

Research Presentation

Department of Political Science and Public Administration
Vrije Universiteit Amsterdam

Luca Bellodi

21 April 2022

Bocconi University and UCL Political Science

WHO GOVERNS?

Hierarchy of Government

Politicians → Bureaucracy → Policy

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FDA says Covid-19 antigen tests may be less sensitive to Omicron variant, but they're still an important tool



By [Jen Christensen](#) and [Jamie Gumbrecht](#), CNN

🕒 Updated 2021 GMT (0421 HKT) December 29, 2021

Particularly when there are crises

Covid vaccines clearly less effective against Omicron, says EMA head

Chief of European drugs regulator says it will take time to reach consensus on variant-targeted vaccines

When can bureaucracy **influence** politicians?

Listen to me

Ideological Agreement and Bureaucratic Influence in the Legislative Arena

Luca Bellodi

What is Influence?

How could we measure the extent to which researchers influence scholarly work?

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Cited by	Luca Bellodi	
	All	Since 2017
Citations	3	3
h-index	1	1
i10-index	0	0

Source: Google Scholar

Cited by	Guy Peters	
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Citations	63817	21286
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...similar for **bureaucracies** influencing politicians.

Motivation

Politicians' use of Bureaucratic Information

Bureaucracy → Information → Politicians

- (i) reduces **uncertainty** over policy outcomes
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Cheap Talk Models of Strategic Communication (Crawford and Sobel 1982; Gailmard and Patty 2012)

Main prediction

Truthful communication is more likely when the sender of the message/information (bureaucracy) has **similar policy preferences** to the receiver (politician)

Measurement

Measurement Strategy

Apply computational linguistics methods to detect the action of “reporting something said by someone” to a large corpus of US floor and committee speeches

The Proposed Measure

“The FED said that higher interest rates will strengthen the economy”

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Three steps:

Step 1: Parse dependency structure and tag parts-of-speech

Step 2: Define and apply extraction rules

Step 3: Analyse quotes and type of information

Step 1: Dependency Parsing

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2. Use *spaCy*, a supervised learning algorithm, to tag parts of speech
3. Detect dependency relations

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ID	Token	Part-Of-Speech	Head (Token ID)	Dependency Relation
1	The	DETERMINER	2	determiner
2	FED	PROPER NOUN	3	nominal subject
3	said	VERB	3	ROOT
4	that	ADPOSITION	9	marker
5	higher	ADJECTIVE	7	adjectival modifier
6	interest	NOUN	7	compound
7	rates	NOUN	9	nominal subject
8	will	VERB	9	auxiliary
9	strengthen	VERB	3	clausal complement
10	the	DETERMINER	11	determiner
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Direct Nominal Recommendation	recommendation + possession modifier	The FED's recommendation is to increase interest rates.

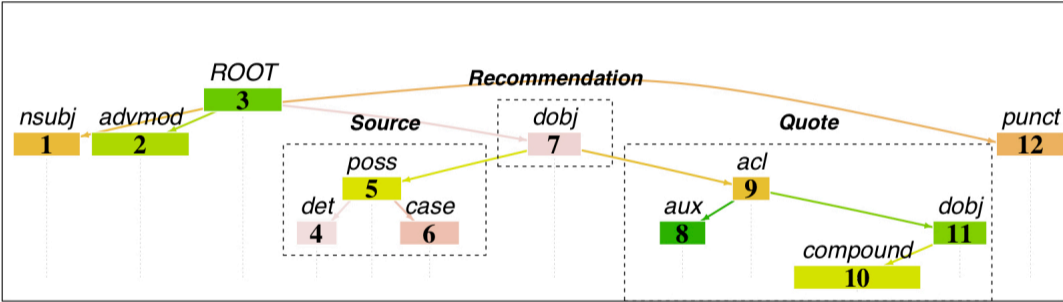
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Direct Nominal Recommendation	recommendation + possession modifier	The FED's recommendation is to increase interest rates.
Indirect Nominal Recommendation	recommendation + possession modifier	I fully endorse the FED's recommendation to increase interest rates.

▸ List of say verbs and recommendation type words

Apply Extraction Rules to Parsed Sentences

Nominal Indirect Recommendation



I fully endorse the FED 's recommendation to increase interest rates .

Step 3: Statistical Facts and Evidence

What type of information do we care about?

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Dictionary analysis, where

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Dict = LIWC dictionary of statistical facts and quantitative evidence (quantifiers and numbers: *total, twice, percentage, equal, whole, multiple, ...*)

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Merge quotes back \rightarrow Speech

$$I_s = \sum_{i=1}^N facts_i$$

Bureaucracies & Corpus

Sample of **Bureaucracies**: 426 agencies.

- Executive Departments: 8.6 %
- Executive Sub-agencies: 53.8 %
- Independent agencies: 30.9 %
- Agencies within the Office of the President: 2.5 %
- Other: 2.0 %

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Sample of **Speeches**: 6.8 million US floor and committee speeches.

- Floor speeches (1980-2016), Stanford University Congressional Repository
- Committee speeches (1990-2019), ProQuest

▸ More on parsing speeches and building corpus

Other data: Ideology and Independence

Key predictor: agency-legislator **ideological distance**

Legislators' **ideology** data: DW-NOMINATE score, accessed at voteview.com.

Agency **ideology** data from Chen and Johnson (2014)

1993-2012, 79 agencies, based on bureaucrats' campaign donations

▸ [More on agency ideology](#)

Methods

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I estimate the following model with OLS:

$$I_{s[l,t,a]} = \gamma_l + \phi_t + \alpha_a + \beta \text{Distance}_{l[a,t]} + \mathbf{X}'_{[l,t]} + u_s$$

- $I_{s[l,t,a]}$ is bureaucratic influence (N. Fact Words) in speech s
- $\gamma_l, \phi_t, \alpha_a$ are legislator, year, agency FE
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Two ways to address OVB at agency and legislator level:

- N. mentions in floor/committee speeches as a covariate
- Agency \times Year and Legislator \times Year FE

Results

Effect of Ideological Distance

DV (Mean 1.07):	Use of Bureaucratic Information (N. Fact Words)				
Model:	(1)	(2)	(3)	(4)	(5)
Ideological Distance	-0.252** (0.085)	-0.236** (0.080)	-0.235** (0.080)	-0.212* (0.084)	-0.244* (0.123)
Agency Mentions	✓	✓	✓		
Legislator Covs.			✓	✓	
Legislator FE	✓	✓	✓	✓	
Year FE	✓	✓	✓		
Agency FE		✓	✓		
Agency-Year FE				✓	✓
Legislator-Year FE					✓
Observations	20,578	20,578	20,548	20,548	20,578
R ²	0.063	0.080	0.080	0.119	0.350

*Clustered (Legislator) SE in parentheses. ***: 0.001, **: 0.01, *: 0.05*

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Studying bureaucratic influence is **normatively** important for bureaucratic legitimacy and evidence-based policy-making.

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Empirical contribution: propose a new transparent and “objective” measure of influence grounded in real-world practices, applicable to other questions in the social sciences.

Research Agenda

How does **Partisanship** Affect Bureaucratic Performance and Accountability?

Partisan Congruence and Rulemaking in the US Federal Bureaucracy

As early as from Weber, bureaucracy → neutral civil service.

It's good to have independent bureaucrats **insulated** from political pressure.

Sharing goals-preferences can boost productivity/quality of output.

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The **project**:

- How partisanship factors into models of bureaucrats' incentives,
- US federal and state bureaucracy,
- Original data on rule-making (rule text, response to comments, judicial review),
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Extend this research project to the **European Union**.

Friendly Oversight

Separation of Power → Executive accountable to Legislative Branch

Theory predicts oversight **increases** when $|x_P - x_A|$ is large.

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*What happens to accountability when **overseer** & **overseen** belong to same party?*

The **project**:

- Neglected role of partisanship in politicians-bureaucrats relationship,
- US context, Congressional Hearings,
- Novel data on identity of witnesses, committee speeches, and actors' ideology.

Populism and Bureaucratic Expertise

The source of legitimacy for delegating authority to bureaucracy is **expertise**.

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The **project**:

- Italian context, local, regional, and ministerial levels of government,
- Novel data on Italian bureaucracies:
 - External consultants hired by public organisations,
 - Hrs. spent on training/education of bureaucrats,
- Methodologically: NLP and quasi-experimental methods.

Fit with Department's Specialism

My research complements some of the department's **specialisms** in PA:

- Policy Narratives,
- Regulatory Governance,
- Public Values,
- Trust and Control,

Opportunities of **collaboration** with researchers working on Crime, Policing, and Security.

Thank you

References i

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Appendix

Appendix

- List of say verbs [▶ View](#)
- Parsing speeches [▶ View](#)
- Validity [▶ View](#)
- Influence: [▶ Qualitative](#) and [▶ Quantitative](#)
- Agency Ideology [▶ View](#)
- Moderating role of independence [▶ View](#)

Robustness Tests:

1. Sensitivity to Outliers/Extreme speeches: $\log(1+ N. \text{ fact words})$ [▶ Results](#)
2. Alternative Estimator (Poisson Regression) [▶ Results](#)
3. No heterogeneous effects between floor and committee speeches [▶ Results](#)
4. One agency used as source in speech [▶ Results](#)
5. Using *tf-idf* of statistical-fact words as DV [▶ Results](#)

Say Verbs and Recommendation-type Nouns

Say verbs: say, tell, show, claim, report, admit, acknowledge, present, explain, state, indicate, recommend, propose, advance, believe, think, affirm, conclude, propose, advise, encourage, argue, contend, set out, inform.

Recommendation-type words: recommendation, advise, suggestion, indication, proposal, attempt, document, idea, project, programme, conclusion, report, program, brief, paper, argument, thesis, statement, survey, study.

▶ Back

Building the Corpus

Floor speeches already parsed and available (Stanford University Congressional Repository)

Committee speeches without meta-data, all in one XML entry.

- 42,277 congressional committee sessions in separate XML files from ProQuest.
- Speeches identifiable from “Title SURNAME” at the beginning of the speech.
- Many individual heard who are not congresspersons.
- Congresspersons listed at the beginning of the file with their respective state in brackets – e.g., Mr. FORD (Texas).
- I extract all the names of congresspersons with a regular expression.
- I parsed all speeches splitting the text by the “Title SURNAME” formula.
- I kept only speeches whose name matched one of the names of congresspersons.
- I merged speeches with ideology data by matching on surname, state, and date of session.

▸ Back

Sample of Speeches

Descriptive Statistics	Floor	Committee
Initial Sample of Speeches	2,501,900	4,454,416
N. Speeches mentioning agencies	335,445	531,668
N. Speeches with agency used as source	32,300	35,127
Oversight Hearings		-11,712
N. Speeches with agency used as source	32,300	23,415
N. Agencies used as source	211	222
Average use of facts and evidence	1.09	1.15
Total N. Speeches	55,814	
N. Unique Agencies used as source	237	
Average use of statistical facts	1.11	

Validation

Main pitfall of dictionary-based approaches: **Context Dependence**

Three validation tests:

- Face Validity
- Out-of-“Corpus” Validation
- Convergent Validity

Face Validity

Score: **1st Quartile** – Sen. Lautenberg, D, 1990: “The Department of Justice acknowledges the problem but offers no solutions .”

Score: **Median** – Sen. Cohen, R, 1995: “The Department of the Navy argues that the risks imposed by consolidating to a **single** nuclear-capable shipyard outweigh the potential cost savings.”

Score: **4th Quartile** – Sen. Durbin, D, 1997: “The US Bureau of Labor Statistics reports that the number of major strikes in the United States has been reduced by more than **90** percent since the middle of this century, from **470** major strikes in **1952** to **37** in **1996**, and the number of workers involved in these strikes has been reduced by **90** percent, from **three million** workers involved in strikes in **1952** to **fewer** than **300,000** in **1996**.”

Out-of-“Corpus” Validation

- Manually labelled sentences from medical blogs from Carrillo-de-Albornoz, Vidal, and Plaza (2018).
- Coders classified sentences of each post as “experience”, “fact”, or “opinion.”
- Outcome is number of sentences classified as “fact” in each post.
- Treatment is score from dictionary analysis of each post.

Estimators:	DV: N. “fact” sentences in post			
	OLS	Poisson	Neg. Bin.	Logit
Dictionary Measure	2.760* (1.296)	0.817*** (0.145)	0.773*** (0.110)	0.540** (0.198)
Observations	480	480	480	480
Pseudo R ²	0.038	0.159	0.048	0.011

Heteroskedasticity-robust standard-errors in parentheses

****: 0.001, **: 0.01, *: 0.05*

Convergent Validity

▶ Back

- Random sample of 500 sentences where agencies are used as source of information
- Dichotomised the statistical-fact score
- Sentences manually coded by an independent researcher
- Task was to mark the sentences containing statistical facts produced by a bureaucracy

		Manual Coding	
		Statistical Facts and Evidence	
		No	Yes
Automated Coding	No	234	37
	Yes	84	145

Accuracy: 0.76, Precision: 0.80, Recall: 0.63, F1: 0.71

Bureaucratic Influence: Qualitative Data

Sen. Patrick Leahy, D-VT, 6th October 1998

13 instances, **Office Management Budget** → source of info

21 statistical-fact words

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Some quotes:

“during the first 6 months of operation, the OMB reported that New England’s dairy farm income rose by an estimated \$2,227 million”

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“the OMB reports that New England suffered a 20% decline in the number of farms with milk cows from 1990 to 1996.”

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Some quotes:

“during the first 6 months of operation, the OMB reported that New England’s dairy farm income rose by an estimated \$2,227 million”

“the OMB reports that New England suffered a 20% decline in the number of farms with milk cows from 1990 to 1996.”

“Evidence reported by the OMB shows that neighbouring farmers get the benefit of the higher Compact price” [...]

Bureaucratic Influence: Quantitative Data

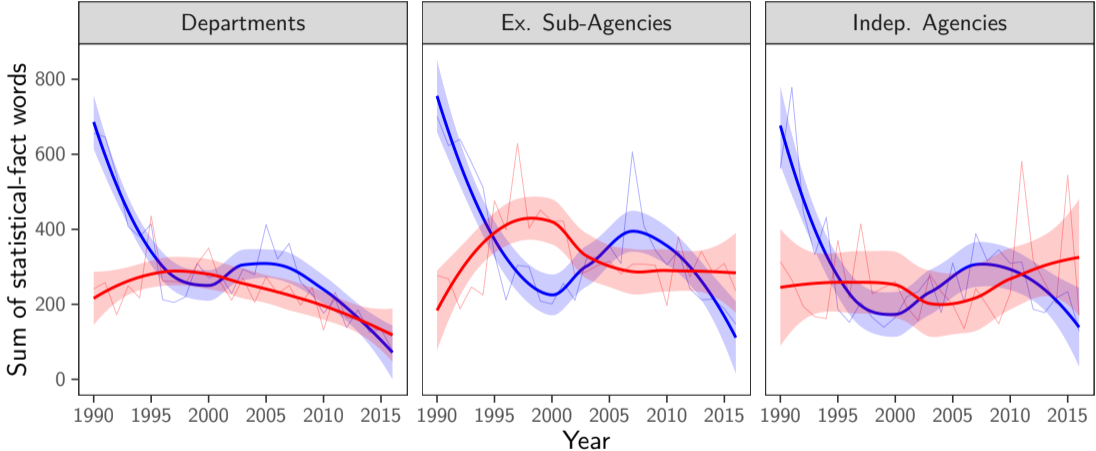


Figure 1: Sum of statistical-fact words across different types of bureaucracies over time.

Agency Ideology

Donation-based ideology estimates from Chen and Johnson (2014).

Bureaucrats donate to political candidates. Agency ideology is a weighted avg. of the DW-NOMINATE scores of politicians who receive the donation, where larger donations (bureaucrats higher up in the hierarchy) are given larger weights.

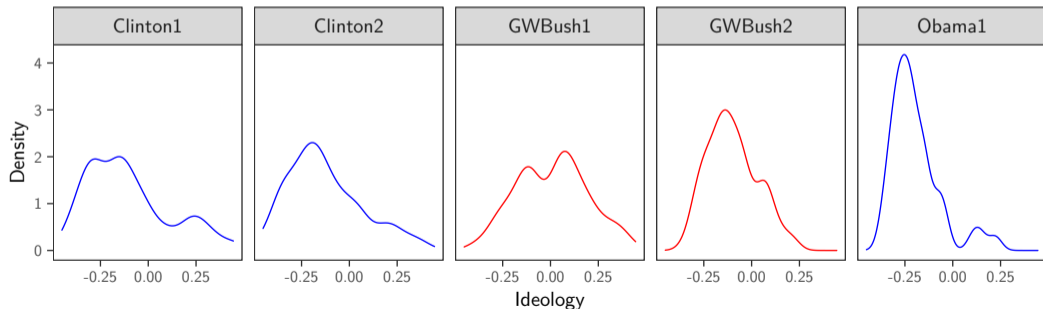


Figure 2: Density plots of agency ideology.

Moderating Role of Statutory Independence

Real-World Example

Edward Scott Pruitt was the Administrator of the U.S. Environmental Protection Agency from February 17, 2017, to July 9, 2018. He was nominated by President Donald Trump and *“he rejects the scientific consensus on climate change”* (Wikipedia).

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Suppose the EPA was a neutral and **independent** bureaucracy, insulated from political appointments and directives.

Moderating Role of Statutory Independence

Real-World Example

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→ Ideological distance plays a weaker role for **independent** agencies.

Measuring Independence

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Three measures of independence:

- Agency can take decisions without political interference
- Appointment/removal limitations and qualification requirements on key agency decision-makers (data from (Selin 2015))
- Bureaucracy is independent agency (dummy)

I compare β across different samples based on whether the agency falls above or below the mean value of the three independence indicators.

Results Across Sub-samples

DV:	Use of Bureaucratic Information (N. Fact Words)					
	Political Review		Decision Makers		Agency Type	
	Above/ Below Mean:	Below	Above	Below	Above	Below
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Ideological Distance	-0.283** (0.106)	-0.102 (0.153)	-0.290* (0.122)	0.013 (0.116)	-0.274* (0.119)	-0.063 (0.154)
Legislator Covs.	✓	✓	✓	✓	✓	✓
Legislator FE	✓	✓	✓	✓	✓	✓
Agency-Year FE	✓	✓	✓	✓	✓	✓
Observations	13,974	6,529	11,985	8,518	12,710	7,838
R ²	0.121	0.237	0.132	0.192	0.139	0.180

*Clustered (Legislator) SE in parentheses. ***: 0.001, **: 0.01, *: 0.05*

Sensitivity to Outliers

DV:	log(1 + N. Fact Words)				
Model:	(1)	(2)	(3)	(4)	(5)
Ideological Distance	-0.076*	-0.070*	-0.070*	-0.060*	-0.069 [†]
	(0.030)	(0.028)	(0.028)	(0.029)	(0.042)
Agency Mentions	✓	✓	✓		
Legislator Covs.			✓	✓	
Legislator FE	✓	✓	✓	✓	
Year FE	✓	✓	✓		
Agency FE		✓	✓		
Agency-Year FE				✓	✓
Legislator-Year FE					✓
Observations	20,578	20,578	20,548	20,548	20,578
R ²	0.071	0.092	0.093	0.135	0.382

*Clustered (Legislator) SE. ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

DV:	N. Fact Words			
Model:	(1)	(2)	(3)	(4)
Ideological Distance	-0.243** (0.079)	-0.232** (0.075)	-0.229** (0.075)	-0.208** (0.078)
Agency Mentions	✓	✓	✓	
Legislator Covs.			✓	✓
Legislator	✓	✓	✓	✓
Year	✓	✓	✓	
Agency		✓	✓	
Agency-Year				✓
Observations	20,365	20,365	20,337	20,218
BIC	74,924.7	74,520.6	74,457.7	79,250.9

*Clustered (Legislator) SE. ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

Speech Type: Floor and Committee Speeches

DV:	N. Fact Words	
Model:	(1)	(2)
Ideological Distance	-0.212*	-0.211*
	(0.103)	(0.103)
Floor Speech (Dummy)	-0.057	-0.058
	(0.059)	(0.058)
Id. Distance \times Floor Speech	-0.038	-0.037
	(0.128)	(0.128)
Legislator Covs.		✓
Legislator, Agency, Year FE	✓	✓
Observations	20,578	20,548
R ²	0.080	0.080

Clustered (Legislator) SE in parentheses.

***: 0.001, **: 0.01, *: 0.05, †: 0.1

One Agency Used as Source

▶ Back

DV:	N. Fact Words	
Model:	(1)	(2)
Ideological Distance	-0.163* (0.081)	-0.165* (0.081)
Legislator Covs.		✓
Legislator FE	✓	✓
Year FE	✓	✓
Agency FE	✓	✓
<i>Fit statistics</i>		
Observations	19,380	19,350
R ²	0.082	0.083
<i>Clustered (Legislator) SE in parentheses</i>		
***: 0.001, **: 0.01, *: 0.05, †: 0.1		

DV: tf-idf of statistical-fact words

DV:	<i>tf-idf</i> of Fact Words				
Model:	(1)	(2)	(3)	(4)	(5)
Ideological Distance	-0.089** (0.029)	-0.083** (0.028)	-0.082** (0.028)	-0.074* (0.029)	-0.085* (0.043)
Agency Mentions	✓	✓	✓		
Legislator Covs.			✓	✓	
Legislator FE	✓	✓	✓	✓	
Year FE	✓	✓	✓		
Agency FE		✓	✓		
Agency-Year FE				✓	✓
Legislator-Year FE					✓
Observations	20,578	20,578	20,548	20,548	20,578
R ²	0.063	0.080	0.080	0.118	0.349

*Clustered (Legislator) SE in parentheses. ***: 0.001, **: 0.01, *: 0.05, †: 0.1*