PSB, and PCdoB on the Left, and PP, DEM, PL, and PSD on the Right. The other large parties that are closer to the center are included in an alternative specification (PDT and PPS on the Left, and PTB, PMDB, and PSDB on the Right).

Table B.1: Most frequent words in the sample (1-100)

Word	Count	Word	Count	Word	Count
publico	22464	qualidade	5789	familia	3780
municipal	20199	ano	5768	tambem	3776
cidade	18368	cultural	5586	lazer	3694
programa	15055	**seguranca**	5546	grande	3690
saude	13601	trabalho	5419	atraves	3679
politico	12052	forma	5373	maior	3677
social	11364	implantar	5306	**ensino**	3662
acao	11332	espaco	4989	mulher	3641
todo	11214	ser	4841	ampliacao	3580
municipio	10890	atividade	4762	sociedade	3553
gestao	10756	implantacao	4740	bem	3534
servico	10680	criacao	4704	crianca	3525
governo	10388	meio	4670	alem	3502
educacao	9919	promover	4666	fortalecer	3426
novo	9860	acesso	4605	comunidade	3320
area	9489	local	4600	renda	3315
desenvolvimento	9286	vida	4560	cidadao	3289
plano	8960	**transporte**	4536	setor	3192
populacao	8222	unidade	4461	melhoria	3128
projeto	8217	recurso	4418	estado	3111
atendimento	7426	esporte	4323	empresa	3075
urbano	7293	bairro	4305	federal	3052
pessoa	6948	construcao	4277	formacao	3027
sistema	6683	direito	4250	conselho	3019
ampliar	6626	proposto	4243	jovem	2982
outro	6625	**ambiental**	4166	objetivo	2978
rede	6586	prefeitura	4129	lei	2965
nao	6565	profissional	3983	apoio	2956
centro	6546	participacao	3960	administracao	2949
escola	6249	secretaria	3908	**escolar**	2948
sao	6185	economico	3850	equipamento	2947
parceria	6120	garantir	3831	rua	2937
cultura	6003	processo	3795		
criar	5978	regiao	3785		

Table and footnotes continue on the next page...

Table B.2: Most frequent words in the sample (101-200)

Word	Count	Word	Count	Word	Count
sobre	2912	rural	2456	assim	2091
uso	2881	privado	2434	santo	2087
integrado	2867	rio	2400	ate	2076
infraestrutura	2853	promocao	2393	deficiencia	2062
mobilidade	2821	**violencia**	2390	**transito**	2061
investimento	2803	especial	2388	evento	2047
diverso	2803	protecao	2387	fundamental	2042
emprego	2775	tecnico	2298	realizar	2016
planejamento	2755	realizacao	2293	problema	2002
condicao	2749	atencao	2288	capacitacao	2001
economia	2736	civil	2267	incentivar	1999
sustentavel	2717	necessario	2258	fortalecimento	1968
pratico	2710	ponto	2254	iniciativa	1957
esportivo	2701	tempo	2252	geracao	1949
melhor	2695	incentivo	2250	central	1943
caso	2691	**agua**	2224	via	1931
obra	2674	implementar	2215	manutencao	1930
cada	2671	numero	2205	praca	1926
visando	2668	meta	2202	permanente	1913
tecnologia	2667	melhorar	2197	conjunto	1900
turismo	2666	popular	2196	prefeito	1894
parque	2661	principal	2195	curso	1890
situacao	2659	estrutura	2195	partir	1881
controle	2647	producao	2189	cidadania	1880
informacao	2625	integracao	2182	oferta	1867
sera	2621	estadual	2167	poder	1851
idoso	2616	inclusao	2162	fisico	1851
basico	2588	desenvolver	2156	regional	1848
ainda	2582	demanda	2154	referencia	1834
assistencia social	2536	junto	2153	equipe	1831
servidor	2529	**aluno**	2137	preciso	1812
necessidade	2496	diretriz	2136	oportunidade	1809
nacional	2488	**meio ambiente**	2107		
humano	2469	voltada	2099		

Policy-related words for the main 6 categories are shown in bold.

Table B.3: All Policy Words Used in Appendix Tables, in 6 Categories

Category:	Word	Frequency Ranking
Health	saude	5
Health	hospital	313
Health	medico	340
Health	pandemia	501
Health	covid	809
Health	vacina	2891
Education	educacao	14
Education	escola	30
Education	ensino	75
Education	escolar	98
Education	aluno	165
Education	professor	290
Transportation	transporte	52
Transportation	mobilidade	105
Transportation	transito	173
Transportation	onibus	299
Public Security	seguranca	38
Public Security	violencia	139
Public Security	guarda	208
Public Security	policia	498
Social Assistance	assistencia social	130
Social Assistance	deficiencia	172
Social Assistance	creche	366
Social Assistance	diversidade	480
Sanitation and Environment	ambiental	60
Sanitation and Environment	agua	150
Sanitation and Environment	meio ambiente	167
Sanitation and Environment	residuo	227
Sanitation and Environment	saneamento	244
Sanitation and Environment	coleta	275

C Tables

Table C.1: First Panel of Table 3 with All Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_0	0.270*	0.925*	0.902*	0.824+				
	(0.064)	(0.110)	(0.118)	(0.476)				
β_1	0.144	0.233*	0.245*	0.246*	0.244*	0.241*	0.259*	
	(0.095)	(0.092)	(0.090)	(0.092)	(0.094)	(0.099)	(0.090)	
β_2	0.145	0.390*	0.401*	0.332+	0.313+	0.550*		
	(0.159)	(0.156)	(0.158)	(0.183)	(0.184)	(0.254)		
β_3	-0.475*	-0.564*	-0.582*	-0.578*	-0.574*	-0.567*	-0.596*	-0.565*
	(0.221)	(0.214)	(0.208)	(0.213)	(0.216)	(0.228)	(0.209)	(0.206)
Cov_1		-0.135*	-0.136*	-0.140*	-0.140*	-0.137*	-0.150*	-0.133*
		(0.017)	(0.017)	(0.018)	(0.018)	(0.021)	(0.021)	(0.025)
Cov_2		0.049*	0.050*	0.048*	0.048*	0.047*	0.054*	0.051*
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Cov_3			0.011	0.012	0.014	0.010	0.007	-0.012
			(0.021)	(0.022)	(0.022)	(0.024)	(0.027)	(0.030)
Cov_4			0.002	0.000	0.000	-0.009	-0.028	-0.033
			(0.021)	(0.020)	(0.021)	(0.024)	(0.026)	(0.027)
Cov_5			0.043	0.039	0.038	0.042	0.090+	0.095*
			(0.035)	(0.035)	(0.037)	(0.041)	(0.048)	(0.046)
Cov_6			0.010	0.006	0.005	0.004	0.028	0.020
			(0.020)	(0.020)	(0.021)	(0.021)	(0.027)	(0.026)
Cov_7			0.000	0.002	0.002	-0.004	-0.007	0.000
			(0.023)	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)
Fixed Effects (FE)								
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. See both the full and the rest of the Table in the next page.

Table C.1: First Panel of Table 3 with All Coefficients (CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cov_8			0.010	0.012	0.012	0.022	0.015	0.005
			(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)
Cov_9				-0.001	-0.002	0.005		
				(0.020)	(0.021)	(0.024)		
Cov_{10}				-0.256	-0.263	-0.212		
				(0.246)	(0.290)	(0.297)		
Cov_{11}				0.058	0.063	0.088		
				(0.040)	(0.051)	(0.060)		
Cov_{12}				0.026	0.033	0.053		
				(0.183)	(0.202)	(0.257)		
Cov_{13}				0.038	0.036	0.452		
				(0.288)	(0.335)	(0.380)		
Observations	256	256	256	256	256	256	256	256
Fixed Effects (FE)								
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcome was normalized to values between zero and one. City covariates are measured pre-treatment and become redundant with Municipality fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).
The covariates are: (1) total number of words in the two documents (log); (2) the absolute difference between them (log); binary variables that indicate whether (3) party 1 is Left-wing; (4) party 2 is Left-wing; (5) the incumbent mayor was a doctor; (6) the incumbent party was among the top 2 in the race; (7) one of the top 2 parties was PT or PSDB; and (8) the incumbent mayor was running for reelection (and top 2). Also, from the 2020 census at the city level: (9) population (log); (10) share of urban population; and (11) family income (2010). Finally, the pre-treatment shares of local budget invested in health (12) and education (13), from the FINBRA dataset.

Table C.2: Second Panel of Table 3 with All Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_0	0.087	0.517*	0.573*	1.091*				
	(0.068)	(0.120)	(0.110)	(0.413)				
β_1	0.153	0.210+	0.231+	0.238+	0.242+	0.249+	0.279*	
	(0.110)	(0.117)	(0.122)	(0.124)	(0.127)	(0.135)	(0.129)	
β_2	0.410*	0.555*	0.511*	0.560*	0.633*	0.475+		
	(0.179)	(0.179)	(0.181)	(0.205)	(0.200)	(0.259)		
β_3	-0.544*	-0.605*	-0.631*	-0.643*	-0.656*	-0.678*	-0.727*	-0.638*
	(0.269)	(0.282)	(0.295)	(0.297)	(0.302)	(0.321)	(0.311)	(0.314)
Cov_1		-0.074*	-0.085*	-0.091*	-0.090*	-0.092*	-0.095*	-0.049*
		(0.020)	(0.019)	(0.020)	(0.019)	(0.024)	(0.023)	(0.022)
Cov_2		0.020+	0.022*	0.023*	0.024*	0.024+	0.019	0.012
		(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.015)	(0.012)
Cov_3			0.053*	0.045+	0.037	0.038	0.025	-0.029
			(0.023)	(0.024)	(0.025)	(0.027)	(0.034)	(0.034)
Cov_4			0.026	0.021	0.022	0.016	0.020	0.006
			(0.026)	(0.027)	(0.027)	(0.029)	(0.033)	(0.034)
Cov_5			-0.057+	-0.047	-0.046	-0.040	-0.034	-0.018
			(0.030)	(0.034)	(0.035)	(0.040)	(0.045)	(0.046)
Cov_6			-0.018	-0.018	-0.017	-0.019	-0.026	-0.054+
			(0.026)	(0.026)	(0.027)	(0.029)	(0.032)	(0.029)
Cov_7			0.013	0.016	0.020	0.021	0.056+	0.032
			(0.023)	(0.023)	(0.024)	(0.029)	(0.033)	(0.031)
Fixed Effects (FE)								
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. See both the full and the rest of the Table in the next page.

Table C.2: Second Panel of Table 3 with All Coefficients (CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cov_8			0.032	0.030	0.028	0.033	0.025	0.045+
			(0.024)	(0.025)	(0.025)	(0.025)	(0.028)	(0.026)
Cov_9				0.003	0.008	0.008		
				(0.015)	(0.016)	(0.017)		
Cov_10				-0.168	-0.183	-0.235		
				(0.212)	(0.237)	(0.271)		
Cov_11				-0.028	-0.048	-0.041		
				(0.039)	(0.038)	(0.045)		
Cov_12				-0.240	-0.278	-0.520*		
				(0.191)	(0.179)	(0.246)		
Cov_13				-0.460	-0.473+	-0.533		
				(0.296)	(0.282)	(0.345)		
Observations	256	256	256	256	256	256	256	256
Fixed Effects (FE)								
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcome was normalized to values between zero and one. City covariates are measured pre-treatment and become redundant with Municipality fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).
The covariates are: (1) total number of words in the two documents (log); (2) the absolute difference between them (log); binary variables that indicate whether (3) party 1 is Left-wing; (4) party 2 is Left-wing; (5) the incumbent mayor was a doctor; (6) the incumbent party was among the top 2 in the race; (7) one of the top 2 parties was PT or PSDB; and (8) the incumbent mayor was running for reelection (and top 2). Also, from the 2020 census at the city level: (9) population (log); (10) share of urban population; and (11) family income (2010). Finally, the pre-treatment shares of local budget invested in health (12) and education (13), from the FINBRA dataset.

Table C.3: Regressions in Figure 9 with All Coefficients

	(1)	(2)	(3)	(4)	(5)
Intercept	0.251*	0.907*	0.817		
	(0.066)	(0.117)	(0.570)		
Leaning	0.189	0.404*	0.320+		
	(0.166)	(0.161)	(0.186)		
Covid	0.540	0.706*	0.689*	0.596+	1.638+
	(0.333)	(0.260)	(0.275)	(0.341)	(0.940)
Leaning x Covid	-1.569*	-1.675*	-1.647*	-1.532*	-4.875*
	(0.767)	(0.603)	(0.632)	(0.653)	(2.429)
Party 1 Left		0.012	0.013	-0.015	-0.014
		(0.021)	(0.022)	(0.030)	(0.034)
Party 2 Left		0.003	0.001	-0.034	-0.051
		(0.021)	(0.021)	(0.027)	(0.031)
Incumbent Doctor		0.044	0.037	0.090*	0.249
		(0.034)	(0.036)	(0.045)	(0.272)
Inc. Party Top 2		0.005	0.007	0.005	0.016
		(0.022)	(0.022)	(0.023)	(0.029)
PT/PSDB in the race		0.009	0.005	0.022	0.021
		(0.020)	(0.021)	(0.027)	(0.032)
Incumbent Top 2		0.006	0.008	0.003	0.003
		(0.023)	(0.023)	(0.024)	(0.028)
Total Words		-0.136*	-0.138*	-0.130*	-0.145*
		(0.017)	(0.018)	(0.025)	(0.028)
Word Difference		0.049*	0.047*	0.050*	0.048*
		(0.010)	(0.010)	(0.011)	(0.013)
Population			-0.001		
			(0.021)		
Urbanization			-0.245		
			(0.293)		
Region FEs	No	No	Yes	No	Yes
City & Year FEs	No	No	No	Yes	Yes
Interacted Covariates	No	No	No	No	Yes

+p<0.1, *p<0.05. See both the full and the rest of the Table in the next page.

Table C.3: Regressions in Figure 9 with All Coefficients (CONTINUED)

	(1)	(2)	(3)	(4)	(5)
Income			0.058		
			(0.052)		
Health Spending			0.031		
			(0.201)		
Education Spending			0.048		
			(0.338)		
Leaning x 2020 Election					-7.651
					(9.239)
Leaning x Incumbent Doctor					-0.511
					(0.702)
2020 Election x Region NE					0.186
					(0.321)
2020 Election x Region SE					0.494
					(0.484)
2020 Election x Region S					0.824
					(0.588)
2020 Election x Region CO					0.719
					(0.739)
2020 Election x Population					0.006
					(0.209)
2020 Election x Urbanization					-0.802
					(2.052)
2020 Election x Income					-0.532
					(0.560)
2020 Election x Health Spending					1.101
					(2.038)
2020 Election x Education Spending					-0.633
					(2.989)
2020 Election x Incumbent Doctor					0.124
					(0.437)
Region FEs	No	No	Yes	No	Yes
City & Year FEs	No	No	No	Yes	Yes
Interacted Covariates	No	No	No	No	Yes

+p<0.1, *p<0.05. See both the full and the rest of the Table in the next page.

Table C.3: Regressions in Figure 9 with All Coefficients (CONTINUED)

	(1)	(2)	(3)	(4)	(5)
Leaning x 2020 Elec x Region NE					-0.742
					(0.712)
Leaning x 2020 Elec x Region SE					-1.708
					(1.063)
Leaning x 2020 Elec x Region S					-2.573+
					(1.351)
Leaning x 2020 Elec x Region CO					-1.898
					(1.609)
Leaning x 2020 Elec x Population					-0.122
					(0.481)
Leaning x 2020 Elec x Urbanization					2.951
					(4.860)
Leaning x 2020 Elec x Income					1.501
					(1.321)
Leaning x 2020 Elec x Health Spending					-4.330
					(5.148)
Leaning x 2020 Elec x Education Spending					0.814
					(7.060)
Leaning x 2020 Elec x Incumbent Doctor					-0.179
					(1.161)
Region FEs	No	No	Yes	No	Yes
City & Year FEs	No	No	No	Yes	Yes
Interacted Covariates	No	No	No	No	Yes

+p<0.1, *p<0.05. The outcome was normalized to values between zero and one. City covariates are measured pre-treatment and become redundant with Municipality fixed-effects.

Table C.4: Polarization of Campaigns During the Pandemic (10 Categories)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Polarization based on 2 Policy Words, 10 CATEGORIES								
β_1	0.097	0.189+	0.198+	0.198+	0.197+	0.193+	0.202+	
	(0.109)	(0.108)	(0.106)	(0.109)	(0.110)	(0.112)	(0.105)	
β_2	0.156	0.393*	0.413*	0.368*	0.406*	0.759*		
	(0.168)	(0.156)	(0.159)	(0.160)	(0.162)	(0.264)		
β_3	-0.393	-0.491+	-0.505*	-0.501*	-0.500*	-0.491+	-0.498*	-0.474+
	(0.253)	(0.252)	(0.247)	(0.254)	(0.255)	(0.261)	(0.248)	(0.242)
$\beta_2 + \beta_3$	-0.237	-0.099	-0.093	-0.133	-0.094	0.268		
	(0.218)	(0.206)	(0.198)	(0.214)	(0.216)	(0.286)		
OUTCOME: Polarization based on 3 Policy Words, 10 CATEGORIES								
β_1	0.085	0.158	0.165+	0.167+	0.167+	0.167+	0.189*	
	(0.097)	(0.098)	(0.097)	(0.099)	(0.100)	(0.101)	(0.096)	
β_2	0.120	0.309*	0.331*	0.310*	0.325*	0.616*		
	(0.136)	(0.133)	(0.136)	(0.143)	(0.141)	(0.229)		
β_3	-0.361	-0.441+	-0.448*	-0.450*	-0.451*	-0.450+	-0.495*	-0.476*
	(0.225)	(0.226)	(0.222)	(0.227)	(0.227)	(0.232)	(0.221)	(0.217)
$\beta_2 + \beta_3$	-0.241	-0.131	-0.117	-0.140	-0.126	0.165		
	(0.197)	(0.183)	(0.178)	(0.186)	(0.188)	(0.234)		
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Doc. Size	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects). Words: CULTURE: Cultura (*culture*), Cultura (*cultural*), Arte (*art*); SPORTS: Esporte (*sport*), Lazer (*leisure*), Esportivo (*sporty*); BUSINESS: Empresa (*Company*), Trabalho (*labor*), Renda (*income*); HOUSING: Habitação (*habitation*), Habitacional (*habitational*), Moradia (*dwelling*).

Table C.5: Polarization of Mayoral Campaigns During the Pandemic (Health)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Platform Polarization with Pandemic-Related Words								
β_1	0.203*	0.289*	0.301*	0.300*	0.300*	0.295*	0.310*	
	(0.087)	(0.089)	(0.088)	(0.089)	(0.091)	(0.096)	(0.086)	
β_2	0.224	0.460*	0.470*	0.422*	0.398*	0.580*		
	(0.157)	(0.156)	(0.154)	(0.184)	(0.183)	(0.246)		
β_3	-0.663*	-0.750*	-0.764*	-0.760*	-0.759*	-0.747*	-0.772*	-0.746*
	(0.204)	(0.212)	(0.206)	(0.210)	(0.213)	(0.226)	(0.206)	(0.205)
$\beta_2 + \beta_3$	-0.439*	-0.289*	-0.294*	-0.338*	-0.361*	-0.168		
	(0.152)	(0.143)	(0.138)	(0.163)	(0.163)	(0.247)		
OUTCOME: Platform Polarization without Health-Related Words								
β_1	0.143	0.226*	0.247*	0.249*	0.247*	0.240*	0.262*	
	(0.113)	(0.111)	(0.108)	(0.110)	(0.111)	(0.117)	(0.107)	
β_2	0.036	0.264+	0.299*	0.238	0.211	0.363		
	(0.147)	(0.143)	(0.142)	(0.158)	(0.160)	(0.240)		
β_3	-0.437+	-0.513*	-0.549*	-0.549*	-0.542*	-0.524+	-0.547*	-0.535*
	(0.262)	(0.261)	(0.250)	(0.255)	(0.257)	(0.272)	(0.248)	(0.246)
$\beta_2 + \beta_3$	-0.401+	-0.249	-0.250	-0.311	-0.331	-0.161		
	(0.215)	(0.199)	(0.184)	(0.202)	(0.212)	(0.264)		
Observations	256	256	256	256	256	256	256	256
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.6: Polarization based on Policy Words (Robustness I)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Polarization based on 3 Words per Category								
β_1	0.156	0.247*	0.261*	0.259*	0.259*	0.266*	0.301*	
	(0.102)	(0.100)	(0.103)	(0.104)	(0.106)	(0.112)	(0.102)	
β_2	0.116	0.370*	0.374*	0.342+	0.292	0.534*		
	(0.163)	(0.161)	(0.167)	(0.191)	(0.190)	(0.248)		
β_3	-0.538*	-0.630*	-0.645*	-0.641*	-0.642*	-0.648*	-0.737*	-0.708*
	(0.237)	(0.233)	(0.234)	(0.236)	(0.239)	(0.253)	(0.233)	(0.230)
$\beta_2 + \beta_3$	-0.421+	-0.260	-0.271	-0.299	-0.350	-0.114		
	(0.217)	(0.197)	(0.195)	(0.215)	(0.215)	(0.296)		
OUTCOME: Polarization based on 4 Words per Category								
β_1	0.198+	0.290*	0.304*	0.303*	0.301*	0.315*	0.369*	
	(0.108)	(0.105)	(0.110)	(0.111)	(0.113)	(0.117)	(0.105)	
β_2	0.115	0.369*	0.380*	0.345+	0.300	0.469+		
	(0.168)	(0.169)	(0.175)	(0.196)	(0.196)	(0.270)		
β_3	-0.695*	-0.787*	-0.805*	-0.804*	-0.800*	-0.821*	-0.945*	-0.919*
	(0.249)	(0.247)	(0.254)	(0.255)	(0.259)	(0.268)	(0.243)	(0.242)
$\beta_2 + \beta_3$	-0.580*	-0.419*	-0.425*	-0.459*	-0.500*	-0.353		
	(0.198)	(0.187)	(0.186)	(0.202)	(0.202)	(0.295)		
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.7: Polarization based on Policy Words (Robustness II)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Polarization based on Policy Words Among the 200 Most Frequent								
β_1	0.158	0.253*	0.262*	0.259*	0.261*	0.271*	0.301*	
	(0.116)	(0.113)	(0.117)	(0.118)	(0.119)	(0.126)	(0.111)	
β_2	0.064	0.328+	0.340+	0.242	0.208	0.374		
	(0.170)	(0.169)	(0.178)	(0.199)	(0.203)	(0.277)		
β_3	-0.533*	-0.628*	-0.639*	-0.633*	-0.635*	-0.644*	-0.729*	-0.704*
	(0.269)	(0.266)	(0.269)	(0.270)	(0.274)	(0.290)	(0.256)	(0.252)
$\beta_2 + \beta_3$	-0.468+	-0.300	-0.299	-0.391	-0.427+	-0.270		
	(0.239)	(0.225)	(0.216)	(0.238)	(0.236)	(0.339)		
OUTCOME: Polarization based on Policy Words Among the 300 Most Frequent								
β_1	0.205	0.306*	0.326*	0.325*	0.321*	0.340*	0.395*	
	(0.127)	(0.122)	(0.127)	(0.128)	(0.130)	(0.137)	(0.123)	
β_2	0.026	0.308+	0.316	0.175	0.130	0.298		
	(0.181)	(0.186)	(0.195)	(0.205)	(0.210)	(0.312)		
β_3	-0.697*	-0.800*	-0.824*	-0.822*	-0.813*	-0.837*	-0.982*	-0.957*
	(0.298)	(0.288)	(0.293)	(0.295)	(0.299)	(0.315)	(0.284)	(0.282)
$\beta_2 + \beta_3$	-0.671*	-0.491+	-0.508+	-0.647*	-0.683*	-0.540		
	(0.282)	(0.265)	(0.260)	(0.279)	(0.285)	(0.393)		
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.8: Polarization based on Wordscores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Polarization based on Wordscores, based on all large parties								
β_1	0.133	0.179+	0.238*	0.242*	0.245*	0.250*	0.266*	
	(0.085)	(0.095)	(0.093)	(0.094)	(0.095)	(0.106)	(0.103)	
β_2	0.398*	0.522*	0.458*	0.476*	0.530*	0.444*		
	(0.158)	(0.162)	(0.152)	(0.171)	(0.165)	(0.223)		
β_3	-0.471*	-0.522*	-0.598*	-0.607*	-0.618*	-0.638*	-0.679*	-0.619*
	(0.218)	(0.238)	(0.232)	(0.234)	(0.237)	(0.262)	(0.257)	(0.256)
$\beta_2 + \beta_3$	-0.072	0.000	-0.140	-0.130	-0.087	-0.194		
	(0.172)	(0.189)	(0.184)	(0.210)	(0.209)	(0.267)		
OUTCOME: Polarization based on Wordscores, based on ALL parties								
β_1	0.116	0.160+	0.224*	0.229*	0.233*	0.239*	0.254*	
	(0.082)	(0.092)	(0.089)	(0.089)	(0.091)	(0.101)	(0.097)	
β_2	0.407*	0.524*	0.462*	0.493*	0.544*	0.484*		
	(0.155)	(0.159)	(0.148)	(0.167)	(0.162)	(0.220)		
β_3	-0.437*	-0.486*	-0.570*	-0.580*	-0.593*	-0.612*	-0.652*	-0.592*
	(0.210)	(0.228)	(0.221)	(0.222)	(0.225)	(0.248)	(0.243)	(0.243)
$\beta_2 + \beta_3$	-0.031	0.038	-0.107	-0.087	-0.049	-0.128		
	(0.173)	(0.189)	(0.183)	(0.206)	(0.204)	(0.263)		
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.9: Polarization based on the Seeded LDA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Polarization based on the SLDA, with 2 seeds per category[a]								
β_1	0.243*	0.267*	0.307*	0.310*	0.315*	0.317*	0.291*	
	(0.113)	(0.118)	(0.119)	(0.119)	(0.122)	(0.128)	(0.128)	
β_2	0.384*	0.456*	0.462*	0.276	0.366+	0.238		
	(0.170)	(0.178)	(0.190)	(0.194)	(0.207)	(0.237)		
β_3	-0.586*	-0.614*	-0.676*	-0.683*	-0.695*	-0.696*	-0.681*	-0.665*
	(0.284)	(0.291)	(0.292)	(0.294)	(0.299)	(0.315)	(0.307)	(0.309)
$\beta_2 + \beta_3$	-0.202	-0.158	-0.214	-0.408	-0.330	-0.458		
	(0.221)	(0.228)	(0.232)	(0.260)	(0.261)	(0.281)		
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).
[a] For Sanitation and the Environment, we also included the word sanitation as a seed, as it directly refers to the name of the category.

Table C.10: Polarization of Mayoral Campaigns During the Pandemic (with Right-Shift)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Platform Polarization based on Policy Words								
β_1	0.146	0.256*	0.253*	0.231*	0.231*	0.278*	0.280*	
	(0.112)	(0.109)	(0.103)	(0.107)	(0.110)	(0.114)	(0.103)	
β_2	0.145	0.391*	0.401*	0.330+	0.314+	0.558*		
	(0.159)	(0.157)	(0.159)	(0.184)	(0.183)	(0.254)		
β_3	-0.479*	-0.599*	-0.593*	-0.556*	-0.554*	-0.624*	-0.629*	-0.599*
	(0.241)	(0.237)	(0.224)	(0.234)	(0.238)	(0.247)	(0.226)	(0.222)
$\beta_2 + \beta_3$	-0.333+	-0.209	-0.192	-0.225	-0.240	-0.066		
	(0.202)	(0.184)	(0.172)	(0.196)	(0.199)	(0.282)		
OUTCOME: Platform Polarization based on Wordscores								
β_1	0.142	0.215+	0.232+	0.237+	0.232+	0.216	0.241+	
	(0.114)	(0.123)	(0.130)	(0.131)	(0.134)	(0.145)	(0.136)	
β_2	0.410*	0.555*	0.511*	0.560*	0.634*	0.468+		
	(0.179)	(0.180)	(0.181)	(0.205)	(0.201)	(0.259)		
β_3	-0.527+	-0.614*	-0.633*	-0.641*	-0.640*	-0.627+	-0.667*	-0.578+
	(0.271)	(0.288)	(0.303)	(0.304)	(0.310)	(0.332)	(0.316)	(0.311)
$\beta_2 + \beta_3$	-0.117	-0.059	-0.121	-0.081	-0.006	-0.159		
	(0.210)	(0.231)	(0.247)	(0.268)	(0.282)	(0.331)		
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come from the regression in equation (11). The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.11: Polarization of Mayoral Campaigns Before the Pandemic (Pre-trends)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OUTCOME: Platform Polarization based on Policy Words							
β_1	-0.075	-0.003	-0.018	-0.018	-0.018	0.018	
	(0.125)	(0.110)	(0.112)	(0.117)	(0.119)	(0.134)	
β_2	0.164	0.429*	0.450*	0.395	0.395		
	(0.237)	(0.204)	(0.205)	(0.252)	(0.257)		
β_3	-0.062	-0.141	-0.129	-0.124	-0.130	-0.222	-0.130
	(0.336)	(0.296)	(0.299)	(0.309)	(0.313)	(0.344)	(0.291)
$\beta_2 + \beta_3$	0.102	0.289	0.321	0.271	0.265		
	(0.223)	(0.223)	(0.231)	(0.263)	(0.265)		
OUTCOME: Platform Polarization based on Wordscores							
β_1	-0.069	-0.022	-0.040	-0.030	-0.026	-0.006	
	(0.122)	(0.123)	(0.119)	(0.118)	(0.114)	(0.117)	
β_2	0.496	0.666*	0.659*	0.830*	0.990*		
	(0.308)	(0.311)	(0.313)	(0.340)	(0.327)		
β_3	-0.199	-0.261	-0.253	-0.276	-0.304	-0.377	-0.410
	(0.337)	(0.335)	(0.325)	(0.325)	(0.318)	(0.324)	(0.292)
$\beta_2 + \beta_3$	0.297+	0.405*	0.406*	0.554*	0.686*		
	(0.173)	(0.165)	(0.170)	(0.199)	(0.188)		
Observations	168	168	168	168	168	168	168
Covariates and Fixed Effects (FE)							
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-
Region FE	No	No	No	No	Yes	-	-
State FE	No	No	No	No	Yes	Yes	-
City FE	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The data only includes 2012 and 2016. The treatment dummy assumes the value of one in 2016. The coefficients come equation 11. The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.12: Polarization of Mayoral Campaigns When the Incumbent Runs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SAMPLE: Incumbent Mayor is NOT Top 2 in the Reelection Race								
β_1	0.260+	0.302*	0.348*	0.311*	0.317*	0.246+	0.184	
	(0.139)	(0.126)	(0.125)	(0.122)	(0.126)	(0.144)	(0.158)	
β_2	0.116	0.380*	0.457*	0.294	0.275	0.528		
	(0.185)	(0.191)	(0.186)	(0.224)	(0.219)	(0.332)		
β_3	-0.778*	-0.736*	-0.831*	-0.729*	-0.753*	-0.568+	-0.503	-0.538
	(0.334)	(0.308)	(0.298)	(0.298)	(0.306)	(0.343)	(0.331)	(0.337)
$\beta_2 + \beta_3$	-0.662*	-0.356	-0.373	-0.435+	-0.478+	-0.040		
	(0.295)	(0.263)	(0.255)	(0.243)	(0.252)	(0.464)		
Observations	141	141	141	141	141	141	141	141
SAMPLE: Incumbent Mayor IS Top 2 in the Reelection Race								
β_1	0.081	0.188	0.191	0.147	0.156	0.116	0.148	
	(0.149)	(0.121)	(0.125)	(0.143)	(0.148)	(0.179)	(0.202)	
β_2	0.196	0.403	0.383	0.389	0.358	0.433		
	(0.299)	(0.262)	(0.260)	(0.316)	(0.326)	(0.456)		
β_3	-0.302	-0.458	-0.456	-0.363	-0.400	-0.325	-0.394	-0.384
	(0.363)	(0.303)	(0.307)	(0.344)	(0.357)	(0.430)	(0.528)	(0.518)
$\beta_2 + \beta_3$	-0.106	-0.054	-0.073	0.026	-0.042	0.108		
	(0.246)	(0.231)	(0.251)	(0.285)	(0.300)	(0.375)		
Observations	115	115	115	115	115	115	115	115
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The coefficients come equation 11. The outcome (polarization based on policy words) was normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.13: Polarization based on an Alternative Leaning Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME: Platform Polarization based on Policy Words								
β_1	0.088	0.106	0.110	0.119	0.118	0.111	0.102	
	(0.129)	(0.109)	(0.110)	(0.113)	(0.113)	(0.116)	(0.111)	
β_2	0.021	-0.044	-0.014	-0.004	-0.016	0.056		
	(0.152)	(0.143)	(0.150)	(0.151)	(0.156)	(0.192)		
β_3	-0.327	-0.244	-0.243	-0.259	-0.257	-0.240	-0.200	-0.225
	(0.319)	(0.272)	(0.274)	(0.282)	(0.283)	(0.289)	(0.278)	(0.277)
$\beta_2 + \beta_3$	-0.305	-0.287	-0.257	-0.263	-0.273	-0.184		
	(0.270)	(0.218)	(0.216)	(0.225)	(0.224)	(0.221)		
OUTCOME: Polarization based on Wordscores								
β_1	0.171	0.185	0.212+	0.214+	0.216+	0.204	0.181	
	(0.121)	(0.125)	(0.127)	(0.128)	(0.131)	(0.135)	(0.127)	
β_2	0.044	0.012	0.143	0.139	0.157	0.213		
	(0.164)	(0.169)	(0.178)	(0.176)	(0.175)	(0.195)		
β_3	-0.584*	-0.551+	-0.591+	-0.591+	-0.600+	-0.570+	-0.486	-0.552+
	(0.293)	(0.302)	(0.307)	(0.310)	(0.317)	(0.328)	(0.311)	(0.303)
$\beta_2 + \beta_3$	-0.540*	-0.539*	-0.449+	-0.452*	-0.442+	-0.357		
	(0.235)	(0.231)	(0.232)	(0.230)	(0.254)	(0.267)		
Observations	256	256	256	256	256	256	256	256
Covariates and Fixed Effects (FE)								
Documents	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election	No	No	Yes	Yes	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes	-	-
Region FE	No	No	No	No	Yes	-	-	-
State FE	No	No	No	No	Yes	Yes	-	-
City FE	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	Yes

+p<0.1, *p<0.05. The leaning measure is the city-level ideology index from (Power and Rodrigues-Silveira, 2019), calculated as the median value of the index based on the congressional vote in 1994-2010. The coefficients come equation 11. The outcomes were normalized to values between zero and one. All covariates are described in footnote 25. City covariates are measured pre-treatment and become redundant with City fixed-effects. The same happens to β_2 and β_1 (year fixed-effects).

Table C.14: The Salience of COVID-19 in 2020 Local Campaigns

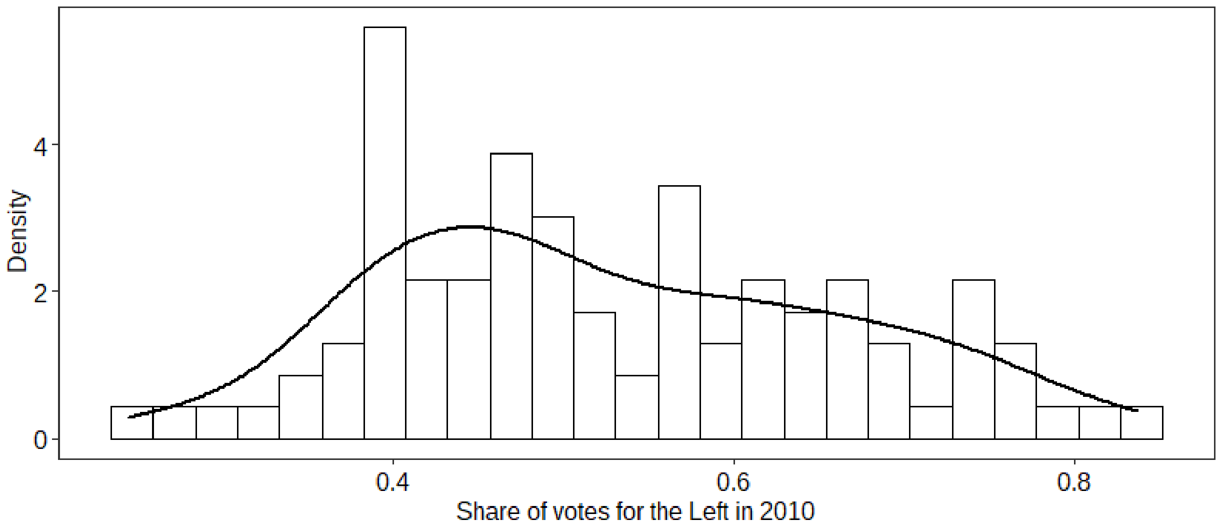
	Medical Doctors		Religious Workers	
Dep. Variable: Occupational Heuristic	(A1)	(A2)	(B1)	(B2)
Dummy 2016 (A)	0.038	0.034	-0.020	-0.059
	(0.024)	(0.032)	(0.045)	(0.068)
Dummy 2020 (B)	0.071*	0.038	-0.099+	-0.120
	(0.024)	(0.037)	(0.056)	(0.080)
Dummy 2016 x High Covid (C)		0.008		0.075
		(0.047)		(0.088)
Dummy 2020 x High Covid (D)		0.066		0.037
		(0.046)		(0.113)
A+C		0.042		0.017
		(0.035)		(0.057)
B+D		0.104*		-0.083
		(0.028)		(0.081)
Observations	1633	1633	565	565

+p<0.1, *p<0.05. The coefficients come from the estimation of the equations described in the notes of Figure 5 in the main text. The dependent variable is a dummy that indicates whether or not each candidate is using the occupational heuristic in the ballot-box name, as defined in the main text. All regressions include fixed-effects by municipality. In Figure 5, all these coefficients were normalized by their standard errors, which are clustered by municipality.

D FIGURES

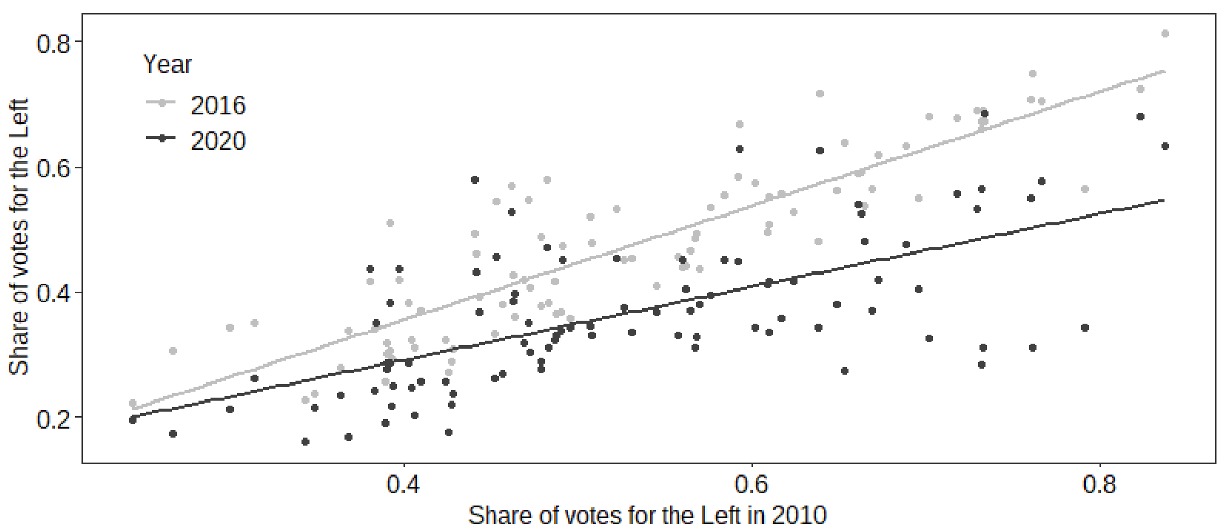
Figure D.1: The Presidential Left-wing Vote in Brazil

The Distribution of the Left-wing Vote in the 2010 Presidential Race



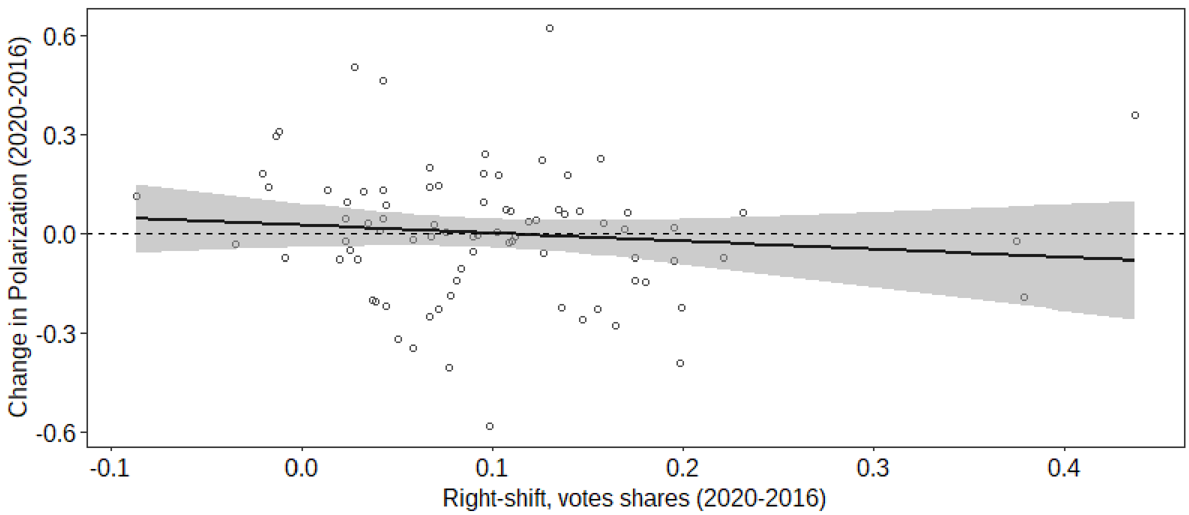
The y-axis shows the density of the variable. The share of votes is calculated based on the PT vote in the second round of the 2010 election.

The Left-wing Presidential Vote is Stable Over Time Across Cities



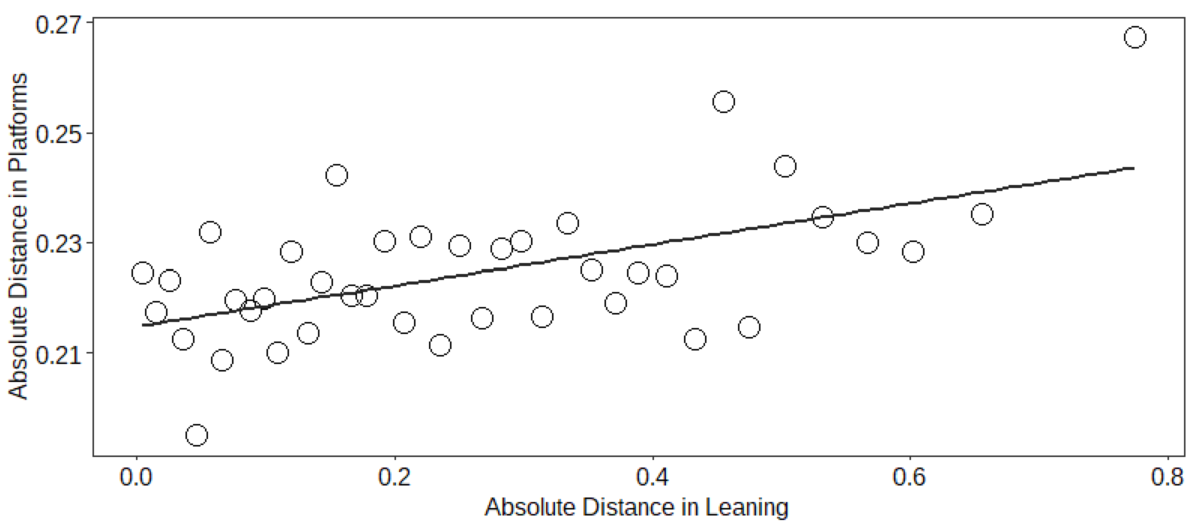
The y-axis shows Left-wing vote in the 2014 and 2018 Presidential races. The x-axis shows the same variable for the 2010 race.

Figure D.2: The Right-shift in the Presidential Vote and Polarization Shifts



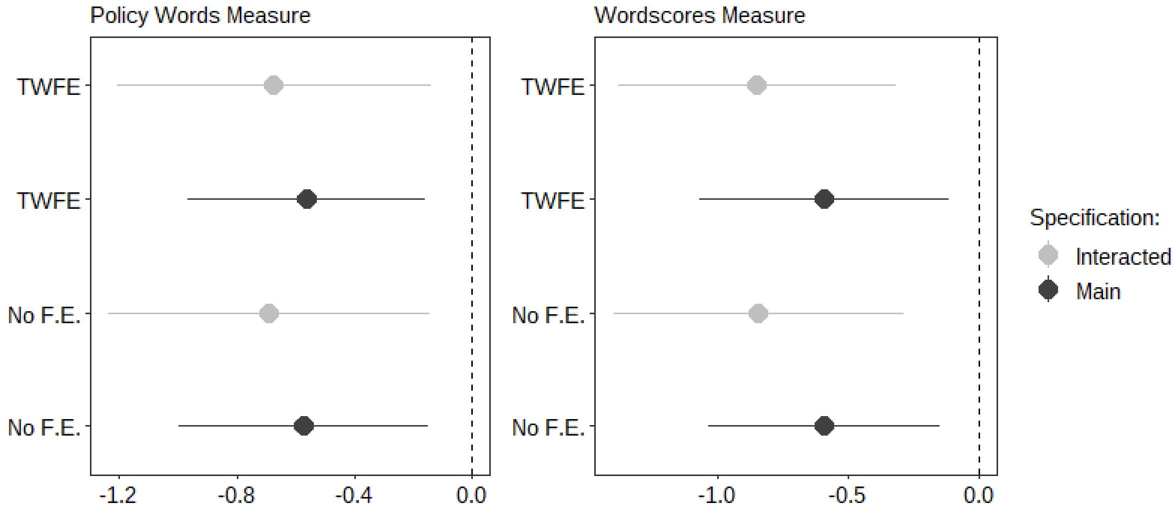
The y-axis shows the change in polarization between 2016-2020, according to the main measure described in the text. The x-axis shows the change in the Right-wing vote between the 2014 and 2018 Presidential races. The p-value of the slope is 0.6.

Figure D.3: Leaning is Correlated with the Average Campaign Platform across Cities



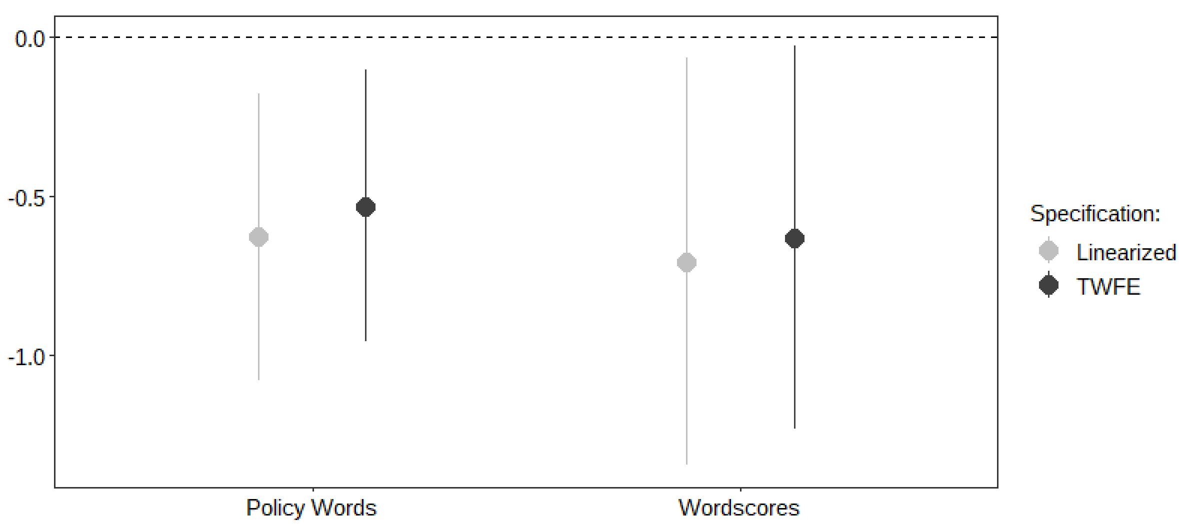
For the top candidates in each city in 2012, we estimate the average shares of policy words for each category, as a proxy for what voters prefer in that city. Then, for every pair of cities in our sample (the plot is based on a total 3,320 pairs in 2012), we compute the absolute distance in both leaning (x-axis) and the average proposal (y-axis) across cities. The line shows the linear fit, and the dots show the average value of the average proposal distance for observations aggregated in 40 bins along the x-axis.

Figure D.4: Treatment Effects after Interaction with Covariates



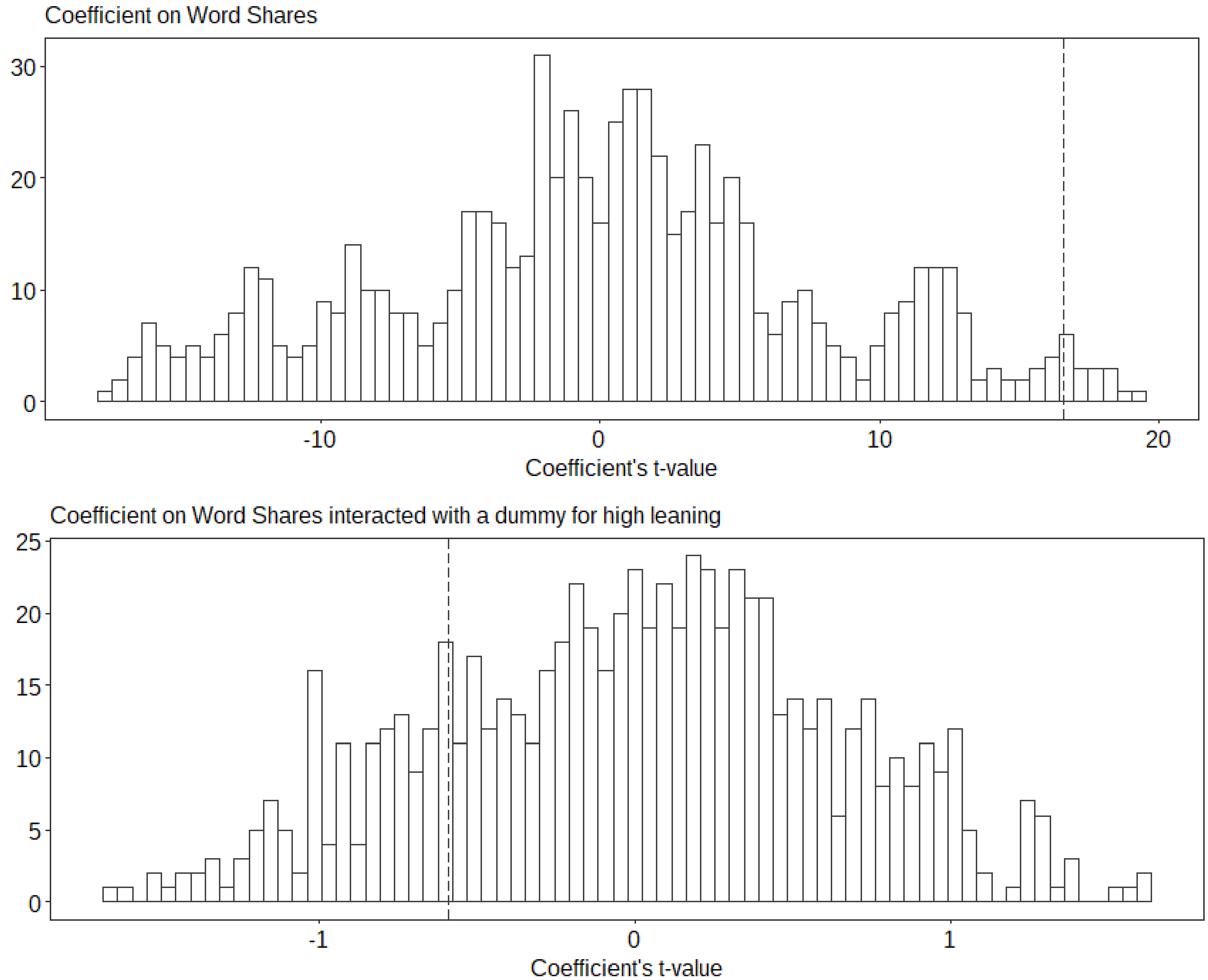
The bars show the 95% CIs. **Main** corresponds to β_3 in columns 5 (No F.E.) and 8 (TWFE) of Table 3. The **Interacted** specification corresponds to the same regressions, but with all election and city covariates (including region dummies) interacted with the treatment dummy (tre_t).

Figure D.5: Treatment Effects after Adjusting for the TWFE Weighting Issues



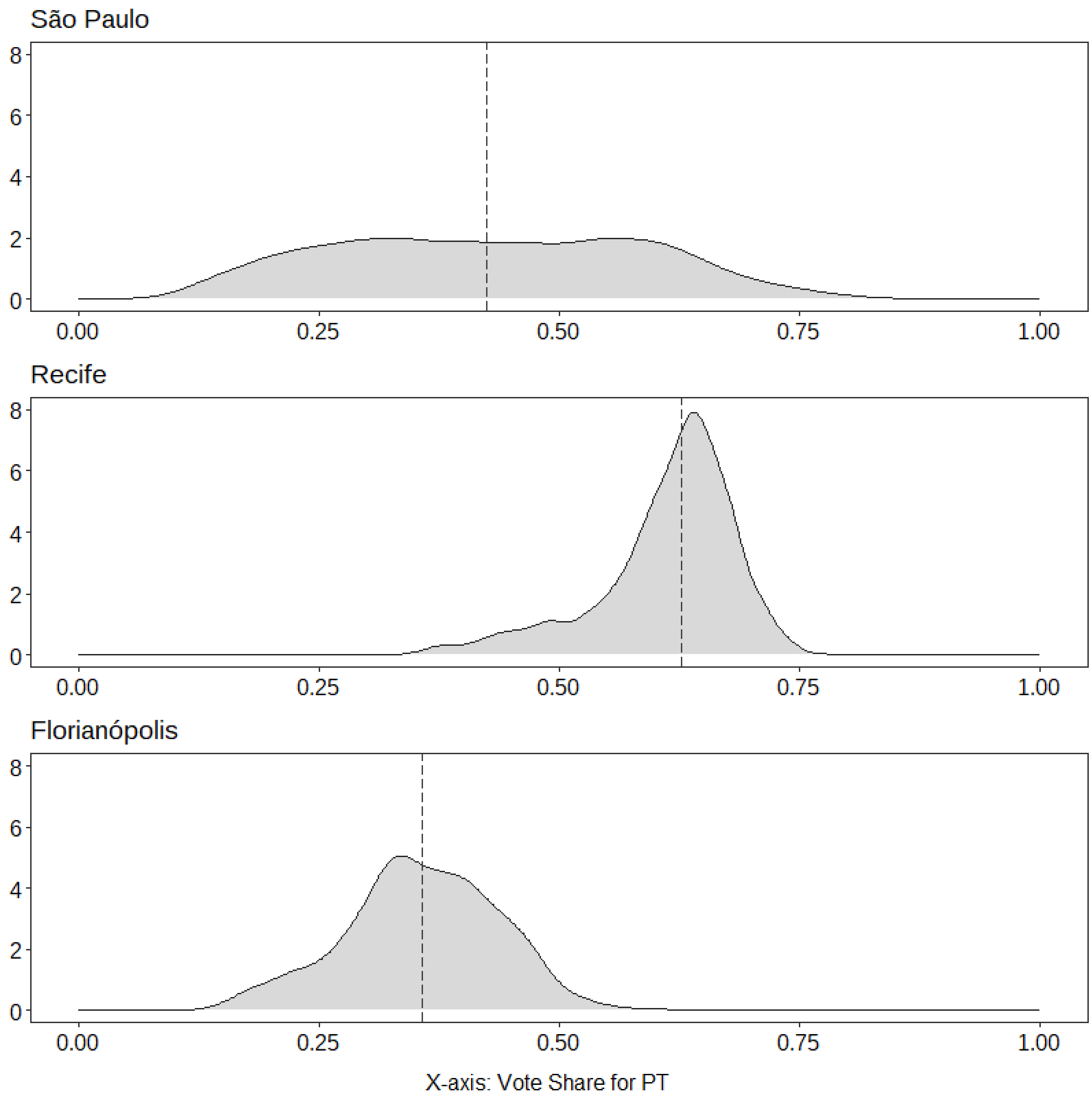
The bars show the 95% CIs. We follow Callaway, Goodman-Bacon, and SantAnna (2024, pg. 18) and use linearity of realized outcomes to estimate a coefficient that recovers an average causal response. We estimate: $\Delta Y_j = \alpha + \gamma \cdot lng_j$, where ΔY is the change in polarization for city j between 2020 and the pre-treatment period, and γ is the average causal response parameter (under the stronger parallel trends assumption in the article). The **Linearized** dots show our estimates of γ.

Figure D.6: Falsification Test of the Correlation between Spending and Proposals



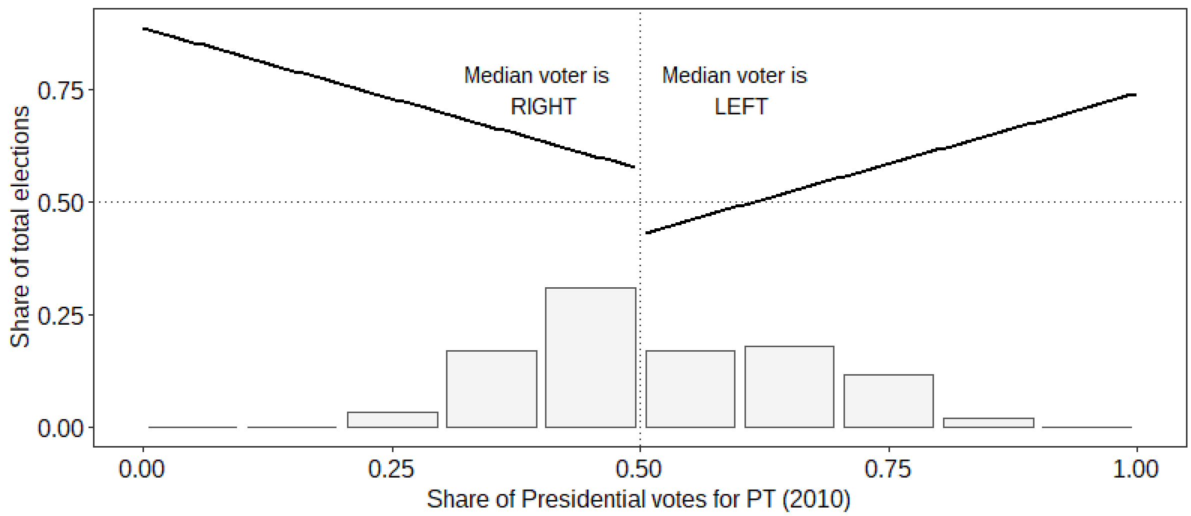
Here we compare the proposals of mayors elected in 2016 to their spending in 2017-2020, based on the categories in Table 2. We first regress the spending share of each category on the word share dedicated to that group, and find that the correlation between proposals and spending is positive (t-value of 19, shown in the vertical line). The level of observations is mayor-category. We then create a placebo distribution where, for each city, we assign the word share of each category to a different label. For example, health words are counted under education. With 6 categories, there is a total of 720 possible permutations, only one of which reflects the correct match. We then estimate the same correlation for our 719 falsified samples, and show the distribution of the t-values in the plot. The second plot shows the distribution of the t-values for the interaction between the coefficient above and a dummy for centrism (leaning above median).

Figure D.7: Density of PT's Vote Share in 2010, at the Ballot Box Level



These are density plots, where the level of observation is the ballot box in each location. The x-axis shows the vote share of PT in the 2010 presidential election, for the selected state capital.

Figure D.8: Presidential Elections are a Good Predictor of Mayoral Election Outcomes



The columns show the distribution of the sample along the x-axis. For every city, the x-variable is L_j as defined in the text. The y-variable is a dummy that assumes one when Right-wing (Left-wing) parties had more than 50% of the vote, for all $L_j < 0.5$ ($L_j > 0.5$). The lines show the predicted values of the y-variable based on a regression where the dependent variable assumes one when Right-wing parties had more than 50% of the vote, and zero otherwise, and the regressor is L_j. We also control for the 2010 household income, the party of the mayor elected in 2008, and election fixed effects. The analysis includes all 95 cities in our sample.

This Figure shows that the voting data in national elections is, in fact, a good predictor for the uncertainty about the median voter in municipal races. While the x-axis shows the percentage of votes for the PT in 2010 (L_j), the y-axis has a measure of the median voter position in the mayoral races of 2012, 2016, and 2020. More precisely, the line on the left-side of the plot ($L_j < 50\%$) shows the expected share of mayoral races where Right-wing parties have more than 50% of the vote. In the same way, the right-side ($L_j > 50\%$) shows the expected share of races where the Left captures the median voter. Overall, in places where leaning is more extreme—e.g., L_j is very low or very high—the median voter for mayor is also more likely to be extreme. On the other hand, where L_j is close to 0.5, the outcome of mayoral races was much less predictable in 2012-2020—in this dimension—than in the more extreme ones. This result is important as it directly connects to the role of district leaning in our theoretical model.