

Measuring Discretion and Delegation in Legislative Texts: Methods and Application to U.S. States

Matia Vannoni[†], Elliott Ash[‡], Massimo Morelli[§]

June 10, 2019

*Prepared for delivery at the Workshop on the Ostrom Workshop (WOW6) conference, Indiana University
Bloomington, June 19-21, 2019. ©Copyright 2019 by author(s)

[†]King's College London, email: matia.vannoni@kcl.ac.uk

[‡]ETH Zurich, email: ashe@ethz.ch

[§]Bocconi University and CEPR, email: massimo.morelli@unibocconi.it

Abstract

Bureaucratic discretion and executive delegation are central topics in political economy and political science. The previous empirical literature has measured discretion and delegation by manually coding large bodies of legislation. Building on recent advances in computational linguistics, we provide a method for measuring discretion and delegation in legal texts, which automates the analysis and allows to study these two aspects on the same body of laws. The method uses information in syntactic parse trees to identify legally relevant provisions, as well as agents and delegated actions. We undertake two applications. First, we build a measure of bureaucratic discretion by looking at the level of legislative detail – namely the number of legally relevant provisions – for U.S. states, and find that this measure increases after the creation of an independent bureaucracy. This is consistent with an agency cost model where a more independent bureaucracy requires more specific instructions (less discretion) to avoid bureaucratic drift. Second, we construct measures of delegation to governors in state legislation. Consistent with previous estimates using non-text metrics, we find that executive delegation increases under unified government.

Introduction

The use of text data in political science has expanded rapidly in recent years (Gentzkow and Shapiro 2010; Lucas, Nielsen, Roberts, Stewart, Storer and Tingley 2015; Roberts, Stewart, Tingley, Lucas, Leder Luis, Gadarian, Albertson and Rand 2014; Grimmer and Stewart 2013), with notable examples including the detection of legislative agendas or topics and estimating the ideological positions of parties (Laver and Garry 2000) or single legislators (Lauderdale and Herzog 2016). The standard approach is to break down the syntactic structure of the text and represent it as a sequence of tokens or phrases, thereby losing the important information encoded in syntax and grammar. This paper shows how to extract this syntactic information and bring it back into the analysis, paving the way for richer text representations in political science.

More specifically, the mainstream approach to political text analysis consists of two steps: de-structuring and re-structuring the text. The former is a process by which the researcher splits the text up into tokens (single words or groups of words which relate to a concept) and prunes the tokens obtained, by deciding which words (and which parts of these words) are ‘meaningful’ for the analysis (and how to weight them) (Monroe, Colaresi and Quinn 2008). The re-structuring phase consists of assigning a probability distribution to these tokens, which tells us how likely a token is associated with a party, a legislator or a topic. To summarize, this approach starts from text as unstructured data and transforms it into structured data (Klebanov, Diermeier and Beigman 2008).

This mainstream "tokenization" approach potentially misses important information in the text. Any piece of written text comes with a ‘language structure’, which conveys a potentially large amount of lexical, syntactic, and semantic information. For example, we would want to know whether mentions of the “governor” in state legislation have the governor as a subject (undertaking an action) or an object (the target or recipient of an action). Here we explore how political science research could benefit from taking this language structure of texts into consideration, building on recent developments in Natural Language Processing

(NLP) techniques.

Simply stated, by looking at the lexical and syntactic features of a sentence, NLP techniques serve to retrieve richer information than a list of tokens. This approach starts by automatically parsing the lexical and syntactic structure of a sentence, hence extracting information on what is the subject, what type of verb is present and so on. Then, this structure is matched against templates – what in computational linguistics are called ontologies – which say what different provision types, such as permissions and entitlements, look like lexically and syntactically. For example, sentences with governor as subject and a strict modal verb (e.g., “governor shall enforce regulations”) can be understood as a delegation of authority. These types of frames follow dependency relations between words in a sentence, and therefore are not constrained by word order (as is the case in N-grams or dictionary matching). The result is a classification of sentences according to their meaning, with information on the agents involved.

This information extraction approach can expand the use of text analysis to the study of a wider range of important topics in political science. Our hope is that these richer sets of data could help answer richer sets of questions. To demonstrate the usefulness of this new approach to text analysis, we undertake two applications in the context of U.S. state legislation. We find in both cases that previous results using standard methods generalize to the larger-scale text data sets.

Our first application looks at bureaucratic discretion. Our motivation comes from [Huber and Shipan \(2002\)](#), who find using manual coding of statutes (the traditional method) that an independent bureaucracy may result in agency drift. As such, legislators would want to put into place a series of control mechanisms in order to restrain the bureaucracy, such as writing more detailed laws. To get at this question, we apply our information extraction method to a unique corpus, which consists of the full text of U.S. state session laws from the 20th century. We find that the introduction of merit systems, namely independent bureaucracies, across U.S. states is associated with statutes containing more legal provisions. This is consistent

with the discretion model in the literature: legislators introduce stronger ex ante control mechanisms to discipline the more independent bureaucracy.

Our second application analyzes executive delegation, as measured by delegation of power from legislature to governor. The previous literature has used standard methods to produce robust evidence that where legislators’ interests converge with the governor’s (namely where they come from the same party), delegation of powers to the executive takes place (Epstein and O’Halloran 1999; Franchino 2004). We test the predictive validity of our approach by applying information extraction to the same dataset. In line with the previous literature, we find that the ratio of statements delegating powers to the governor, discounted by the ratio of statements constraining the governor, increases in unified government situations.

Legislative Information Extraction

In this section we summarize the method of legislative information extraction. The approach relies on computational linguistics tools to produce parse data – statistical representations of the syntactic and lexical content in legislative clauses. For example, it will identify the subject and verb of a sentence, the adjectives that describe the subject, and the objects of the verb. Meanwhile we construct “frames” – a set of tags or rules which identify relevant clauses from the linguistics data – which, in our applications, provide measures of discretion or delegation. For example, a frame could be “governor subject with permissive modal verb (e.g. may)”, which would indicate a permission for the governor. We apply these types of frames to the parse data to construct datasets for empirical analysis.

Automated methods to extract relevant information from legislative texts have recently been used for both federal laws (Al-Ubaydli and McLaughlin 2017) and state laws (Vakilifathi 2016). Vakilifathi (2016), the closest paper to ours, measures the level of statutory discretion in statutes regulating charter schools by counting the number of mandatory and optional statements, which are based on dictionaries of words and phrases. The author identifies these

statements mainly by looking at modal verbs, associating ‘shall’ to mandatory sentences and ‘may’ to optional ones. She also includes in the analysis some alternative optional and mandatory phrases. Our method has some advantages over this approach. Using parse information and frames allows us to filter out false positives: the modal counting method would treat “shall not be expected” as mandatory, while our frame rules would not.

Automated legislation information extraction is possible because computers can now quickly and reliably extract detailed lexical and syntactic information from large corpora. This technology – from computational linguistics – is known as syntactic dependency parsing. Parsers produce interpretive data on the syntactic structure of a sentence – the words and the grammatical relations between them (Jurafsky and James 2000). This includes, first, the parts of speech (POS) – verb, noun, adjective, etc. Moreover, the method tells us whether a noun is the subject (the agent) or the object (the target) of the sentence. It tells us rich information about the verb – whether it is the main verb or just an auxiliary, whether it is active or passive, and so on. A detailed discussion is provided in the Appendix.

In the demonstrations reported below, our dependencies are produced using the Python package spaCy (Choi, Tetreault and Stent 2015; Honnibal, Johnson et al. 2015). The spaCy parser obtains state-of-the-art performance on the standard computational linguistics metrics. Like most parsers, it is trained on corpora of hand-parsed sentences (Goldberg and Nivre 2012).

A key step in legislative information extraction is to consider what information is available from the syntactic parser and then to define a set of provision types that are relevant to the research question (Soria, Bartolini, Lenci, Montemagni and Pirrelli 2007; Saias and Quaresma 2004). For example, one might be interested in statements that expand the governor’s powers, versus statements that constrain them. With this goal in mind, one can identify a set of lexical units that could serve as tags or rules for identifying relevant provisions (van Engers, van Gog and Sayah 2004; Lame 2003). These “frames” can then be applied to the syntactic parser to create the dataset for use in the analysis.

In most research, constructing frames can be done using large-scale repositories of coded frames. These are dictionaries of words and dependencies that have been annotated to serve a theme, such as making a promise. Examples of these frame dictionaries include FrameNet (Baker, Fillmore and Lowe 1998; Ruppenhofer, Ellsworth, Petruck, Johnson and Scheffczyk 2006) and WordNet (Villata, Rizzi, Governatori and Dragoni 2016).

In the case of legislative information extraction, we analyze a set of legal provision frames that are probative of the content of laws. These include delegation, prohibition, permission, and entitlement. Our approach for extracting these items is based on Ash, MacLeod and Naidu (2017). Other work that has engaged with legal provision types using syntactic features includes Lame (2003), Saias and Quaresma (2004), and Ceci, Lesmo, Mazzei, Palmirani and Radicioni (2011).

In defining these legal provisions, we start by deciding which modal and special verbs are associated with them. For instance, legal provisions which delegate authority, such as “The Governor shall act.” These “delegations” contain strict modals, such as ‘shall’ (unlike permissions, which would take a permissive modal such a “may”). Unlike prohibitions (which are negative – e.g. “shall not”), delegations are positive. In addition, delegations could be articulated through a number of “delegation verbs,” such as ‘require’, ‘expect’ and so on. An example of this would be ‘The Governor is expected to’. A detailed and reproducible articulation of the tags and rules underlying our frames may be found in the Appendix.

The final stage of the process is to match the lexical and syntactic structure of the provision types with that of the sentences in the text. We then extract the number of delegations, prohibitions and so on for each jurisdiction and over time. We also have important associated information, such as who or what is the subject of the provision. For example, in the second application below we identify provisions where the subject is for the term ‘governor’.

¶

¹A subtler approach in future work could identify synonyms for governor, using WordNet or using word embeddings (Mikolov, Sutskever, Chen, Corrado and Dean 2013).

U.S. State Session Laws Corpus

Our information extraction approach is applied to a unique dataset consisting of the full text of U.S. state session laws from the 19th century to the 21st century. This corpus was introduced by [Ash \(2016\)](#). The session laws consist of all the new statutes enacted by a legislature during a session, which are published annually or biennially. We process this raw data by removing all non-statute material from the texts and merging them. For consistency across states, the dataset is built biennially.

The type of corpus used for the analysis is crucial in computational linguistics. Legislation is particularly suitable for information extraction, as it tends to follow a rigid structure, which is rather consistent across entities and time. This makes detecting provision types easier. Also, the issue of co-referencing, namely the use of a pronoun as a subject of a sentence which refers to the subject of the previous sentence, is a problem in computational linguistics, especially when applied to newspaper articles ([Van Atteveldt, Kleinnijenhuis and Ruigrok 2008](#)). Legislation tends to be more precise and use fewer pronouns, making the identification of the subject of each sentence easier.

Bureaucratic Discretion in U.S. States

In recent decades, the literature on bureaucracy has focused on whether politicians delegate tasks to bureaucrats and how they do so. In other words, they look at what control instruments legislators put in place to manage policy implementation ([McCubbins and Schwartz 1984](#); [McCubbins, Noll and Weingast 1987](#); [Levine and Forrence 1990](#); [Epstein and O'Halloran 1994](#); [Martin 1997](#); [Gailmard and Patty 2012](#)). Legislators can use either ex ante or ex post control mechanisms ([Martin 1997](#)). Ex post control mechanisms refer, for instance, to the hiring and firing of bureaucrats. Different forms of ex ante mechanisms can be put in place, such as administrative procedures ([McCubbins, Noll and Weingast 1987](#)), but the literature has recently focused on the level of detail of legislation. Detailed laws, they argue,

are used to micro-manage policy implementation (Huber and Shipan 2002). The delegation literature studies whether these two types are substitutes (Huber and Shipan 2008).

Building on these ideas, we ask whether after the introduction of an independent bureaucracy, which weakens the legislators' capacity to control bureaucrats ex post, legislators write more detailed legislation, as a form of ex ante control mechanisms. We take the introduction of merit systems in the civil service in U.S. states as a natural experiment for this purpose.

2

Measuring Discretion through Legislative Detail

The level of detail of legislation is central in analyzing bureaucratic discretion. For example, Huber and Shipan (2002) seek to examine the variation in the level of detail of the statutes implementing the federal Medicaid program across U.S. states. First, they select the relevant statutes for Medicaid by searching legal databases. Second, they manually code the policy specificity of the words contained in these statutes. They distinguish between procedural and policy language, arguing that procedural language is less constraining than policy language (Huber and Shipan 2002). The logic is that

a bureaucrat can comply with the need to write a report or to consult particular groups or to conclude his or her work in a specified time period without being sharply constrained with respect to the policy actually implemented. But if the statute says to do X, the bureaucrat cannot do Y (at least without some risks) (Huber and Shipan 2002, p.48).

In their large N analysis of the level of detail of legislation across different jurisdictions, Huber and Shipan (2002) use instead a rather 'crude' measure the length of legislation as proxy for the discretion left to bureaucrats: the longer the statutes, the greater the effort to

²The use of the design of bureaucratic agencies to measure their discretion is a well established practice in the literature (Volden 2002; Wood and Bohte 2004).

reduce discretion. In this case, they do not look at the distinction between procedural and policy language.

The approach in our paper is a compromise between these two extremes. On the one hand, we appreciate that the distinction between procedural and policy language cannot be easily applied to different cases. On the other hand, the length of legislation alone is too “extreme” solution to this problem. We need to find categories applicable to legislation in general that give us a more valid proxy of the level of detail of legislation than the length.

The solution is to look for *legally* (rather than *policy*) relevant information from texts. Applying the information extraction techniques described above, we count the most common types of legal provisions.

Econometrics

We test the effect of the introduction of an independent bureaucracy on our measure of discretion; more provisions means less discretion. We analyze 50 U.S. states from 1900 to 2000.

The estimating equation is

$$\log(\text{LegalProvisions}_{st}) = \alpha \text{Merit}_{st} + \beta X_{st} + \gamma_s + \delta_t + \phi_s t + \varepsilon_{st} \quad (1)$$

where $\log(\text{LegalProvisions}_{st})$ represents the logged number of legal provisions in the statutes of the state for every biennium, Merit_{st} is the variable which measures the introduction of a comprehensive merit system, X_{st} is a vector of time-varying state characteristics, γ_s and δ_t are state and time (biennium) fixed effects and $\phi_s t$ represents state-time trends³. The equation is estimated using ordinary least squares and standard errors are clustered to allow

³Controlling for time fixed effects accounts for the competing explanation based on vertical delegation of powers from the federal to the state level. Indeed, it might be argued that the creation of an independent agency and more regulation co-occur when more competences are given to the states. Yet, if we assume that the delegation of competences from the federal to the state level occurs at the same time for all the states (which is usually the case), then time fixed effects control for this.

serial correlation within state.

Results

Table 1 shows the results for the fixed-effects regression. The introduction of the civil service is statistically associated with higher levels of detail in legislation (Column 1).

Table 1: Civil Service Reform and Legislative Detail

	(1) Leg Detail	(2) Leg Detail	(3) Leg Detail	(4) Leg Detail	(5) Leg Detail	(6) Leg Detail
Introduction Civil Service	0.987** (0.0704)	0.137* (0.0632)	0.149* (0.0585)	0.157* (0.0653)	0.147* (0.0713)	0.131* (0.0595)
Introduction of Drafting System		0.0755 (0.0816)	0.0831 (0.0757)	0.0775 (0.0813)	0.0764 (0.0813)	0.0820 (0.0792)
Divided Government		-0.0256 (0.0297)	-0.0252 (0.0294)	-0.0255 (0.0291)	-0.0359 (0.0312)	-0.0255 (0.0288)
Constant	8.639** (0.0371)	-2.209* (0.930)	-0.412 (1.138)	-2.189* (0.932)	-2.095* (0.979)	-2.303* (0.892)
Observations	2,448	1,438	1,382	1,438	1,438	1,485
State FE	X	X	X	X	X	X
Time FE		X	X	X	X	X
State-Specific Trends		X	X	X	X	X
Lagged DV			X			
Reform Year				X		
Interaction					X	

Notes: Column 1 shows the results for the OLS regression model with state fixed effects. Column 2 adds biennium fixed effects, time-varying controls (introduction of drafting system and divided government) and state-specific time trends. Column 3 adds the lagged dependent variable. Columns 4 and 5 use the same specification of Column 2, but respectively add a dummy variable for the reform year and the interaction between divided government and the introduction of the merit system. Column 6 uses as treatment variable the introduction and the repeal of merit system. In all models standard errors are clustered by state. **p<.01; *p<.05; +p<.1.

The coefficient and standard errors are robust across specifications. First, there is no change from adding the lagged dependent variable (Column 3), which addresses the issues of long-term serial correlation in state panel data documented by [Caughey, Xu and Warshaw \(2017\)](#). Second, there is no change from adding controls for Divided Government (Column 2) or Divided Government interacted with Civil Service Reform (Column 5). This means that our results are not driven by the correlated changes in government structure documented in the previous section. Adding a separate dummy variable for the year of the reform (Column 4) does not change the results either, meaning that the effect happens after the introduction

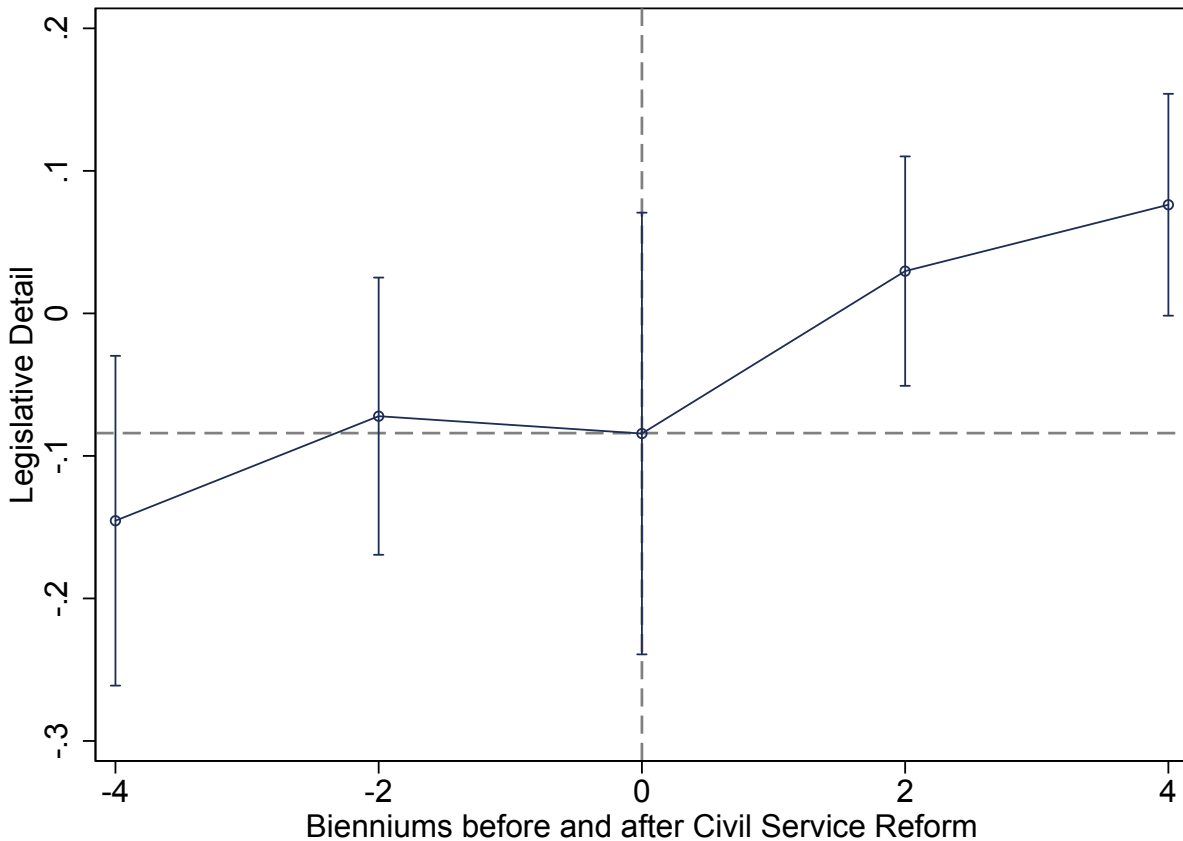


Figure 1: Event Study Graph

of the merit system and not contemporaneously with it. We also incorporate in the main independent variable the repeal of the merit system, as it occurred in 15 states from 1996. Column 6 in Table 1 shows the results, which are similar.

Figure 1 shows an event study graph. This graph shows the residuals of the logged number of provisions plotted against a small subset of bienniums, namely four bienniums before the civil service reform and four bienniums after. ⁴ In other words, this plot shows the deviation in provisions in the years before and after the reform, relative to the year of reform. Results suggest no evidence for pre-trends and that the effect on legislative complexity takes place the next biennium after the introduction of an independent bureaucracy.

These findings are consistent with the idea that after the establishment of an indepen-

⁴The regression includes state and time fixed effects, state-time trends, clustered standard errors and the time-varying controls discussed above.

dent bureaucracy, legislators start writing more detailed statutes in order to micro-manage policy implementation. The reform of the civil service and the introduction of an independent bureaucracy prevent legislators from using ex post control mechanisms, such as firing bureaucrats at will. Hence, legislators start putting in place ex ante control mechanisms, such as writing detailed legislation.

An additional set of model specifications and robustness checks are reported in Table A7, which shows the results for the regression models with different types of provisions as dependent variables. Results are robust across types, suggesting an increase in entitlements, permissions, constraints, and obligations associated with the introduction of an independent civil service. ⁵

Finally, in the Appendix we also test whether divided government has an effect on legislative complexity in those years where the merit system was not in place. Results in Table A8 show that in those years there is no effect of divided government on legislative complexity, providing further evidence that divided government is not driving the results.

Executive Delegation in US States

The delegation literature focuses on the substitutability of control mechanisms, but also on actor's preferences. This is the focus of our second application.

Delegation scholars agree that where the preferences of the actor A and the actor B converge, more delegation will take place (Huber and Shipan 2002, 2008). Strong evidence for this claim has been found in different contexts by different studies. Hence, a strong relationship is present between traditional measures of delegation and preference convergence. Therefore we expect a relation to be present between the new measure which is derived with our information extraction approach and preference convergence.

Volden (2002) studies welfare boards in US state governments. He finds that, where

⁵This finding is relevant to the discussion on the difference between statutory discretion and level of detail of legislation.

the preferences of the legislature and the governor are aligned, namely where they come from the same party, legislators will give governors appointment powers over welfare boards. Scholars studying the powers of governors in the U.S. states emphasize the importance of the institutional design of the governor office, such as appointment powers, control over the budget, term limit and so on (Beyle 1990, 2007; Krupnikov and Shipan 2012; Kousser and Phillips 2012). Most studies look at the institutional design of the administrative agency or executive body to which authority is delegated.

This so called ally principle has also been tested in another way, namely by looking at the content of the legislation enacted by those who delegate powers (Huber and Shipan 2008). Epstein and O'Halloran (1999) introduce a novel measure of statutory executive delegation, which consists of two components: the delegation ratio, namely the amount of authority delegated to executive branch, and the constraint ratio, namely the degree of constraining exerted on the executive branch. The former is measured with the proportion of provisions in a legislative act that delegate policy authority and the latter with the number of constraints. The total measure of statutory executive delegation is given by the share of provisions delegating powers in an act, weighted by the constraints imposed on executive action. As explained by Franchino (2004), the measure is the following:

$$d_i = D_i/M - [(C_i/TC) - (D_i/M)] \quad (2)$$

In the formula above, d_i is the total statutory executive delegation enjoyed by the actor i , M is the total number of provisions/statements in an act, D_i is the number of delegating provisions referring to the actor i , C_i is the number of constraints referring to the actor i and TC is the total number of possible constraints. D_i/M is the delegation ratio and C_i/TC is the constraint ratio.

Epstein and O'Halloran (1999) apply this measure to the delegation of powers from the Congress to the executive, finding less delegation when the executive and the legislative do not share the same policy preferences, namely in a divided government situation. Franchino

(2004) corroborates this finding, by applying this method to the delegation of powers in the EU. He looks at the Council of Ministers, which might be considered the equivalent of the second legislative chamber in the EU political system and which consists of Member States' heads of state and government. He finds they delegate more to the Commission (the equivalent of the executive) where Member States' preferences converge. In conclusion, robust empirical evidence from traditional methods supports the ally principle.

The process by which researchers have so far applied this formula is the following. First, researchers identify a group of relevant pieces of legislation, according to some guidelines, such as previous research, as in Epstein and O'Halloran (1999), or the relevant jurisprudence, as in Franchino (2004). Then, they manually code provisions according to whether they grant policy discretion or not. Finally, they identify potential categories of procedural constraints and manually counts their frequency in the documents.

This approach has some disadvantages. First, it is time and resource consuming. Indeed, the manual coding requires substantial knowledge of the legal documents and the broad legal system under study. Moreover, the coders need to go through hundreds of documents and at least partially cross validate results. In fact, manual coding requires substantial judgments on a series of important aspects: which documents to sample, which statements are relevant, what the potential categories of procedural constraints look like and so on. This also makes replicating studies using this method in other contexts rather difficult.

In this section, we use the information extraction method discussed above to measure statutory executive delegation. We introduce a reduced form of the statutory executive delegation formula proposed by Epstein and O'Halloran (1999), where we do not have to make a subjective judgment on the number of possible constraints in a piece of legislation. We calculate the constraint ratio by simply dividing the number of constraints by the total number of statements. Then, we take the delegation ratio and we subtract the constraint ratio to it.

$$d_i = (D_i - C_i)/M_i \quad (3)$$

With this formula, we do not (need to) make a subjective call on what pieces of legislation and provisions are relevant for delegation ex ante. Our information extraction approach allows the identification of provision types, based on lexical and syntactic rules, as explained above, and the subjects of those provisions. Hence, we modify the formula so that we divide the difference between the delegation ratio and the constraint ratio by the number of provisions referring to the actor i . In our case, that actor is the governor.

Econometrics

We now proceed to the analysis of executive delegation. If our new approach is valid, we will expect a positive relationship between government unity and statutory executive delegation. As explained above, the latter is given by the difference between the number of delegating statements and constraints divided by the total number of statements with governor as subject, as seen in the formula above.

The variable measuring unified government is taken from [Klarner \(2003\)](#). Data is available from 1935 to 2010. The measure used in the main text takes value 0 with divided government (where the two chambers and the governor are not controlled by the same party) and value 1 in the situation where a single party controls all three institutions.

We test whether executive delegation is associated with government unity, across the 50 U.S. states from 1935 to 2010. This panel data allows to control for state fixed effects (time-invariant state characteristics) and year fixed effects (variables that change over time, but not across entities, such as the influence from the federal level). We also include state-specific time trends to control for confounding trends. Finally, we also add the lagged dependent variable to our model, to control for the effect of past levels of delegation on current ones. Finally, we control for the introduction of the civil service because, as seen above, it has an

effect on the number of provisions in the statutes. Standard errors are clustered by state, to allow serial correlation within state in the outcome variable.

Results

Before showing the results of the regression analysis, we discuss some descriptive statistics (see the Appendix for more detail). The left panel in Figure 2 shows the delegation ratio averaged across states from 1900. The graph suggests a negative trend roughly until WWII, then an increase in delegation until the 1980s and then again a decreasing trend. Trends in delegation to US state governors are very similar to trends in delegation to the executive at federal level, as shown in Figure 5.10 in Epstein and O'Halloran (1999, p. 138). The right panel in Figure 2 shows, instead, the constraint ratio averaged across states from 1900. We can see that the constraint ratio is constant until the 1950s, but then we note a constant increase. Again, this is very similar to the trends in constraints to the executive in the US at federal level identified in Figure 5.11 in Epstein and O'Halloran (1999, p. 139).

These preliminary findings are also in line with anecdotal evidence on the powers of governors provided by the literature. For instance, Rosenthal (1982) finds that after WWII the governor dominated state politics, with few exceptions (e.g. Florida and Colorado), but in the 1980s the situation became more balanced. This provides support for the decrease in executive delegation since the 1980s, seen in Figure 2. Also, Ruhil and Camões (2003) suggest that overall the powers of governors increased in the aftermath of the Great Depression. Again, this is in line with the slight increase in executive delegation in the 1930s in Figure 2.

Table 2 shows the results of the fixed effects regression analysis with the measure of executive delegation discussed above as dependent variable. Results are robust to different specifications. A positive relationship is present between unified government and executive delegation, which suggests that where a single party controls the legislature and the executive, legislators tend to delegate more powers to the executive.

Figure 2: Average Delegation Ratio and Constraint Ratio

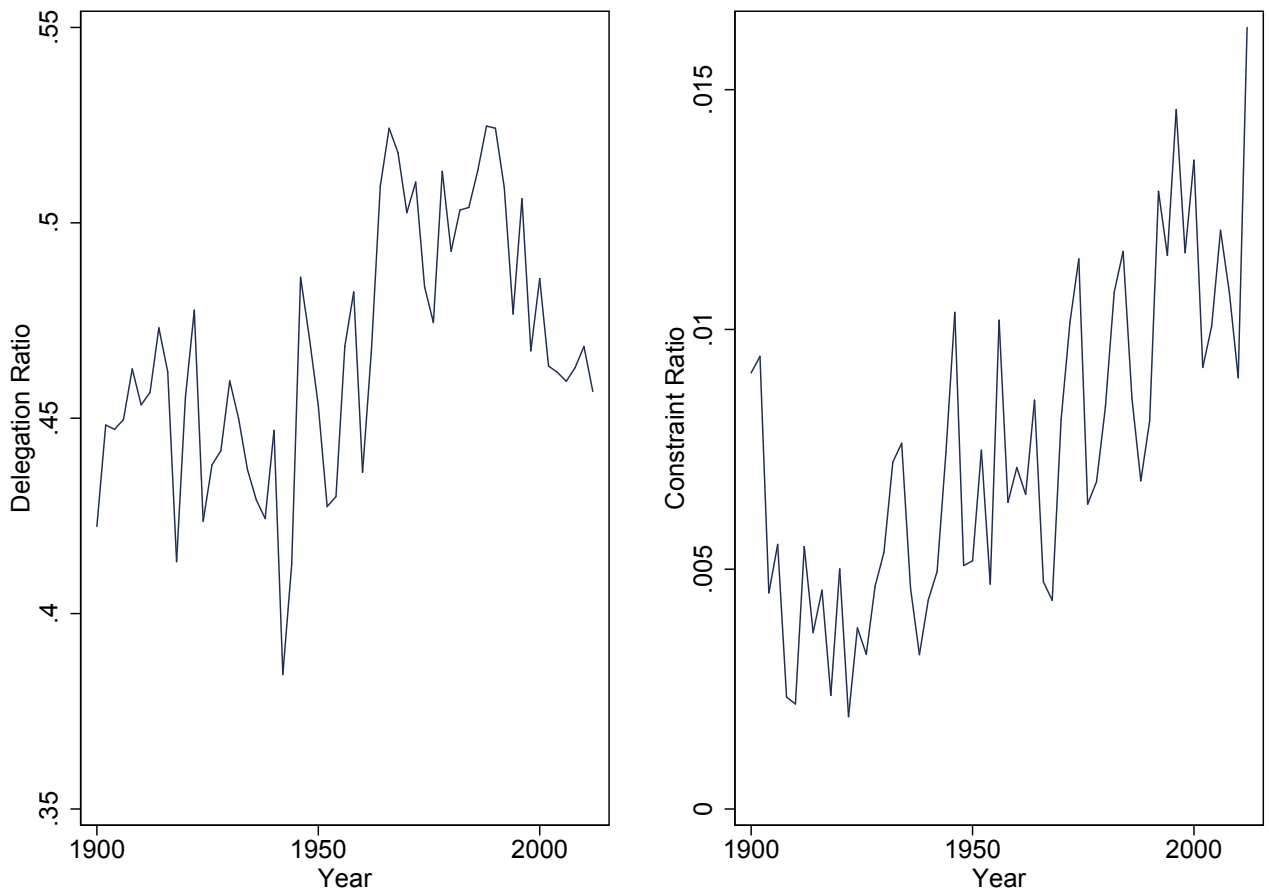


Table 2: Effect of Unified Government on the Executive Delegation to the Governor

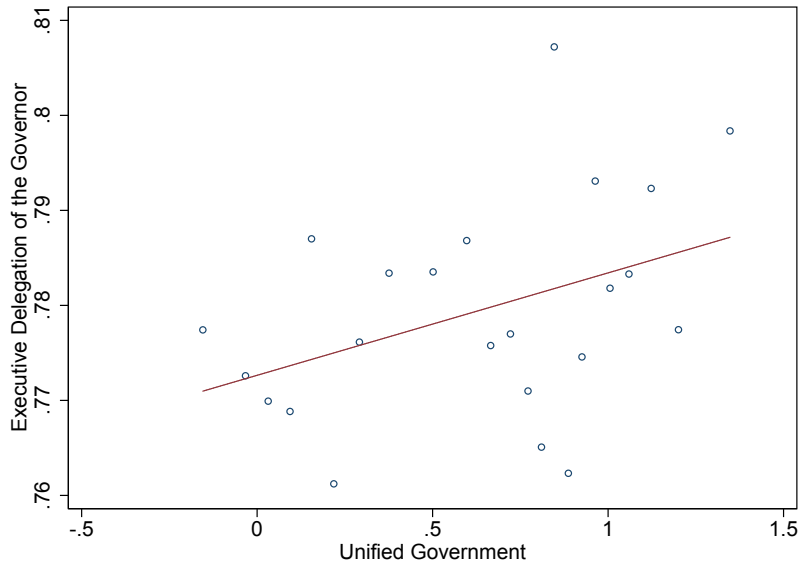
VARIABLES	(1) Delegation	(2) Delegation	(3) Delegation
Unified Government	0.0108+ (0.00574)	0.0117* (0.00538)	0.00997+ (0.00559)
Constant	0.773** (0.00359)	1.567** (0.147)	2.055** (0.0770)
Observations	2,259	2,208	2,212
State FE	X	X	X
Year FE	X	X	X
State-time Trends		X	X
Lagged DV		X	
Civil Service			X

Notes: Column 1 shows the results for the OLS regression model with state and biennium fixed effects. Column 2 adds state-specific time trends and the lagged dependent variable. Column 3 adds the introduction of an independent civil service as control. In all models standard errors are clustered by state. **p<.01; *p<.05; +p<.1.

Figure 3 shows the binned scatterplot from the multivariate regression above. This is a non-parametric method of plotting the conditional expectation function (which describes the average y-value for each x-value). To make the figure, we regressed the independent and dependent variables on the control variables (in this case, state and year dummies) and generated residuals. Then, we grouped the residualized variable in the horizontal axis into 23 equal sized bins, computed the mean of the residuals of each variable within each bin and created a scatterplot of these 23 data points. Each point shows the average level of delegation for a given level of unified government, holding the controls constant. The positive coefficient in the regression is reflected in the positive slope in the figure.

In conclusion, we find evidence for a significant and positive relationship between unified government and the statutory executive delegation to the governor. In other words, when the legislators and the governor are from the same party and hence they converge in their

Figure 3: Effect of Unified Government on the Executive Delegation to the Governor



policy preferences, the former delegate more powers to the latter. This is in line with the findings of a long tradition of delegation studies and hence we can validate our information extraction approach to measure executive delegation.

Conclusion

In this work, we introduce a new approach to political text analysis – instead of treating text as a ‘bag of words’, we look at richer language representations. By looking at the lexical and syntactic features of texts, we can classify statements according to their meaning. Above, we show how to retrieve some legal provisions, namely delegations, entitlements, and prohibitions, from legal texts.

We illustrate the validity of this approach, by testing two predictions commonly accepted in the literature: the introduction of a merit system in the civil services of US states is associated with an increase in the number of legal provisions contained in statutes and that the number of provisions delegating powers to the governor in U.S. state session laws are associated with government unity.

This is only one of the many potential contributions computational linguistics can make to social research. Future research should, for instance, use the approach above to extract information about exceptions, loopholes or suspensions from legal texts. Recent work in legal studies uses an approach similar to the one discussed above to extract suspension norms (Ceci et al. 2011; Palmirani, Ceci, Radicioni and Mazzei 2011). Other work has tried to retrieve exceptions, which are another sub-category of efficacy provision and represent a modification of the norm where the rules are restricted with respect to the original scope (Palmirani et al. 2011). Loopholes have also been recently studied in tax legislation from a computational linguistic perspective.

This focus can be interesting for political scientists studying the effect of gridlock and vetoes on decision-making, a growing area of scholarship. This could open the doors for a new research agenda which looks at the effect of gridlocks on the realized content of legislation.

References

- Al-Ubaydli, Omar and Patrick A McLaughlin. 2017. “RegData: A numerical database on industry-specific regulations for all United States industries and federal regulations, 1997–2012.” *Regulation & Governance* 11(1):109–123.
- Ash, Elliott. 2016. “The political economy of tax laws in the US states.”
- Ash, Elliott, Bentley MacLeod and Suresh Naidu. 2017. “The language of contract: Promises and power in union collective bargaining agreements.” *working paper* .
- Baker, Collin F, Charles J Fillmore and John B Lowe. 1998. The berkeley framenet project. In *Proceedings of the 36th Annual Meeting of the Association for Computational Linguistics and 17th International Conference on Computational Linguistics-Volume 1*. Association for Computational Linguistics pp. 86–90.
- Beyle, Thad. 1990. “The Powers of the Governor in North Carolina: Where the Weak Grow Strong-Except for the Governor.” *North Carolina Insight* March.
- Beyle, Thad. 2007. “Gubernatorial Power: The Institutional Power Ratings for the 50 Governors of the United States.” *University of North Carolina at Chapel Hill* .
- Caughey, Devin, Yiqing Xu and Christopher Warshaw. 2017. “Incremental Democracy: The Policy Effects of Partisan Control of State Government.” *The Journal of Politics* 79(4):1342–1358.
- Ceci, Marcello, Leonardo Lesmo, Alessandro Mazzei, Monica Palmirani and Daniele P Radicioni. 2011. Semantic annotation of legal texts through a framenet-based approach. In *International Workshop on AI Approaches to the Complexity of Legal Systems*. Springer pp. 245–255.
- Choi, Jinho D, Joel R Tetreault and Amanda Stent. 2015. “It Depends: Dependency Parser Comparison Using A Web-based Evaluation Tool.” *ACL* pp. 387–396.

- Epstein, David and Sharyn O'Halloran. 1994. "Administrative procedures, information, and agency discretion." *American Journal of Political Science* pp. 697–722.
- Epstein, David and Sharyn O'Halloran. 1999. "Delegating Powers New York."
- Franchino, Fabio. 2004. "Delegating powers in the European Community." *British Journal of Political Science* 34(2):269–293.
- Gailmard, Sean and John Patty. 2012. "Formal Models of Bureaucracy." *Annual Review of Political Science* 15(1):353–377.
- Gentzkow, Matthew and Jesse Shapiro. 2010. "What Drives Media Slant? Evidence from US Daily Newspapers." *Econometrica* 78(1):35–71.
- Goldberg, Yoav and Joakim Nivre. 2012. "A Dynamic Oracle for Arc-Eager Dependency Parsing." *Proceedings of COLING 2012: Technical Papers, COLING 2012, Mumbai, December 2012*. pp. 959–976.
- Grimmer, Justin and Brandon M Stewart. 2013. "Text as data: The promise and pitfalls of automatic content analysis methods for political texts." *Political Analysis* 21(3):267–297.
- Honnibal, Matthew, Mark Johnson et al. 2015. "An Improved Non-monotonic Transition System for Dependency Parsing." *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, Lisbon, Portugal, 17-21 September 2015* pp. 1373–1378.
- Huber, J.D. and C.R. Shipan. 2002. *Deliberate Discretion?: The Institutional Foundations of Bureaucratic Autonomy*. Cambridge University Press.
- Huber, John D. and Charles R. Shipan. 2008. *Politics, Delegation, and Bureaucracy*. Oxford, UK: Oxford University Press.
- Jurafsky, Daniel and H James. 2000. *Speech and Language Processing: an Introduction to Natural Language Processing, Computational Linguistics, and Speech*. London, UK: Pearson Education.

- Klarner, Carl. 2003. "Measurement of the Partisan Balance of State Government." *State Politics and Policy Quarterly* 3:309–19.
- Klebanov, Beata Beigman, Daniel Diermeier and Eyal Beigman. 2008. "Lexical Cohesion Analysis of Political Speech." *Political Analysis* 16(4):447–463.
- Kousser, Thad and Justin H Phillips. 2012. *The power of American Governors: Winning on Budgets and Losing on Policy*. Cambridge, UK: Cambridge University Press.
- Krupnikov, Yanna and Charles Shipan. 2012. "Measuring Gubernatorial Budgetary Power: A New Approach." *State Politics and Policy Quarterly* 12(4):438–455.
- Lame, Guiraud. 2003. Using text analysis techniques to identify legal ontologies's components. In *Workshop on Legal Ontologies of the International Conference on Artificial Intelligence and Law*. pp. 50–61.
- Lauderdale, Benjamin and Alexander Herzog. 2016. "Measuring Political Positions from Legislative Speech." *Political Analysis* 24(3):374–394.
- Laver, Michael and John Garry. 2000. "Estimating Policy Positions from Political Texts." *American Journal of Political Science* pp. 619–634.
- Levine, Michael E. and Jennifer L. Forrence. 1990. "Regulatory Capture, Public Interest, and the Public Agenda: Toward a Synthesis." *Journal of Law, Economics and Organization* 6:167–198.
URL: <http://www.jstor.org/stable/764987>
- Lucas, Christopher, Richard A Nielsen, Margaret E Roberts, Brandon M Stewart, Alex Storer and Dustin Tingley. 2015. "Computer-assisted text analysis for comparative politics." *Political Analysis* 23(2):254–277.
- Martin, Elizabeth M. 1997. "An informational theory of the legislative veto." *Journal of Law, Economics, and Organization* 13(2):319–343.

- McCubbins, Mathew D, Roger G Noll and Barry R Weingast. 1987. "Administrative procedures as instruments of political control." *Journal of Law, Economics, and Organization* 3(2):243–277.
- McCubbins, Mathew and Thomas Schwartz. 1984. "Congressional Oversight Overlooked: Police Patrols versus Fire Alarms." *American Journal of Political Science* 28(1):165–179.
- Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S Corrado and Jeff Dean. 2013. Distributed Representations of Words and Phrases and their Compositionality. In *Advances in Neural Information Processing Systems 26*, ed. C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani and K. Q. Weinberger. Curran Associates, Inc. pp. 3111–3119.
- Monroe, Burt L, Michael P Colaresi and Kevin M Quinn. 2008. "Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict." *Political Analysis* 16(4):372–403.
- Palmirani, Monica, Marcello Ceci, Daniele Radicioni and Alessandro Mazzei. 2011. FrameNet model of the suspension of norms. In *Proceedings of the 13th International Conference on Artificial Intelligence and Law*. ACM pp. 189–193.
- Roberts, Margaret E, Brandon M Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder Luis, Shana Kushner Gadarian, Bethany Albertson and David G Rand. 2014. "Structural Topic Models for Open-Ended Survey Responses." *American Journal of Political Science* 58(4):1064–1082.
- Rosenthal, Alan. 1982. "The State of State Legislatures: An Overview." *Hofstra L. Rev.* 11:1185.
- Ruhil, Anirudh VS and Pedro J Camões. 2003. "What lies beneath: the political roots of state merit systems." *Journal of public administration research and theory* 13(1):27–42.

- Ruppenhofer, Josef, Michael Ellsworth, Miriam RL Petruck, Christopher R Johnson and Jan Scheffczyk. 2006. *FrameNet II: Extended Theory and Practice*. Berkeley, CA: International Computer Science Institute.
- Saias, JosÃ and Paulo Quaresma. 2004. Using nlp techniques to create legal ontologies in a logic programming based web information retrieval system. In *Workshop on Legal Ontologies and Web based legal information management of the 9th International Conference on Artificial Intelligence and Law, Edinburgh, Scotland*.
- Soria, Claudia, Roberto Bartolini, Alessandro Lenci, Simonetta Montemagni and Vito Pirrelli. 2007. Automatic extraction of semantics in law documents. In *Proceedings of the V Legislative XML Workshop*. pp. 253–266.
- Vakilifathi, Mona. 2016. “Constraining Bureaucrats Today Knowing You’ll Be Gone Tomorrow: The Effect of Legislative Term Limits on Statutory Discretion.” *Policy Studies Journal*.
- Van Atteveldt, Wouter, Jan Kleinnijenhuis and Nel Ruigrok. 2008. “Parsing, Semantic Networks, and Political Authority Using Syntactic Analysis to Extract Semantic Relations from Dutch Newspaper Articles.” *Political Analysis* 16(4):428–446.
- van Engers, Tom M, Ron van Gog and Kamal Sayah. 2004. “A case study on automated norm extraction.” *Legal knowledge and information systems, Jurix* pp. 49–58.
- Villata, Serena, Williams Rizzi, Guido Governatori and Mauro Dragoni. 2016. “Combining NLP Approaches for Rule Extraction from Legal Documents.”
- Volden, Craig. 2002. “Delegating power to bureaucracies: Evidence from the states.” *Journal of Law, Economics, and Organization* 18(1):187–220.
- Wood, B Dan and John Bohte. 2004. “Political transaction costs and the politics of administrative design.” *Journal of Politics* 66(1):176–202.

Appendix: Measuring Discretion and Delegation in Legislative Texts: Methods and Application to U.S. States

Matia Vannoni^{*}, Elliott Ash[†], Massimo Morelli[‡]

June 10, 2019

^{*}King's College London, email: matia.vannoni@kcl.ac.uk

[†]ETH Zurich, email: ashe@ethz.ch

[‡]Bocconi University and CEPR, email: massimo.morelli@unibocconi.it

Legal Ontologies

The construction of a legal ontology starts with the identification of the lexical units. Table A1 shows the lexical units associated with the four ontologies we choose to look at in this paper. These categories are based on [Ash, MacLeod and Naidu \(2017\)](#).

Table A1: Lexical Units

STRICT MODALS	'shall', 'must', 'will'
PERMISSIVE MODALS	'may', 'can'
DELEGATION VERBS	'require', 'expect', 'compel', 'oblige', 'obligate', 'have to', 'ought to'
CONSTRAINT VERBS	'prohibit', 'forbid', 'ban', 'bar', 'restrict', 'proscribe'
PERMISSION VERBS	'allow', 'permit', 'authorize'
ENTITLEMENT VERBS	'have', 'receive', 'retain'

Table A2 shows the syntactic structure of the provisions analysed in this work, written in Python-like programming language, to make replication easy. As discussed in the main body, a delegation is characterised by three structures, all positive: either a strict modal followed by an (active) verb, or a strict modal followed by a delegation verb, or a delegation verb without strict modal. Examples are respectively: 'The Governor shall act', 'The Governor shall be required to' and 'The Governor is expected to'. Constraints are characterised by a negative structure with either a modal, or a permission verb, or a positive structure with a strict modal and a constraint verb. Examples are: 'The Governor shall not', 'The Governor is not allowed' and 'The Governor shall be prohibited to'. Permissions are characterised by a positive structure with either a permission verb or a permissive modal with no special verb (a non-special verb is any verb which does not fall into the categories in Table 1 in the main body), or a negative structure with a constraint verb. Examples are: 'The Governor is allowed to', 'The Governor may act' and 'The Governor is not prohibited to'. Finally, entitlements are characterised by a positive structure with either an entitlement verb or a strict modal and a (passive) verb, or a negative structure with a delegation verb. Examples are: 'The Governor retains the power to', 'The Governor shall be considered' and 'The Governor is not compelled to'.

Table A2: Code for Provision Syntactic Structure

Delegation	not item['neg'] and item['strict_modal'] and item['active_verb']
	not item['neg'] and item['strict_modal'] and item['delegation_verb']
	not item['neg'] and not item['md'] and item['delegation_verb']
Constraint	item['neg'] and item['md'] and not item['delegation_verb']
	not item['neg'] and item['strict_modal'] and item['constraint_verb'] item['neg'] and item['permission_verb']
Permission	not item['neg'] and item['permission_verb']
	not item['neg'] and item['permissive_modal'] and not item['special_verb'] item['neg'] and item['constraint_verb']
Entitlement	not item['neg'] and item['entitlement_verb']
	not item['neg'] and item['strict_modal'] and item['passive'] item['neg'] and item['delegation_verb']

Syntactic Parsing

Although several parsing methods are present, we use dependency parsing, as suggested by recent developments in NLP (Dell’Orletta, Marchi, Montemagni, Plank and Venturi, 2012, Montemagni and Venturi, 2013). The parser models sentence structure over the words contained in the sentence and the grammatical relations between them (Jurafsky and James, 2000). A dependency relation consists of a head word and a dependent word, related to each other through a functional dependency. Examples of functions are nominal subject, direct object, and so on. More formally, a dependency structure $G = (V, A)$ consists of vertices V , the set of words in a sentence, and arcs A , the head-dependent and grammatical relations (Jurafsky and James, 2000, Choi and Palmer, 2012). Usually dependencies are displayed as (projective) ‘parse trees’, which represent the relations between words in a recursive hierarchical structure. Dependency trees are graphs where: 1) there is a single head, with no incoming arc; 2) each vertex (apart from the head) has at least one incoming arc; 3) there is

a unique path from the root node to each vertex (Jurafsky and James, 2000, Goldberg and Nivre, 2012). Figure A1 in the Appendix shows an example of a dependence parse tree.

The widely used transition-based parsing algorithm works as follows (Jurafsky and James, 2000, Bird, Klein and Loper, 2009, Goldberg and Nivre, 2012, Honnibal, Johnson et al., 2015). The input is a list of tokens. The algorithm works through three transition operators, applied to the list of tokens: 1) the LEFT action asserts a head-dependent relation between the top word in the ‘stack’ (the list of words yet to be processed) and the one beneath and removes the lower word from the stack; 2) the RIGHT action asserts a head-dependent relation between the first and second words in the stack and removes the word at the top; 3) the SHIFT action removes the word from the initial list of tokens and places it into the stack.

To speed up the parser, the algorithm is greedy: once a dependency has been assigned, the token is removed from the stack and cannot be reassigned. For every token in the sentence, the parser consults a rulebook (the so-called ‘oracle’) that returns a transition (LEFT, RIGHT, or SHIFT) based on the current state. This ‘oracle’, a key piece of the parser software, is constructed by the developers to optimize accurate parsing based on training data.

The parser is trained on an annotated corpus of standard English articles. This corpus does not include legal documents. But we find that it does quite well on most sentences in our corpus of statutes.

We apply these parser methods to the text of state statutes. Although several implementations are available, such as SyntaxNet, NLTK, and CoreNLP, in this work we use spaCy, one of the most accurate and fastest parsers available today (Choi, Tetreault and Stent, 2015, Honnibal, Johnson et al., 2015).¹ After each sentence is parsed, we match up the extracted dependency relations to our set of syntactic units for delegations, prohibitions, and so on.

¹spaCy uses a transition-based approach, similar to the one described above (Choi and Palmer, 2012). The ‘oracle’ used by spaCy is from Goldberg and Nivre (2012). Several minor technical features make spaCy more complex than a simple transition-based parser, such as the use of an improved non-monotonic transition system, which relaxes the greedy algorithm approach and allows the parser to ‘go back’ on its decisions (Honnibal, Johnson et al., 2015).

If a sentence matches one of these categories, it is counted as a legal provision. To measure legislative detail, we count the number of legal provisions published in the state session laws for each state and each biennium.

The following sentences are from the California Government Code 11508 - (a) and 65852 - (a): “The agency shall consult the office, and subject to the availability of its staff, shall determine the time and place of the hearing”; “A local agency may, by ordinance, provide for the creation of accessory dwelling units in areas zoned to allow single-family or multifamily use”. Below in Figure A1, we provide the dependence trees for parts of these two sentence.

² The letters below the words represent the part of speech (POS) tags. A prerequisite of syntactic dependency parsing, indeed, is POS tagging. The latter assigns labels (‘tags’) to the tokens in a sentence according to their function, such as noun, verb, and adjective.³ For instance, in the sentence above, ‘(the) agency’ is a noun and ‘consult’ is a verb. Although POS tagging provides important information on the single token, it does not say much about the token’s relations with the other tokens in a sentence. This is where dependency parsing comes into play.

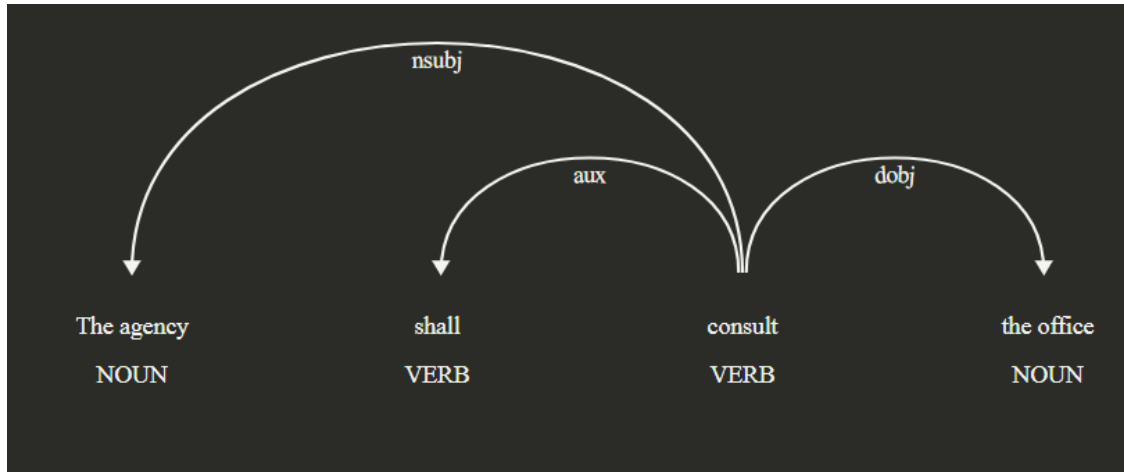
The arcs above the sentence in Figure A1 represent the syntactic relations between words. First of all, the parser identifies the head of the sentence, normally the main verb (‘consult’ and ‘provide’, respectively in the first and second sentence). The parser then identifies the subject of the sentence (‘the agency’ and ‘a local agency’, respectively in the first and second sentence) through the nominal subject (nsubj) relation. The subject may also be a clause. Finally, the parser looks at the other side of the sentence and, in the case of the second sentence, identifies two prepositions, namely ‘for’ and ‘of’, and two objects of this preposition, namely ‘the creation’ and ‘accessory dwelling units’, or in the case of the first sentence, directly the object ‘the office’.⁴

As it can be seen, the first sentence is a delegation, as it is an active and positive sentence

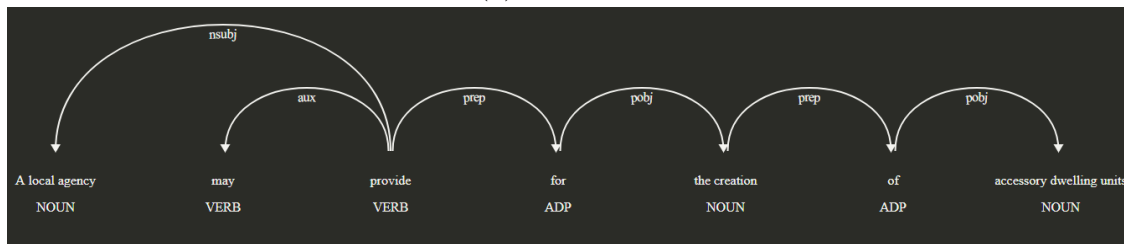
²This figure is taken from displaCy, a graphical interface for Spacy, the dependency parser used here.

³A full list of POS tags can be found [here](#) (accessed June 2017).

⁴ A full list of dependencies can be found in [De Marneffe and Manning \(2008\)](#).



(a) Delegation



(b) Permission

Figure A1: Dependency Parse Tree

which contain a strict modal, namely ‘shall’. This is close in spirit to the ‘the Agent shall act’ example of delegation provided above. Conversely, the second sentence is a permission, as it is positive and active, with a permissive modal, namely ‘may’, followed by a normal verb. This is very similar to the ‘the Agent may act’ example of permission discussed above.

Table A3 shows an example of the results of the data building step (i.e. a single observation in the new dataset created). This is an example of a permission, with governor as subject. In this case the Governor is allowed to give the prize ‘Arkansas Traveler’ to every individual she feels worthy of this award. One of the main advantages of the new approach proposed above is that not only does it allow classifying statements according to their content, but it also allows to detect the subject of the statement. This in turn allows to extrapolate information on who is bound or entitled to do what.

Table A3: Example of Permission

Full sentence	[...]the Governor of the State of Arkansas be authorized to designate and appoint distinguished visitors, citizens, and former citizens, who have distinguished themselves in various fields of endeavor as an Arkansas Traveler
Subject tags	'DT', 'NNP', 'IN', 'DT', 'NNP', 'IN', 'NNP'
Subject branch	'the', 'governor', 'of', 'the', 'state', 'of', 'arkansas'
Verb	'authorize'
Permission verb	True
Passive	True
Subject	'Governor'
Object tags	['IN'], ['TO', 'VB', 'CC', 'VB', 'JJ', 'NNS', ',', 'NNS', ',', 'CC', 'JJ', 'NNS', ',', 'WP', 'VBP', 'VBN', 'PRP', 'IN', 'JJ', 'NNS', 'IN', 'NN', 'IN', 'DT', 'NNP', 'NNP', ',', ''], ['VB']
Object branches	['that'], ['to', 'designate', 'and', 'appoint', 'distinguished', 'visitor', ',', 'citizen', ',', 'and', 'former', 'citizen', ',', 'who', 'have', 'distinguish', '-pron-', 'in', 'various', 'field', 'of', 'endeavor', 'as', 'an', 'arkansas', 'traveler', ',', ''], ['be']

State Session Laws

The dataset consists of full text of US state session laws, namely the collection of statutes enacted by a legislature, published every year or every two years from 1900 to 2000. The collection of statutes was retrieved from heinonline.com. For old statutes, only the scanned copy was available. Figure A2 shows the scanned copy of a page from a statute enacted in the Texas Legislature for the 1889 session. As it can be seen, although the statute is old, the quality of the digitised version is rather good.

It should be noted that the laws in the dataset give the flow, rather than the stock of legislation. In other words, the dataset contains also statutes which amend or repeal previous legislation or laws which failed or were vetoed. A team of research assistants was hired to review samples of the dataset and found that the presence of these statutes do not vary significantly within state over time.

The raw text was processed as follows. First, all pages were appended and non-statute material (e.g. headers, footers, table of contents, indexes) was removed. Then, the text was segmented into individual bills, acts and resolutions, using text markers (e.g. 'Chapter' followed by a number) to identify the start of a new statute. Indicators specific to some

TITLE 2.—OF OFFENSES AND PUNISHMENTS.

CH. 1.—DEFINITION AND DIVISION OF OFFENSES.

§116, Art. 52 to §121, Art. 57. See Penal Code.

CH. 2.—PUNISHMENTS IN GENERAL.

§122, Art. 58 to §140, Art. 73. See Penal Code.

TITLE 3.—OF PRINCIPALS, ACCOMPLICES AND ACCESSORIES.

CH. 1.—PRINCIPALS.

§141, Art. 74 to §148, Art. 78. See Penal Code. §149. Presence and participation. Annotated. §150 to §155. See Penal Code.

§149. Presence and participation. (1.) A principal offender under the law of this state is one who, being present when the offense is actually committed by another, and knowing the unlawful intent of such other, aids by acts or encourages by words the party engaged in the commission of the unlawful act. Would the State, in prosecuting such an aider and abettor as a principal offender, for an offense committed primarily in a foreign country, and consummated in this, be required to show a similar or analogous provision of the law of the foreign country? Fernandez v. S., 25 App. 838.

All persons are principals who are guilty of acting together in the commission of an offense, and this includes not only those who are present at the commission of the offense, but those who, though absent, are doing their part in connection with and in furtherance of the common design.

It is further provided by statute (Penal Code, Art. 76) that "all persons who shall engage in procuring aid, arms or means of any kind to assist the commission of an offense while others are executing the unlawful act, and all persons who endeavor at the time of the commission of the offense to secure the safety or concealment of the offenders, are principals, and may be convicted and punished as such."

It is also a well settled general rule that when several persons conspire or combine together to commit any unlawful act, each is criminally responsible for the acts of his associates or confederates, committed in furtherance or in prosecution of the common design for which they combine.

Evidence in this case tends to show that previous to the homicide the accused repeatedly declared his intention to kill the deceased, and that, on the evening of, but before the killing, he went to the house of deceased and told deceased's family to tell him that he and George Nixon, Aaron Nixon and Bill Evans were coming to his house that night to kill him; that about dark on that night the defendant and the said Nixons and the said Evans met at a certain house where they prepared arms and ammunition, and whence they went in the direction of the house of the deceased; that, just before the killing, George Nixon called the deceased from his house to the fence, and, while they were talking at the said

TITLE 2.—OF OFFENSES AND PUNISHMENTS.

CH. 1.—DEFINITION AND DIVISION OF OFFENSES.

§115, Art. 52 to §121, Art. 57. See Penal Code.

CH. 2.—PUNISHMENTS IN GENERAL.

§122, Art. 58 to §140, Art. 73. See Penal Code.

TITLE 3.—OF PRINCIPALS, ACCOMPLICES AND ACCESSORIES.

CH. 1.—PRINCIPALS.

§141, Art. 74 to §148, Art. 78. See Penal Code. §149. Presence and participation. Annotated. §150 to §155. See Penal Code.

§149. Presence and participation.

(1.) A principal offender under the law of this state is one who, being present when the offense is actually committed by another, and knowing the unlawful intent of such other, aids by acts or encourages by words the party engaged in the commission of the unlawful act. Would the State, in prosecuting such an aider and abettor as a principal offender, for an offense committed primarily in a foreign country, and consummated in this, be required to show a similar or analogous provision of the law of the foreign country? Fernandez v. S., 25 App. All persons are principals who are guilty of acting together in the commission of an offense, and this includes not only those who are present at the commission of the offense, but those who, though absent, are doing their part in connection with and in furtherance of the common design.

It is further provided by statute (Penal Code, Art. 76) that "all persons who shall engage in procuring aid, arms or means of any kind to assist the commission of an offense while others are executing the unlawful act, and all persons who endeavor at the time of the commission of the offense to secure the safety or concealment of the offenders, are principals, and may be convicted and punished as such."

It is also a well settled general rule that when several persons conspire or combine together to commit any unlawful act, each is criminally responsible for the acts of his associates or confederates, committed in furtherance or in prosecution of the common design for which they combine.

Evidence in this case tends to show that previous to the homicide the accused repeatedly declared his intention to kill the deceased, and that, on the evening of, but before the killing, he went to the house of deceased and told deceased's family to tell him that he and George Nixon, Aaron Nixon and Bill Evans were coming to his house that night to kill him; that about dark on that night the defendant and the said Nixons and the said Evans met at a certain house where they prepared arms and ammunition, and whence they went in the direction of the house of the deceased; that, just before the killing, George Nixon called the deceased from his house to the fence, and, while they were talking at the said

471

(a) Scanned Text

(b) OCR

Figure A2: Example of State Session Law

states were also taken into consideration. Again, a team of research assistant checked the validity of this segmentation process.

Bureaucratic Discretion in US States

Introduction of Merit System

The table below shows the dates of the adoption of the merit systems across US states. We rely on two main secondary sources, namely [Ujhelyi \(2014\)](#) and [Ting, Snyder, Hirano and Folke \(2013\)](#). Where the dates are the same in these two sources, no further research is carried out. Where these two dates differ, we look for further secondary and primary sources. In some cases, no sources were available and hence we relied on [Ujhelyi \(2014\)](#) ‘as default’. In those cases where we find that primary sources contradict his findings, we specify it in the Notes column.

Table A4: Dates of Adoption of Merit Systems

State	Introduction Merit System			Notes
	Ujhelyi (2014)	Ting et al. (2013)	This Paper	
AK	1960	1960	1960	Same
AL	1939	1939	1939	Same
AR	1969	1968	1969	Ujhelyi (2014) as default
AZ	1968	1968	1968	Same
CA	1913	1913	1913	Same
CO	1919	1918	1918	Colorado Constitution amended in 1918
CT	1937	1937	1937	Same
DE	1968	1966	1966	Law enacting merit system passed in 1966
FL	1967	1968	1967	Florida statute enacted in 1967
GA	1945	1953	1945	Georgia constitution amended in 1945
HI	1955	1955	1955	Same
IA	1967	1966	1966	Iowa Code enacted in 1966
ID	1967	1969	1967	Ujhelyi (2014) as default
IL	1905	1905	1905	Same
IN	1941	1941	1941	Same
KS	1941	1941	1941	Same
KY	1960	1954	1960	Law passed in 1960
LA	1952	1940	1952	Ujhelyi (2014) as default
MA	1885	1885	1885	Same
MD	1921	1921	1921	Same
ME	1937	1937	1937	Same
MI	1941	1937	1940	Ujhelyi (2014) as default
MN	1939	1939	1939	Same
MO	1945	1946	1945	Constitution amended in 1945
MS	1977	1976	1976	Code enacting merit system adopted in 1976
MT	1976	1976	1976	Same
NC	1949	1949	1949	Same
ND	1975	1974	1975	Ujhelyi (2014) as default
NE	1975	1974	1975	Ujhelyi (2014) as default
NH	1950	1954	1950	Ujhelyi (2014) as default
NJ	1908	1908	1908	Same
NM	1961	1962	1961	Ujhelyi (2014) as default
NV	1953	1953	1953	Same
NY	1883	1883	1883	Same
OH	1913	1913	1913	Same
OK	1959	1958	1959	Merit system adopted in 1959
OR	1945	1945	1945	Same
PA	1963	1968	1963	Ujhelyi (2014) as default
RI	1939	1939	1939	Same
SC	1969	1973	1969	Ujhelyi (2014) as default
SD	1973	1968	1973	Ujhelyi (2014) as default
TN	1937	1937	1937	Same
UT	1963	1962	1963	Ujhelyi (2014) as default
VA	1943	1942	1943	Ujhelyi (2014) as default
VT	1950	1950	1950	Same
WA	1961	1961	1961	Same
WI	1905	1905	1905	Same
WV	1989	1989	1989	Same
WY	1957	1956	1957 10	Personnel Act adopted in 1957

Introduction of Reference and Drafting System

The table below shows the year of the introduction of a reference and drafting system in the US states. We consider the date of introduction of a separate office purposefully in charge of providing legislators help with the searching, storing and drafting of bills. Before the establishment of such an office, these functions were usually performed to a certain degree by the state librarians and/or the attorney general. Where information on the drafting system is not available (for 25 states), we take into consideration the introduction of a reference system (missing for 18 states). In most cases, the introduction of a reference system precedes the introduction of a drafting system or they occur together. Information is gathered from the following sources: Book of States 1935 Chapter 2, Rothstein (1990) and Squire (2012). In those cases where information is not straightforward we add a note. As mentioned in the main text, this information is present only for those states which established these services before 1935. To our knowledge, after that date no information is present.

Table A5: Dates of Introduction of Reference and Drafting System

State	Legislative Reference	Legislative Drafting
AL	1907	1907
AR	1917	
AZ	1917	1917
CA	1904	1913
CO	1931	1931
CT	1907	1901
GA	1914	1929
IA	1911	1911
IL	1913	1913
IN	1907	1907
KS	1929	1929
LA	1921	
MA	1910	1920
MD	1916	1916
ME	1917	
MI	1907	1917
MT	1909	
NC	1915	1915
ND	1909	1909
NE	1911	1911
NH	1913	1913
NJ	1914	
NM	1921	
NY	1890	1909
OH	1913	1913
PA	1909	1909
RI	1907	1926
SD	1907	1907
TX	1909	
VA	1914	1914
VT	1911	1912
WI	1901	1901

Descriptive Statistics

Table A6: Descriptive Statistics

VARIABLES	N	mean	sd	min	max
Divided Government	2,311	0.370	0.483	0	1
Introduction Civil Service	2,499	0.520	0.500	0	1
Introduction and Repeal Civil Service	2,550	0.506	0.500	0	1
Introduction of Drafting System	1,632	0.848	0.359	0	1
Log Delegation	2,497	8.355	0.913	3.219	11.09
Log Permission	2,497	7.542	0.984	2.485	10.32
Log Constraint	2,497	6.228	1.047	1.609	9.421
Log Entitlement	2,497	7.980	0.940	2.833	10.69
Log Total Provisions	2,497	9.173	0.935	4.094	11.93
Reform Year Dummy	2,550	0.0184	0.135	0	1

Robustness Checks

Table A7 below shows the effect of the introduction of the merit system on the different types of provisions, namely entitlements, constraints, permissions and delegations. Results in Table A8 show that in those years there is no effect of divided government on legislative complexity.

Table A7: The Effect of the Divided Government on the Different Types of Provisions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Entitlement	Entitlement	Entitlement	Constraint	Constraint	Constraint	Permission	Permission	Permission	Delegation	Delegation	Delegation
Introduction Civil Service	0.985** (0.0714)	0.132* (0.0619)	0.143* (0.0584)	1.284** (0.0765)	0.0899 (0.0701)	0.106+ (0.0624)	1.109** (0.0734)	0.145* (0.0562)	0.157** (0.0510)	0.896** (0.0711)	0.134+ (0.0720)	0.146* (0.0647)
Constant	7.449** (0.0376)	-6.185** (0.932)	-4.058** (1.085)	5.535** (0.0403)	-8.658** (1.229)	-6.201** (1.291)	6.943** (0.0387)	4.589** (1.008)	5.688** (1.396)	7.871** (0.0374)	-5.055** (0.975)	-2.817* (1.143)
Observations	2,448	1,438	1,382	2,448	1,438	1,382	2,448	1,438	1,382	2,448	1,438	1,382
State FE	X	X	X	X	X	X	X	X	X	X	X	X
Time FE		X	X	X	X	X		X	X		X	X
State-Specific Trends		X	X	X	X	X		X	X		X	X
Controls		X	X	X	X	X		X	X		X	X
Lagged DV			X			X			X			X

Notes: Columns 1-3, Columns 4-6, Columns 7-9, Columns 10-12 show respectively the results for the OLS regression models with the (logged) number of entitlements, constraints, permissions and delegations as dependent variable. The specifications for the different dependent variables are the same. The first model uses state fixed effects, the second model adds biennium fixed effects, time-varying controls (introduction of drafting system and divided government) and state-specific time trends and the third model adds the lagged dependent variable. **p<.01; *p<.05; +p<.1.

Table A8: The Effect of the Divided Government on the Number of Provisions in Years with No Merit System

VARIABLES	(1) Leg Detail	(2) Leg Detail	(3) Leg Detail
Divided Government	0.0139 (0.0577)	-0.00556 (0.0664)	0.00573 (0.0710)
Constant	8.631** (0.0142)	-0.102 (72.36)	190.8 (143.9)
Observations	974	554	508
State FE	X	X	X
Time FE		X	X
State-Specific Trends		X	X
Controls		X	X
Lagged DV			X

Notes: Column 1 shows the results for the OLS regression model with state fixed effects. Column 2 adds year fixed effects, time-varying controls (introduction of drafting system) and state-specific time trends. Column 3 adds the lagged dependent variable. In all models standard errors are clustered by state. **p<.01; *p<.05; +p<.1.

Executive Delegation in US States

Descriptive Statistics

Table A9: Descriptive Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Constraint Gov	4,032	0.526	1.341	0	21
Entitlement Gov	4,032	3.199	4.740	0	91
Statements Gov	4,032	59.84	70.52	0	858
Delegation Gov	4,032	27.68	35.36	0	527
Permission Gov	4,032	14.07	20.44	0	283
Unified Government	2,311	0.630	0.483	0	1
Executive Delegation	3,907	0.7325	.01821	-0.0601	1

References

- Ash, Elliott, Bentley MacLeod and Suresh Naidu. 2017. “The language of contract: Promises and power in union collective bargaining agreements.” *working paper* .
- bird, steven, ewan klein and edward loper. 2009. “Natural language processing with python.”
- Choi, Jinho D, Joel R Tetreault and Amanda Stent. 2015. “It Depends: Dependency Parser Comparison Using A Web-based Evaluation Tool.” *ACL* pp. 387–396.
- Choi, Jinho D and Martha Palmer. 2012. “Guidelines for the CLEAR Style Constituent to Dependency Conversion.” *Center for Computational Language and Education Research , University of Colorado Boulder , Institute of Cognitive Science, Technical Report 01-12* .
- De Marneffe, Marie-Catherine and Christopher D Manning. 2008. Stanford Typed Dependencies Manual. Technical report Technical report, Stanford University, Revised for Stanford Parser v. 1.6.2 in February 2010.
- Dell’Orletta, Felice, Simone Marchi, Simonetta Montemagni, Barbara Plank and Giulia Venturi. 2012. The SPLeT-2012 shared task on dependency parsing of legal texts. In *Proceedings of the 4th Workshop on Semantic Processing of Legal Texts*.
- Goldberg, Yoav and Joakim Nivre. 2012. “A Dynamic Oracle for Arc-Eager Dependency Parsing.” *Proceedings of COLING 2012: Technical Papers, COLING 2012, Mumbai, December 2012*. pp. 959–976.
- Honnibal, Matthew, Mark Johnson et al. 2015. “An Improved Non-monotonic Transition System for Dependency Parsing.” *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, Lisbon, Portugal, 17-21 September 2015* pp. 1373–1378.
- Jurafsky, Daniel and H James. 2000. *Speech and Language Processing: an Introduction to Natural Language Processing, Computational Linguistics, and Speech*. London, UK: Pearson Education.

- Montemagni, Simonetta and Giulia Venturi. 2013. “Natural Language Processing And Legal Knowledge Extraction.”
- Rothstein, Samuel. 1990. “The Origins of Legislative Reference Services in the United States.” *Legislative Studies Quarterly* pp. 401–411.
- Squire, P. 2012. *The Evolution of American Legislatures: Colonies, Territories, and States, 1619-2009*. Legislative Politics And Policy Making University of Michigan Press.
URL: https://books.google.it/books?id=5uw_e0pgMQMC
- Ting, Michael M, James M Snyder, Shigeo Hirano and Olle Folke. 2013. “Elections and reform: The adoption of civil service systems in the US states.” *Journal of Theoretical Politics* 25(3):363–387.
- Ujhelyi, Gergely. 2014. “Civil service rules and policy choices: evidence from US state governments.” *American Economic Journal: Economic Policy* 6(2):338–380.