Do Elections Moderate or Polarize Political Rhetoric?

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Introduction

Two views of elections

1. Moderating effect
   - Incentive to converge towards median or Swing voters
2. Polarizing effect
   - Incentive to diverge, to mobilize core voters (Glaeser et al., 2005)

Not much evidence on which view is more accurate

We study communication strategies of political **leaders** on Twitter

- Does their political rhetoric become more or less polarized before elections?

Polarization between whom?

Mostly focus on *populist* vs *mainstream* politicians

- This competition has become dominant in many countries:
  - CDU vs AfD in Germany
  - ÖVP vs FPÖ in Austria
  - Macron vs Le Pen in France
  - Podemos, Vox, CUP vs Psoe, PP and C's in Spain
- Populist platforms very similar across countries, perhaps more so than for other political groups

Mainly studied on *demand* side (why vote for populist parties)
We focus on *supply* side, contrasting communication strategies of populist vs non-populist politicians (as well as L/R) in several countries

- **Convergence or divergence as election approaches?**

Also study other measures of rhetorical polarization, not based on populist / non-populist distinction

Independently of turnout

- Key issue is targeting
- Even when the relevant margin is turnout, incentives to polarization are related to who hears the message
- Fundamental not to mobilize voters for the opponents
- When turnout is not relevant what matters is targeting different audiences

Why Twitter

- More followed than speeches or party manifestos used in previous studies
- High frequency data
- More freedom of expression than traditional media
- Free platform for challengers
- Easier to target specific audiences
- Until 2023 Twitter analytics allowed to obtain breakdowns of followers by key characteristics

What we do

Data: almost 4 million Tweets of about 400 political leaders in 21 countries between 2013-2022

- 15 EU plus Australia, Brazil, Mexico, Norway, UK, US
- Study *bigrams* within tweets

Methodology: Estimate quarterly polarization

- Ease with which one can correctly identify politician's type, based on his words
  - Robust to *finite sample bias* and *trends in verbosity* Gentzkow et al. (2019)
- Political types: Populist (P) vs Non-Populist (NP), or other partitions (L vs R, IN vs OUT of govt.)
  - Also study polarization among all politicians in each country (agnostic about type)

Study patterns of polarization around elections

- Exploit staggered elections across countries

Preview of main results

Elections have a polarizing effect on political rhetoric:

- Polarization peaks around and before election dates
  - Particularly between P vs NP
  - More so in plurality & presidential elections

- Effect is present:
  - Within topics: same issues are framed differently
  - Between topics: P and NP speak about different issues

- Before election, P vs NP draw attention to different issues.

  Relative to opposite type:
  - P engage more in general propaganda (anti-establishment, direct appeal to voters)
  - NP speak more about policy issues

Related literature

- Gentzkow et al. (2019)
  - Develop a method to measure group differences in high-dimensional choices,
  - Study congressional speeches by session of Congress
- DiTella et al. (2023)
  - Study candidate manifestos, find convergence between first round (or primary) and final elections in France and US
- Zhang et al. (2025)
  - Show how politicians polarize policy-relevant public debates, no analysis of elections
- Large literature on populism and social media, but mostly on voters' side:
  - Guriev and Papaioannou (2022); Guriev et al. (2021); Manacorda et al. (2022)
  - On populist communication: Cassell (2020); Aslanidis (2018)

3 fold contribution

- Data
- Apply GST to different issue and extend their methodology to more than 2 parties
- Study rhetorical polarization around elections
- Supply-side contribution to literature on social media and populism. Elections are different!
- Opportunism vs. ideology in communication strategies of politicians

Outline

- Data
- Methodology
- Evidence on rhetorical polarization
  - General time patterns
  - Event studies around elections
  - Heterogeneity
  - Robustness
- Conclusions

Data on politicians: Populist vs Non-Populist

- All candidates for head of government (2001-2022)
- Leaders of main parties with vote shares $\geq 5\%$ in at least one election in 2010-22
  - Some leaders of parties $< 5\%$ (eg. Meloni)
- Classify politicians as P / NP (Funke et al. (2023), ChatGPT, human coding)
- Criteria:
  - People vs Elites
  - Anti-establishment
  - Emphasis on national sovereignty
  - Personalized communication and leadership style
- 29 (out of 367) unsure $=>$ classify as P if their party is populist
  - 13 ambiguous $=>$ classify as P and robustness check

Some Examples

	Populist	**Non-Populist**
Populist Party	Le Pen, Weidel Meloni	Romney, Bush May, Cameron
Non-Populist Party	Sanders, Kurz, Babiš	Macron, Obama Tusk, Renzi

NP tend to be incumbents, *P* challengers or niche parties. Limited overlap between P-NP leaders and P-NP parties. Higher linguistic complexity among NPs characteristics

Data on Politicians: Left vs Right

- Classify politicians as Left/Right based on ChatGPT
- 82 ambiguous cases (no switch though): used party affiliation and the 'RILE' index from the Manifesto project
- 64 leaders assigned to L and 24 to R in this way. Robustness with all L or all R.
- Similar characteristics – descriptives

Table: Sample Composition

	Populist	**Non Populist**
Left	0.11	0.59
Right	0.13	0.17

Data on Politicians II

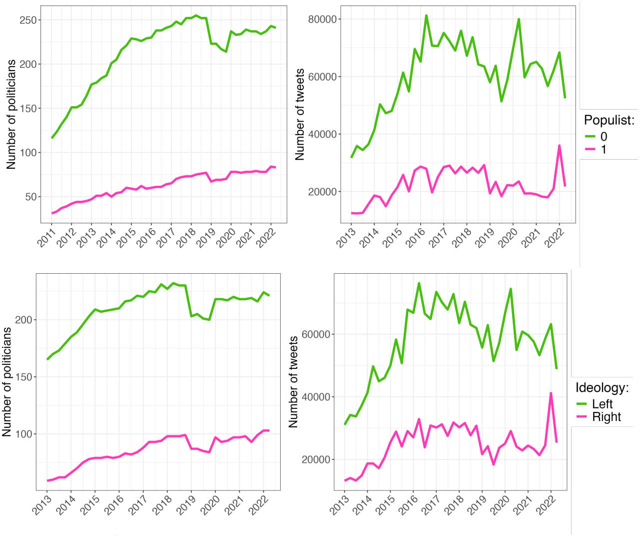


Figure: Number of politicians active on Twitter per calendar quarter, and number of tweets

International connections

- Variant of homophily index: connections (followers) among politicians. Weighted and unweighted by of politicans in each node

Table: Cross-Country Coleman Index by Politician Type, 2013-22 average

	Populist	Non-populist	Difference	P-value
H_i^{cross} (mean)	-0.035	-1.187	1.152^{***}	0.000
H_i^{cross} (weighted mean)	0.016	-0.851	0.867^{***}	0.000

Data on Bigrams

- Tweets are translated in English, common words are removed
- Extract 40 mln bigrams from 4 mln tweets
- Restrict to ≈ 7000 most frequent bigrams, used in at least 10 quarters, and at least 25 times in at least 1 quarter (about 50 % of tweets)

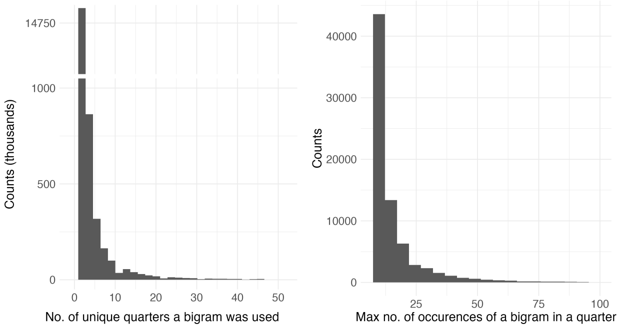


Figure: No. of unique quarters a bigram was used (left panel), Max no. of occurrences in a quarter (right panel).

Data on Topics

- Classification of tweets based on policy/non-policy content, and on most relevant topics (immigration and health)
- Non-policy includes political propaganda (anti-establishment, elections, self promotion, etc.)
- Used 2 human coders to agree on classification of 2200 tweets and BERT to classify the tweets in our sample in these topics
- Assign bigram to topic if it appears in tweets about that topic in at least 40% of cases
- 64% of bigrams assigned to at least one topic

Confusion matrix

Estimation with two political types - GST (2019)

- Utility of politician i from using bigram j in quarter t:

$$U_{ijt} = \alpha_{jt} + X_{it}\gamma_{jt} + Z_i\beta_{jt} + \phi_{jt}P_i \qquad (1)$$

  - $P_i = 1$ if i is populist, 0 otherwise
  - Z_i, X_{it} other features of i (country*quarter, gender, education, being in govt., being a candidate, age); **no strategic interactions between politicians allowed**
  - α_{jt} FE for popularity of bigram j in quarter t

- Probability that i uses bigram j in quarter t :

$$q_{ijt}^{P_i} = \frac{exp(U_{ijt})}{\sum_k exp(U_{ikt})}, \qquad P_i = 0, 1 \qquad (2)$$

- Estimate (1)-(2) by Poisson ML $=> \left\{\hat{q}_{ijt}^{P_i}\right\}$, $P_i = 0, 1$
  - Parametrize with observed verbosity of each politician
  - Penalize large $|\phi_{jt}|$ and other parameters to avoid **small sample bias**
    - Penalty on $|\phi_{jt}|$ minimizes Bayesian Information Criterion, penalty on other parameters set at 10^{-5} as in GST more

Partisanship between P and NP

Posterior that $P_i = 1$, conditional on bigram j (neutral prior 1/2):

$$\rho_{ijt} = \frac{\hat{q}^1_{ijt}}{\hat{q}^1_{ijt} + \hat{q}^0_{ijt}}$$

Partisanship of i averages ρ_{ijt} over all j and possible values of P_i

$$\pi_{it} = \frac{1}{2} \sum_j [\hat{q}^1_{ijt} \hat{\rho}_{ijt} + \hat{q}^0_{ijt}(1 - \hat{\rho}_{ijt})]$$

- Measures *average* predictability of i's *type* (P vs NP), given a single bigram
- Each i is either P or NP $=>$ π_{it} averages true type P_i and his "clone" $1 - P_i$, with neutral priors
  - If P and NP always use same bigrams, then $\pi_{it} = 1/2$
  - If they always use different bigrams, then $\pi_{it} = 1$
- $\hat{\pi}^k_{it}$ is partisanship of i within topic k in quarter t

Other measures of heterogeneity – multidimensional

Two political types:

- Replace (P vs NP) with (R vs L)

Four Political types:

- Two political dimensions: P vs NP *and* R vs L
- Utility of politician i from using bigram j in quarter t:

$$U_{ijt} = \alpha_{jt} + X_{it}\gamma_{jt} + Z_i\beta_{jt} + \phi_{1jt}P_i + \phi_{2jt}R_i$$

$R_i = 1$ if i is Right, 0 if Left

$=>$ Three measures of partisanship, defined as predictability:

- of granular type: (P, R) or (P, L) or (NP, R) or (NP, L)
- of P or NP
- of R or L

Other measures of heterogeneity - Chi-square

Agnostic on political types => estimate $\hat{q}_{ijt}$ imposing $\phi_{jt} = 0$. we use probabilities of word usage to deal with finite sample bias

How different is i from other politicians of same country c?

$$\chi^2_{ict} = \sum_j \frac{(\hat{q}_{ijt} - \hat{q}_{jt})^2}{\hat{q}_{jt}} \qquad \text{where } \hat{q}_{jt} = \frac{1}{n_c} \sum_{i \in c} \hat{q}_{ijt}.$$

Related to predictability of individual with features X_{it} within country c, conditional on a single bigram, with neutral prior $1/n_c$

$$\pi_{ict} = \frac{1}{n_c}[1 + \chi^2_{ict}]$$

- Partisanship measures predictability of *$i's$ type* (P vs NP) or *type* (L vs R) in entire sample
- χ^2_{ict} related to predictability of *individual with features X_{it}* within its country

Other measures of partisanship

- Average partisanship in quarter t : $\pi_t =$ Average π_{it} over all i
- Partisanship of i at quarterly distance d from national election, π_{id}
  - $\pi_d =$ Average π_{id} over i with same d
- Partisanship of i *within* topic k : computed for bigrams within topic k
  - Aggregated across topics weighted by topic frequency
- Partisanship of i *between* topics: estimated with topic (rather than bigrams) as unit of speech
- Distinctiveness of bigram j of P speech
  - By how much a neutral observer would change her posterior that $P_i = 1$ if j was removed from the vocabulary

And similarly for χ^2

Most distinctive P-NP bigrams

2015 Q3		*2020 Q1*	
Non-Populists	**Populists**	**Non-Populists**	**Populists**
climate change	live periscope	will continue	via youtube
the anniversary	asylum seeker	public health	work people
renewable energy	border control	the anniversary	fake news
will continue	good morning	every day	will also
Syrian refugee	press release	president Trump	many people
prime minister	dont miss	need help	hundred thousand
welcome refugees	must read	climate change	open border
nuclear deal	people want	social distancing	u live
young people	illegal immigrants	renewable energy	good morning
press conference	real change	now need	will fight
refuge crisis	leave EU	wash hand	border control
Iran nuclear	close border	economic impact	asylum seeker
year ago	Jeremy Corbyn	take action	together will
deal Iran	people country	good news	govern work
Greek crisis	enough enough	New York	close border

Quantifying average polarization I

- Partisanship in Tweets of P vs NP is larger and more volatile then in US Congressional speeches
  At the peak:
  - 1 bigram $\approx$ .54
  - GST: 5 1 bigram $\approx$ .51
- P vs NP partisanship and χ^2_t move together over time
  - Corr $(\pi_t \ , \chi^2_t) = 0{,}84$. But Corr $(\pi_{it} \ , \chi^2_{ict}) = 0{,}11$.

Average quarterly partisanship

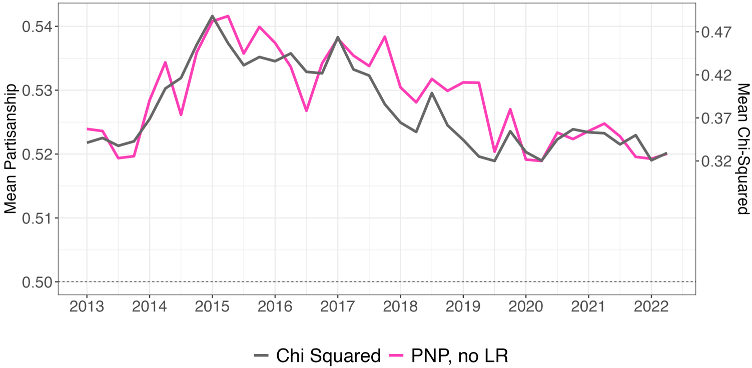


Figure: Average partisanship and χ^2 by quarter

Quantifying average polarization II

- P vs NP are more polarized than R vs L
- *Placebo partisanship:* Random assignment of 2 political types
  - Replicate estimation of $q_{ijt}^{P_i}$ 100 times, with random assignment of dummy variable P_i
  - Finite sample bias not entirely removed
    - Small sample of bigrams, or heterogeneous sample of politicians

Average quarterly partisanship

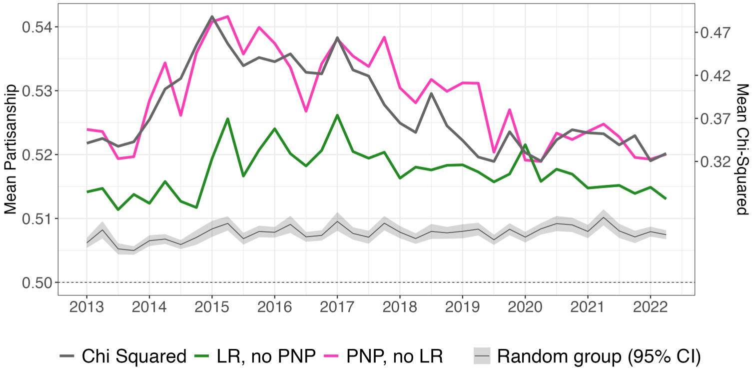


Figure: Average partisanship and χ^2 by quarter

other models χ^2 fixation index

The 2015 Refugee shock

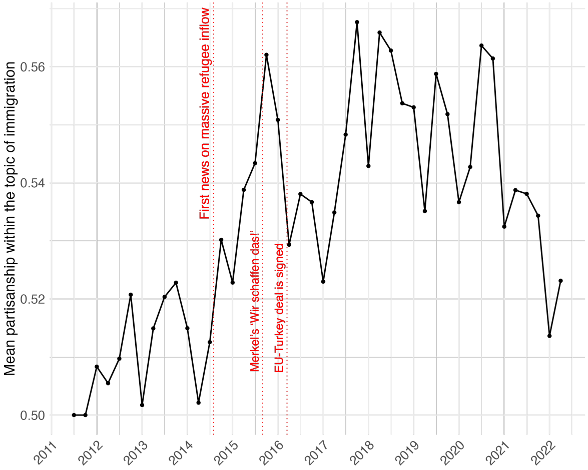


Figure: Partisanship within the topic of immigration over time

The 2015 Refugee shock

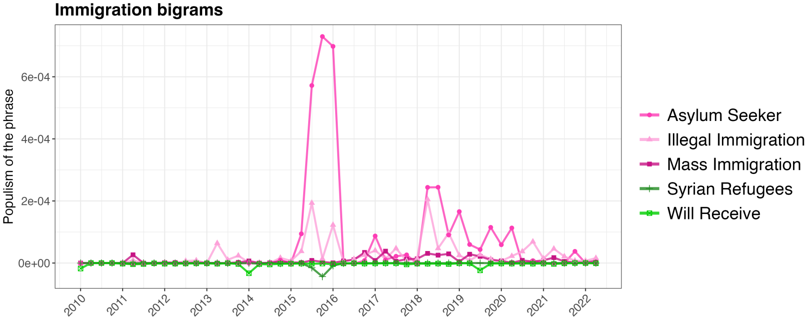


Figure: Most partisan immigration bigrams over time

Distinctiveness of bigram j of P speech

- By how much a neutral observer would change her posterior that $P_i = 1$ if j was removed from the vocabulary

The COVID-19 shock

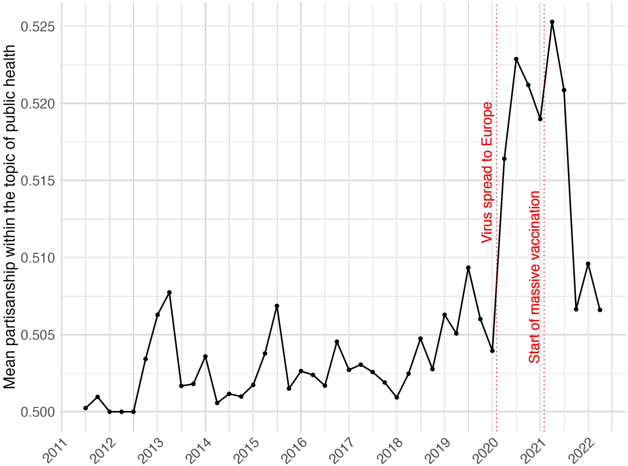


Figure: Partisanship within the topic of public health over time

back

The COVID-19 shock

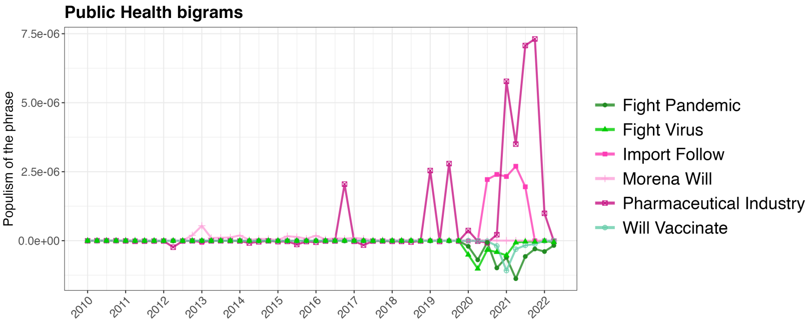


Figure: Partisanship within the topic of public health over time

back

Polarizing effect of elections

Rhetoric always more polarized closer to election date

- Election: of national legislature and of president

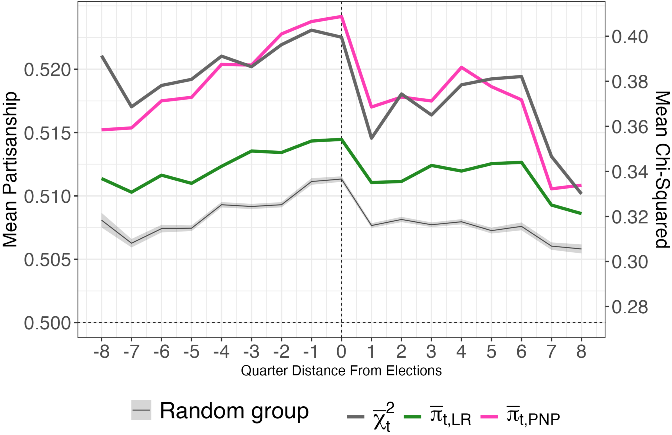


Figure: Average partisanship at quarterly distance from election date.

other models

Predictability over the political cycle

- $\hat{\pi}_t$ measures average predictability of types, conditional on a single bigram
- Compute expected predictability after observing a sequence of $n \in \{1, 2, .., 20\}$ bigrams in different quarters:
  - *expected posterior probability that an observer with a neutral prior correctly identifies a politician's type for the observed sequence of phrases*
- One tweet (five bigrams) raises predictability by:
  - **6 p.p.** two years after an election
  - **11 p.p.** in the election quarter (**12 p.p.** at the peak of the refugee crisis)

  $\Rightarrow$ 80% increase in predictability around elections

Predictability after observing n bigrams

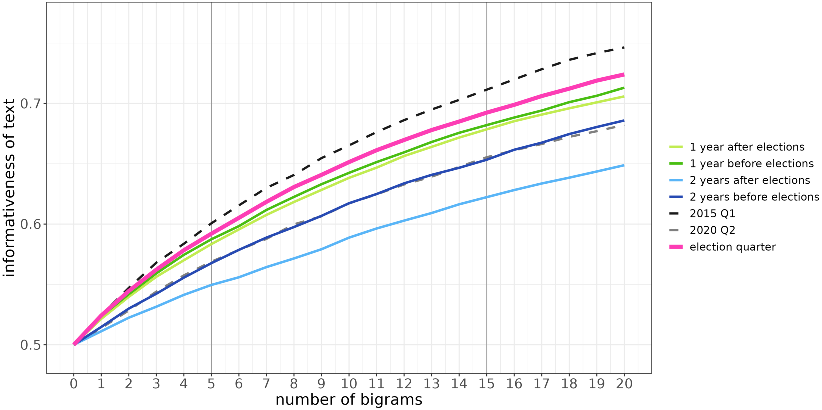


Figure: Posterior belief of an observer with a neutral prior after reading a given number of bigrams

Event study

- To isolate effect of elections from other shocks, and from changing composition of politicians, estimate:

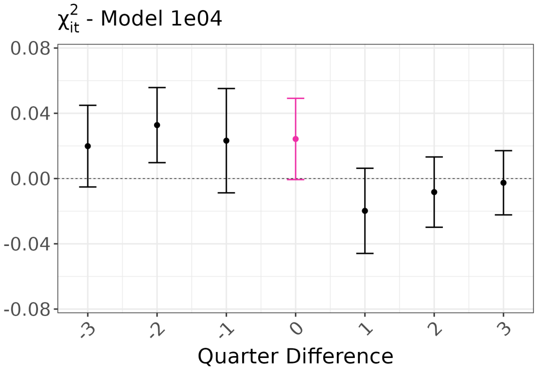
$$Y_{it} = \sum_{d(i,t)=-3}^{3} \beta_{d(i,t)} D_{d(i,t)} + \gamma_i + \delta_t + \tau_{el(i,t)} + \epsilon_{it},$$

where:

- $Y_{it} = \pi_{it}$ or χ^2_{ict}
- $D_{d(i,t)}$ =1 if at Q distance $d(i,t)$ from election
- β measures effect of being at distance $d(i,t)$ from election, relative to other quarters, for the same i
- $\tau_{el(i,t)}$ are dummies for the closest elections for i at date t
- SE clustered at country - (closest) election level

Event study on χ^2_{ict}

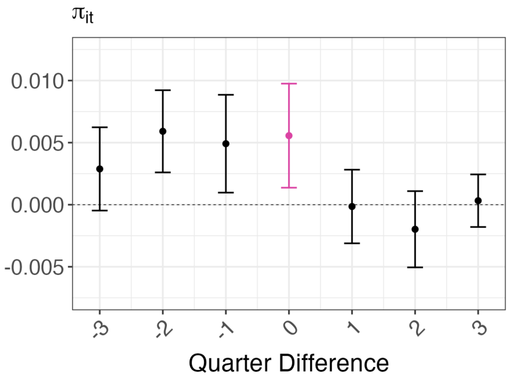
- Polarizing effect of election quarter on χ^2_{ict} $\approx$ 5% of SD of χ^2_{ict} over entire sample



Errors clustered at the country-elections level, 95% CI

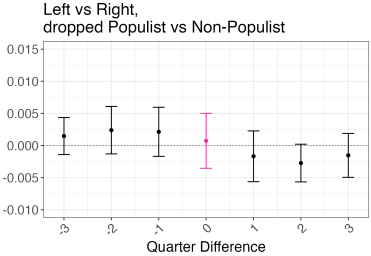
Event study on π_{it}

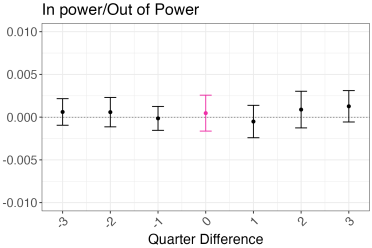
- Polarizing effect of election quarter on $\pi_{it} \approx$ 10-15% of SD of π_{it} over entire sample



Errors clustered at the country-elections level, 95% CI

Event study on π_{it}: other groups

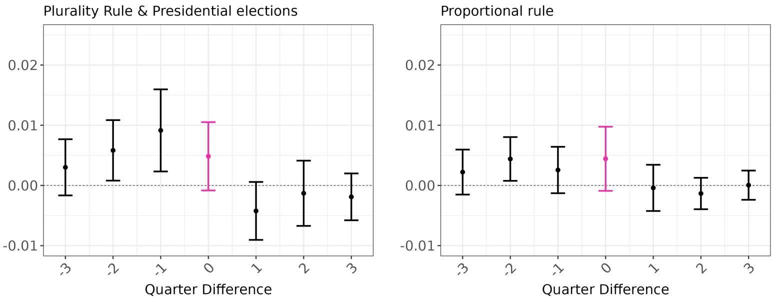




Errors clustered at the country-elections level, 95% CI

Heterogeneity by political institutions

- Group elections by political institutions:



Plurality rule includes US, UK, Australia, France + presidential regimes (Mexico and Brazil), and all presidential elections with > 1 candidate

Further Heterogeneity

- Being a candidate Candidate
- English speaking English

Robustness

- Robust to:
  - Staggered diff-in-diff (Sun and Abraham, 2021) robustness 1
  - Size of time window around election robustness 2
  - Different thresholds for bigram selection robustness 3
  - Snap elections Snap
- Politicians are more active near elections. Is this a concern?
  - Not at the intensive margin - verbosity is a parameter when estimate $\left\{\hat{q}_{ijt}^{P_i}\right\}$, verbosity pattern
  - Little / no variation at extensive margin, since few elections in each quarter and politicians are uniformly active No. politicians
  - Robust to random selection of 220 active politicians per quarter Fixed sample size results

Mechanisms

Aims of communication strategies in the proximity of elections

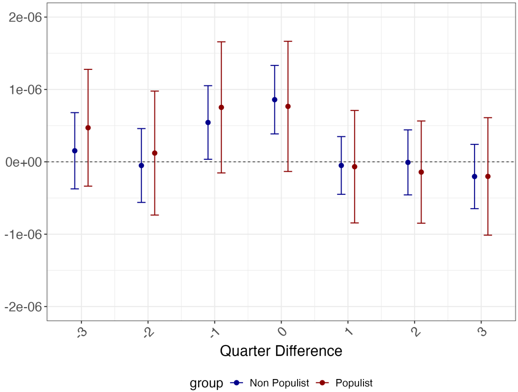
1. **Communicate specific policy positions**
   $\rightarrow$ Divergence when speaking about the same topic ?
2. **Draw attention to specific topics**
   $\rightarrow$ Do they speak about different topics?
3. **Change voters' beliefs and political preferences**
   $\rightarrow$ Both within and between topics dynamics
4. **Cycles in populist distinctiveness?**
   $\rightarrow$ Populist as challengers appealing to dissatisfied voters

Distinctive features of populist rhetoric

- Populism is a thin-centered ideology, with no distinctive policy views (Mudde and Kaltwasser, 2012)
  - both left-wing and right-wing populism
- But distinctive political rhetoric
  - anti-establishment, people vs corrupt elites, personalized communication
  - General propaganda (anti-establishment, elections, self promotion, etc.), unrelated to policy issues
- *Populist distinctiveness*: $\hat{\rho}_{ikt} = \Pr(P_i = 1 \ / \ topic \ k)$ given neutral prior
  - $\hat{\rho}_{ikt} > 1/2 =>$ topic k is distinctive of P,
  - $\hat{\rho}_{ikt} < 1/2 =>$ topic k is distinctive of NP

Populist distinctiveness

- As the election approaches, language is becoming more populist for both P and NP



Event study estimates for speech distinctiveness y_{it} for populist and non-populist politicians

- both groups adopt more populist phrases closer to the election

Summary

- **Elections have polarizing effect on political rhetoric**
  - In general within each country
  - Stronger effect on P vs NP than on other political types
  - Stronger for plurality rule & presidential elections
- **Direction** of rhetorical changes before elections:
  - both P and NP adopt a more populist language
  - NP draw attention to policy issues (CHECK)
  - P engage more in non-policy (e.g. propaganda) (CHECK)

Overall, suggestive that

- **opportunistic motives** (rather than intrinsic) drive surge of polarization on the supply side
- P vs NP seek to compete for **different groups of voters**

Other questions yet to be addressed

- Other rhetorical differences between P vs NP around elections
  - Emotionality, complexity, other topic classifications
- Do voters like / dislike partisanship? Depending on the policy at stake?
  - Observe likes received by tweets by topic

Data on Politicians. Characteristics

Table: Differences between Populists and Non-Populists Leaders

Variable	Populist	Non-Populist	Difference	p-value
Age (in 2010)	47.29	47.51	0.22	0.92
Male	0.75	0.77	-0.02	0.78
Higher Education	0.86	0.91	-0.05	0.34
Year of First Tweet	2012.8	2012.4	0.40	0.33
Years in parliament (as of 2010)	7.16	9.36	-2.2	0.14
% Time in govt coal. (2010-22)	24	38	-14	0.00
Ever in govt coal. (1990-2010)	0.57	0.79	-0.22	0.00
Niche Party	0.52	0.17	0.35	0.00

back

Data on Politicians. Characteristics

Table: Differences between Left and Right Leaders

Variable	Right	Left	Difference	p-value
Age (in 2010)	47.74	47.24	0.51	0.73
Male	0.75	0.76	-0.01	0.80
Higher Education	0.88	0.93	-0.04	0.17
Year of First Tweet	2012	2013	-0.56	0.06
Years in parliament (as of 2010)	8.74	7.77	0.97	0.47
% Time in govt coal. (2010–22)	0.36	0.37	-0.01	0.83
Ever in govt coal. (1990–2010)	0.76	0.76	-0.001	0.98
Niche Party	0.19	0.33	-0.13	0.01

back

Penalization. Details I

Estimate parameters $\{\alpha_t, \gamma_t, \beta_t, \phi_t\}_{t=1\ldots T}$ by minimizing the following penalized objective function (GST):

$$\sum_j \Big[\sum_t \sum_i m_{it} \exp(\alpha_{jt} + X_{it}\gamma_{jt} + Z_i\beta_{jt} + \phi_{jt} Pop_i)$$

$$- c_{ijt}(\alpha_{jt} + X_{it}\gamma_{jt} + Z_i\beta_{jt} + \phi_{jt} Pop_i)$$

$$+ \psi(|\alpha_{jt}| + ||\gamma_{jt}|| + ||\beta_{jt}||) + \lambda_j |\phi_{1jt} + \phi_{2jt}| \Big], \quad \psi = 1e-05$$

Table: Median λ_j values across models

Model	Median λ_j
P-NP, dropped Left-Right	7.61e-05
Left-Right, dropped P-NP	8.04e-05
Left-Right, P-NP together	8.47e-05

back

Penalization. Details II

Larger values of $\lambda_j \rightarrow$ more zero coefficients $\phi_{jt} \rightarrow$ less predictive power for a political type

Table: Mean number of bigrams with non-zero coefficients (out of 7059) by quarters

Model	Mean No.
P-NP, dropped Left-Right	207
Left-Right, dropped P-NP	229
Two affiliations model:	
P-NP	144
Left-Right	169

back

Most distinctive bigrams

Table: The most partisan populist and non-populist bigrams in 2015 Q3 and 2020 Q2

2015 Q3		*2020 Q2*	
Non-Populists	**Populists**	**Non-Populists**	**Populists**
climate change	**asylum seeker**	prime minister	good morning
prime minister	live periscope	climate change	live matter
young people	press release	president trump	via youtube
press confer	Greek people	young people	common sens
refugee crisis	good morning	small business	health care
Greek crisis	**illegal immigration**	crisis will	black live
human right	must read	Hong Kong	asylum seeker
year ago	Jeremy Corbyn	year ago	day may
look forward	Le pen	recovery plan	fake new
nuclear weapon	take care	can us	can see
welcome refuge	leave EU	save million	new book
accept refuge	real change	supply chain	today news
good news	don't like	social security	wash hands
Iran nuclear	social security	press conference	world health
debt relief	people want	support companies	exit strategies

back

Confusion Matrix

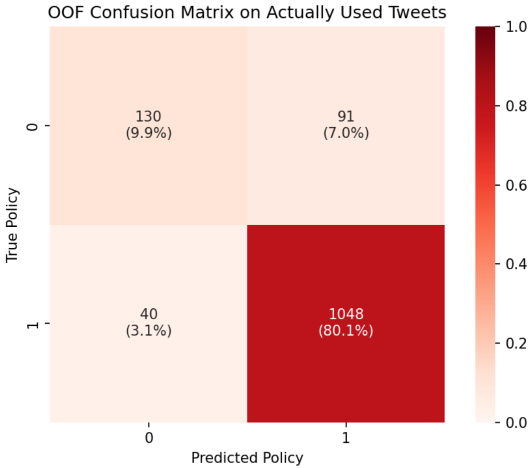


Figure: confusion

back

Fixation index

What fraction of χ^2_{ct} is due to heterogeneity *between* vs *within* groups?

Partition c in groups $g = 1, 2$ of size n_g, with $\hat{q}_{gjt} = \frac{1}{n_g} \sum_{i \in g} \hat{q}_{ijt}$

Heterogeneity *between groups*:

$$\bar{\chi}^2_{ct} = \sum_{g \in c} \frac{n_g}{n_c} \sum_j \frac{(\hat{q}_{gjt} - \hat{q}_{jt})^2}{\hat{q}_{jt}}$$

Fixation index:

$$F_{ct} = \frac{\bar{\chi}^2_{ct}}{\chi^2_{ct}}$$

- If groups are identical, $F_{ct} = 0$ (all heterogeneity is *within* g)
- If groups made up of identical individuals, $F_{ct} = 1$ (all heterogeneity is *between* g)

back

Fixation index for P vs NP relative to other groups

- Take balanced sample of at most 15 politicians per country always active
- Compute F_{ct} for all partitions of country c in 2 non-empty groups
- Take average of F_{ct} over time $\rightarrow \mathrm{F}_c$
- Compute distribution of F_c over all possible groups

F_c corresponding to P vs NP tends to be in the upper-tail of this distribution

Percentile in distribution of F_c

				Percentiles	
Country	Leaders	Populists	Right	PvsNP	RvsL
Australia	13	4	3	75.78	96.02
Austria	7	2	2	68.25	68.25
Belgium	14	1	0	99.99	-
Brazil	8	3	2	14.96	86.61
Czech Republic	6	2	3	32.26	90.32
Denmark	12	2	5	87.49	65.27
Finland	13	0	1	-	93.36
France	15	4	6	99.99	66.81
Germany	10	1	1	29.35	99.80
Hungary	4	3	4	28.57	-
Italy	15	6	5	99.68	50.87
Mexico	14	3	8	98.63	99.16
Netherlands	14	3	3	33.10	7.79
Norway	9	0	0	-	-
Poland	12	3	5	64.00	72.45
Slovenia	6	0	1	-	19.36
Spain	13	5	3	41.56	97.85
Sweden	7	2	1	31.75	9.52
United Kingdom	10	2	3	68.10	95.11
United States	15	2	6	76.40	99.99

back

Observed Frequencies - χ^2

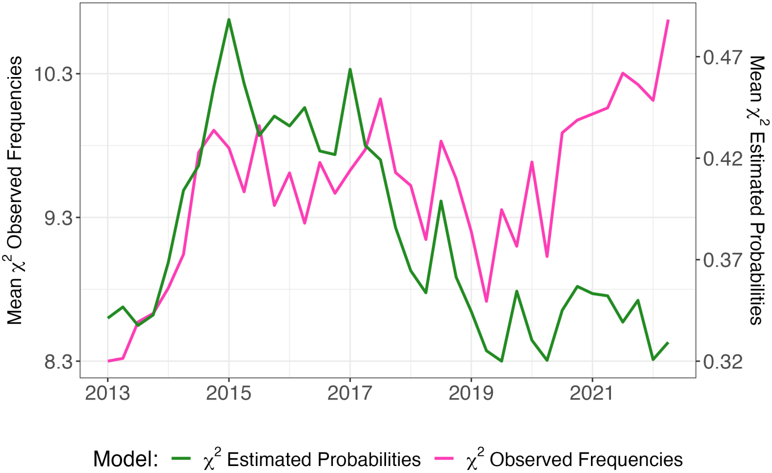


Figure: Average χ^2 over time

back

Average quarterly partisanship: other models

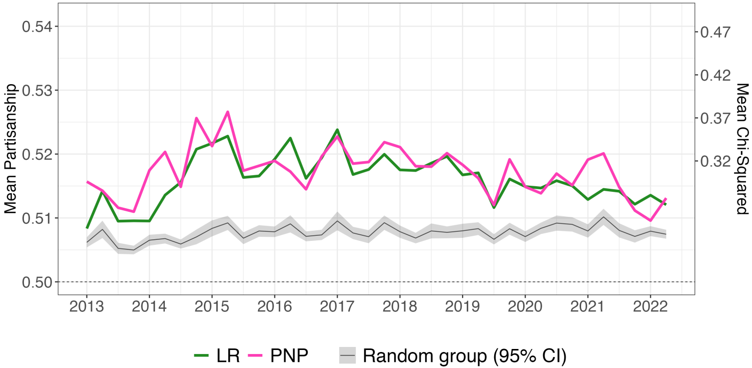


Figure: Average partisanship by quarter by dimensions for the models with 4 types

back

Polarizing effect of elections: other models

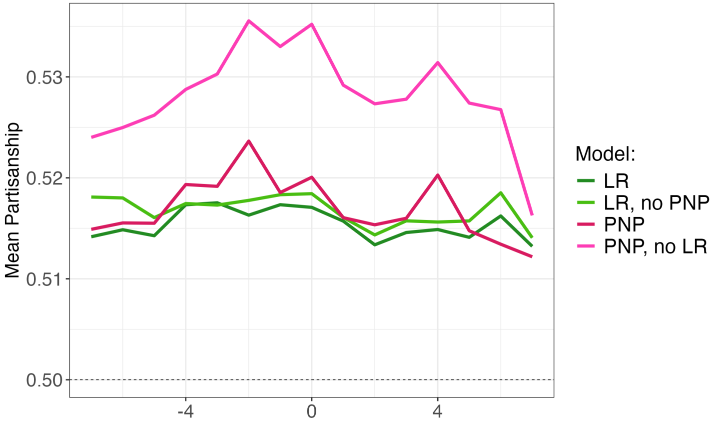
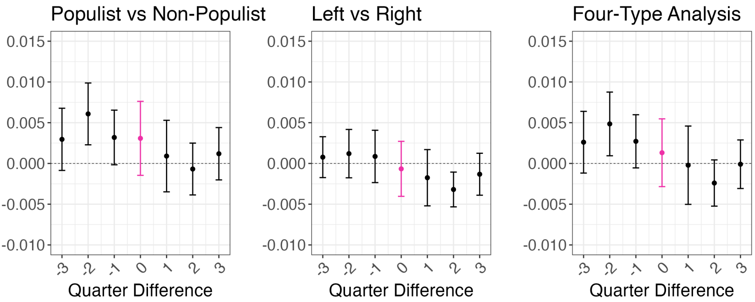


Figure: Average partisanship at quarterly distance from election date.

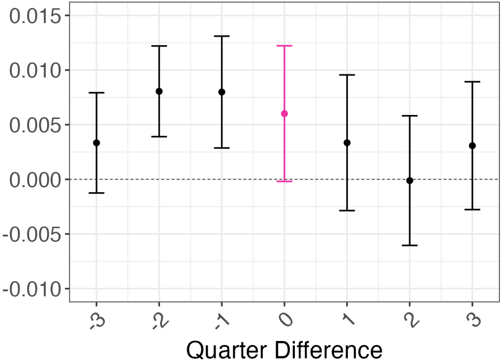
back

Event study: Other Results



back

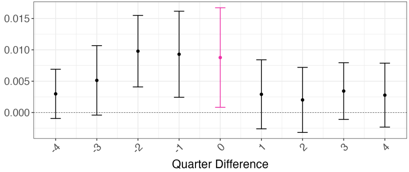
Event study. Staggered adoption

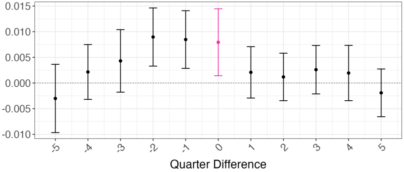


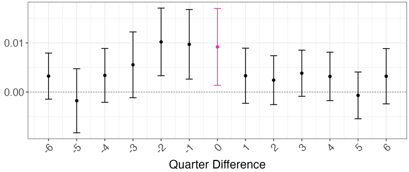
- avoid using already treated units as a control

back

Event study. Different time windows

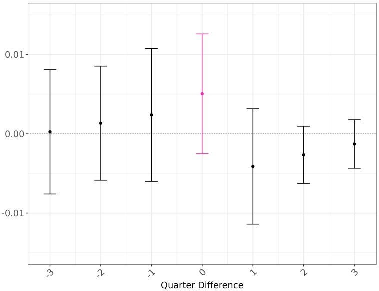




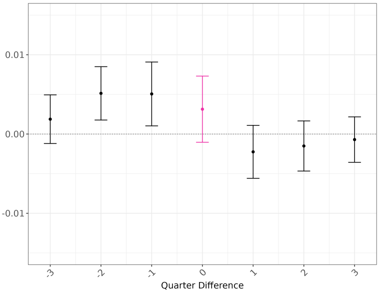


back

Snap Elections



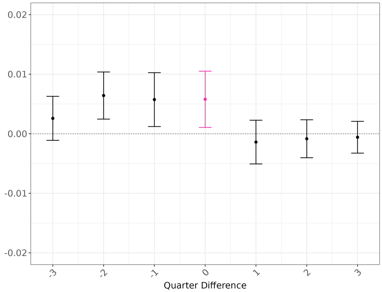
Snap Elections



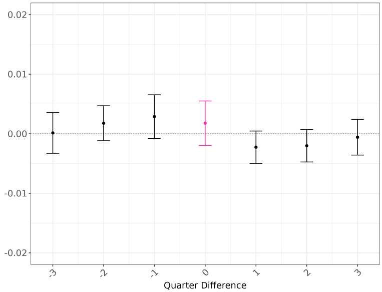
Not Snap Elections

back

Candidate



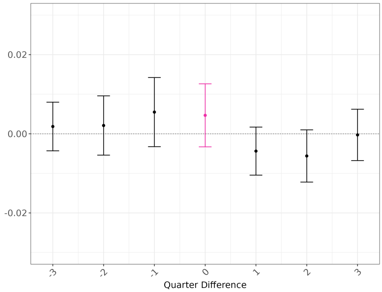
Candidate



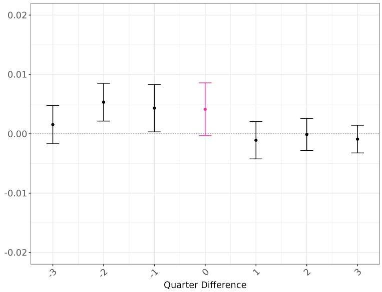
Not Candidate

back

English Speaking



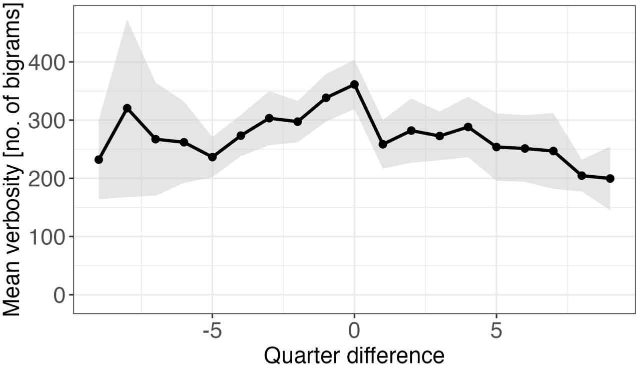
English-speaking Countries



Not English-speaking Countries

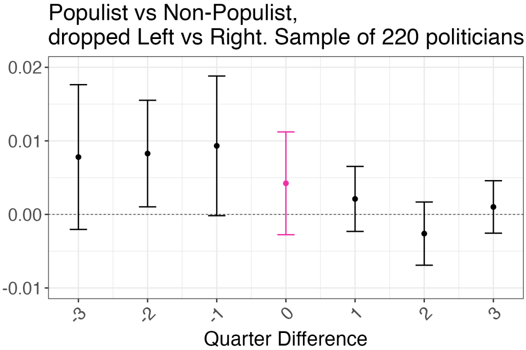
back

Verbosity



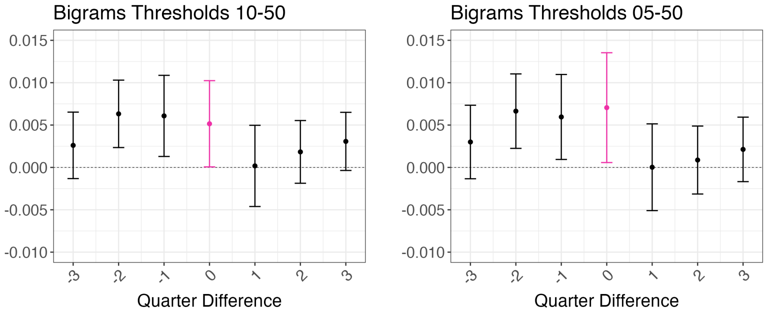
back

Fixed sample size of 220 politicians



back

Event study. Different bigram selection



back

Number of active politicians I

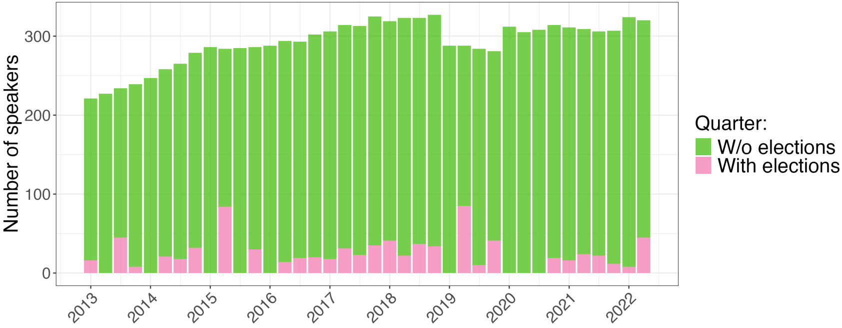


Figure: Number of speakers per calendar quarter

back

Number of active politicians II

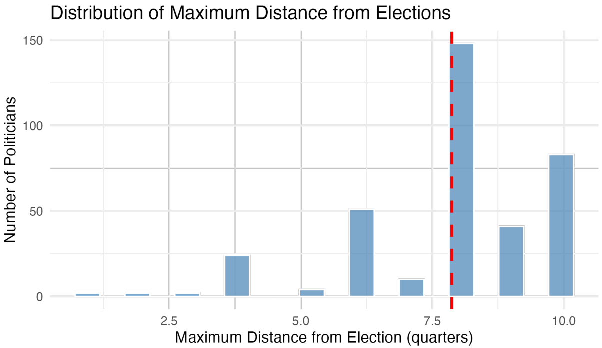


Figure: Number of speakers per quarter distance from elections

- 97.8% of politicians appear in both elections and non-elections periods
- average number of quarters present: 14

back

References

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