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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. Drawing from computational linguistics, we provide an automated procedure for measuring discretion and delegation in legal texts to facilitate large-scale empirical analysis. 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 produce a measure of bureaucratic discretion by looking at the level of legislative detail for U.S. states and find that this measure increases after reforms giving agencies more independence. This effect 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 potentially vital 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.

With some exceptions, the mainstream approach to political text analysis is a bag-of-words (or bag-of-phrases) representation. First, the text is split up into tokens (single words or groups of words which relate to a concept) and filtering the set of informative tokens (Monroe, Colaresi and Quinn 2008). Second, tokens are assigned a probability distribution to analyze associations with a speaker, party, topic, or another covariate. In a knutshell, this approach starts from text as unstructured data and transforms it into a frequency distribution over tokens (Klebanov, Diermeier and Beigman 2008).

This mainstream approach potentially misses essential 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.[1] 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 Natural Language Processing (NLP) techniques.

By looking at the lexical and syntactic features of a sentence, NLP techniques serve to retrieve richer information than a list of tokens. Our rule-based labeling approach starts by automatically parsing the lexical and syntactic structure of a sentence, extracting information on what is the subject, what type of verb is present, and so on. The structure is matched against *frames*, templates that determine what different provision types 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 to the role of governor. Our role labeling rules follow dependency relations between words in a sentence and therefore are not constrained by word order (as is the case with N-grams or dictionary matching). The result is a classification of sentences according to their meaning, with information on the agents involved. We validate the method against hand-annotated language features from Franchino (2004) and against a simple baseline using standard lexicon methods.

This information extraction approach can expand the use of text analysis to the study of a broader range of topics in political science. We hope 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 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 trend is consistent with the discretion model in the literature: legislators introduce stronger ex-ante control mechanisms to discipline the more independent bureaucracy.

The second application analyzes delegation of powers from the legislature to the governor. The previous literature has used standard datasets to produce robust evidence that under unified government (governor and legislature controlled by the same party), the delegation of powers to the executive is more likely to take place (Epstein and O'Halloran 1999; Franchino 2004). Using a new measure of delegation constructed from the syntactic parse, we find confirming evidence for this empirical regularity. In line with the previous literature, we find that the number of statements delegating powers to the governor, discounted by statements constraining the governor, increases in unified government situations.

Legislative Information Extraction

This section summarizes 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 legal 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 role labeling rules – 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, an extraction rule could be "governor subject with permissive modal verb (e.g. may)", which would indicate a permission for the governor. We apply these types of extraction rules to the parse data to construct datasets for empirical analysis. The method can be understood as a form of rule-based semantic role labeling using the domain-specific structure of legal language.

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 extraction rules (based on ontologies) allows us to filter out false positives: the modal counting method would treat “shall not be expected” as mandatory, while our extraction rules would not. [2]

Syntactic Dependency Parsing

Automated legislative information extraction is possible because computers can now quickly and reliably extract detailed lexical and syntactic information from large corpora. A key technology in this area is syntactic dependency parsing, developed in computational linguistics. Dependency parsing produces annotations on the syntactic structure of a sentence – the words and the grammatical relations between them (Jurafsky and James 2000).

First, parsers tag the parts of speech (POS) – verb, noun, adjective, etc – of each word in a sentence. This identifies the function of each word. Second, parsers tag dependencies – the function relations between each word in the sentence. A dependency relation consists of a headword and a dependent word, related to each other through a functional dependency. Examples of functional dependencies are nominal subject (linking a subject and a verb), direct object (linking a verb and a direct object), attribute (linking an adjective and the noun it describes), and so on.

The dependency parser tells us whether a noun is the subject or the object 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 key category of verb in statutes is the modal verb, which in legal language assign responsibilities and grant permissions. These annotations provide the ingredients from which our extraction rules build measures of delegation.

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). We inspected many samples and were happy with its performance on statute language. More detail is provided in the appendix.

Extraction Rules

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 extraction rules can then be applied to the syntactic parser output to create the dataset for use in the analysis.

In most research, constructing extraction rules can be done using large-scale repositories of coded ontologies. These are dictionaries of words and dependencies that have been annotated to serve a theme, such as making a promise. An example of these ontology dictionaries is FrameNet (Baker, Fillmore and Lowe 1998; Ruppenhofer, Ellsworth, Petruck, Johnson and Scheffczyk 2006). Lexicons of synonyms and categories, such as WordNet (Miller 1995), can be useful for constructing ontologies. Other work that has engaged with legal provision types using syntactic features includes Lame (2003), Saias and Quaresma (2004), Ceci, Lesmo, Mazzei, Palmirani and Radicioni (2011), and Ash, MacLeod and Naidu (2017).

Thanks to the linguistic regularities in legal language, the syntactic markers obtained from dependency parsing can be used to label semantic roles. From an extensive examination of example statements, we know (for example) that a subject attached to an active verb is the agent. A (direct or indirect) object, in turn, is the patient. The use of modal verbs "shall," "will," "must," "can," and "may" in legal language are universally deontic, whereas in common language they would often refer to non-deontic cases such as conditional or future tense. From these semantic labels, we construct the following categories: delegation, prohibition, permission, and entitlement (see Table 1). In defining these legal provisions, we start by deciding which modal and special verbs are associated with them. For instance, legal provisions that 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. Besides, delegations could be articulated through several "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 extraction rules may be found in Table 1. As enumerated in the table, a delegation is characterized by one of two structures: 1) a non-negated strict modal followed by an active verb ('Governor shall act"), or 2) a non-negated non-permissive modal (either a non-modal or a strict modal) followed by a delegation verb ("Governor is expected to"). Constraints are characterized by 1) a negated modal ("Governor shall not"), a negated permission verb ("Governor is not allowed"), or a non-negated constraint verb ("Governor shall be prohibited from"). Permissions are characterized by a 1) non-negated permission verb ("Governor is allowed to"), 2) a non-negated permissive modal followed by a non-special verb ("The Governor may act"),[3], or a 3) negated constraint verb ("Governor is not prohibited from"). Finally, entitlements are characterized by 1) a non-negated entitlement verb ("Governor retains the power to"), 2) a non-negated strict modal followed by a passive verb ("Governor shall be considered"), or 3) a negated delegation verb ("Governor is not obligated to").

A key feature of our approach, relative to lexicon-based approaches that for example count modal verbs, is that the subject of any given legal provision is identified by the parser. A potential issue in this regard is co-referencing: namely, the use of a pronoun as a subject of a sentence which refers to a subject of a previous sentence. While coreference resolution

Table 1: Lexical Units and Pseudocode for Extraction Rules

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'
Extraction Rules	
Delegation	strict modal + active verb + not negation not permissive modal + delegation verb + not negation
Constraint	modal + not delegation verb + negation strict modal + constraint verb + not negation permission verb + negation
Permission	permission verb + not negation permissive modal + not special verb + not negation constraint verb + negation
Entitlement	entitlement verb + not negation strict modal + passive + not negation delegation verb + negation

is a major problem in most language domains, such as newspaper articles (Van Atteveldt, Kleinnijenhuis and Ruigrok 2008), legislation uses relatively few pronouns, making the identification of the subject of each sentence easier. In our case, we found in samples of the data that our measures of delegation were unaffected by the use of co-reference resolution. Therefore we chose not to run co-reference resolution on the whole corpus (which would have been computationally demanding) for this analysis.

As mentioned, this process is similar to semantic role labeling (SRL). Semantic role labeling software, such as AllenNLP's implementation of PropBank, would serve to identify "who does what to whom" by labeling agents, patients, and associated verbs. The information from SRL, along with the modality modifier, could in principle deliver equivalent information for use in extracting legal provisions. But in our experiments comparing an SRL approach to the dependency-parse approach, we got better results with the latter for legal language. Our sense is that SRL annotates subtler relations in sentences, which are less transparent and rely more on the specific features of the training corpus. The training corpus for SRL is non-legal language, and we have not fully assessed the performance of off-the-shelf SRL on legal language. In contrast, we have analyzed many samples of dependency parsing on legal language and were pleased with the results. It is necessary to note that our legal ontology would not work well on non-legal language. We expect that techniques such as SRL will be needed to extend these methods to broader language domains.

Validation

In this section we provide some validation for our method in the context of identifying delegations and constraints in texts. First, we compare our machine-annotated counts to hand-annotated counts from a previous paper. Second, we compare it to the lexicon-based strategy of counting modals.

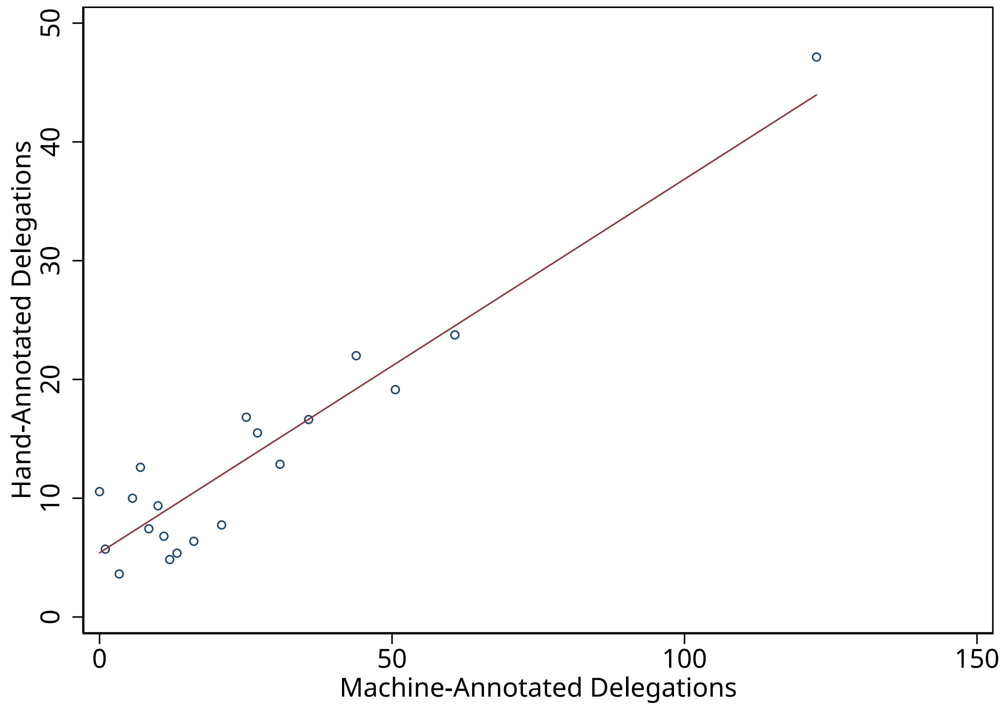
To compare machine annotations to hand annotations, we apply our information extraction technique to the corpus from Franchino (2004). This dataset contains more than 150 European Communities (EC) legislative acts, hand-coded with the number of delegations and constraints. Our machine coding identifies delegations and constraints by counting the number of matches to the respective rules articulated in Table 1.

Figure **??** Panel A shows the binned scatterplot of the relationship between our machine-annotated counts (horizontal axis) and Franchino's hand-annotated counts (vertical axis) for delegations. The measures are strongly correlated, with an R^2 of 0.44. We can see that the machine-coded measure identifies about twice as many delegations as the hand annotations, probably because the human annotators treated related/redundant statements as a single delegation.

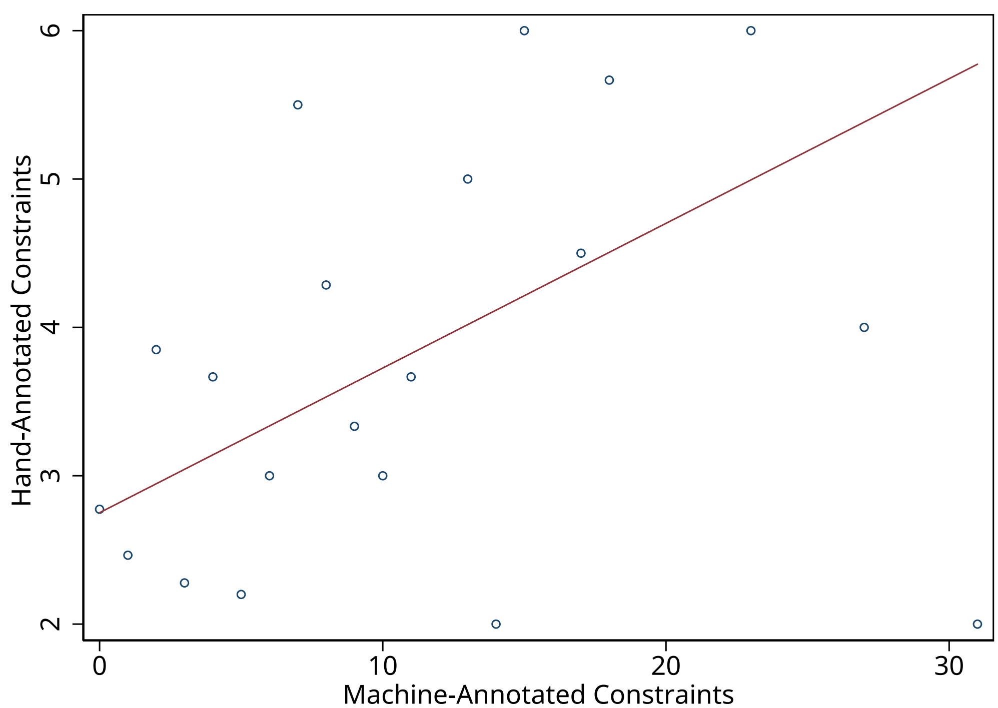
Figure **??** Panel B shows the same figure for constraints. While the measures are clearly correlated, the performance is much lower with $R^2 = 0.06$. Again, the machine coding measure identifies more constraints than hand coding. The low R^2 for constraints may be due to the subjective nature of coding constraints in the EU data (Franchino 2004). In the future, we should work further on validating the constraint measure in the U.S. state context.

Figure 1: Validation with Franchino (2004): Delegation and Constraint Counts

Panel (A)



Panel (B)



Next, we compare our method for measuring delegations to a more standard lexicon-based approach based on counting modal verbs. For this validation exercise and for the empirical demonstrations below, we use a unique dataset consisting of the full text of U.S. state session laws from the 19th century to the 21st century. This corpus, introduced by Ash (2016), consists 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.

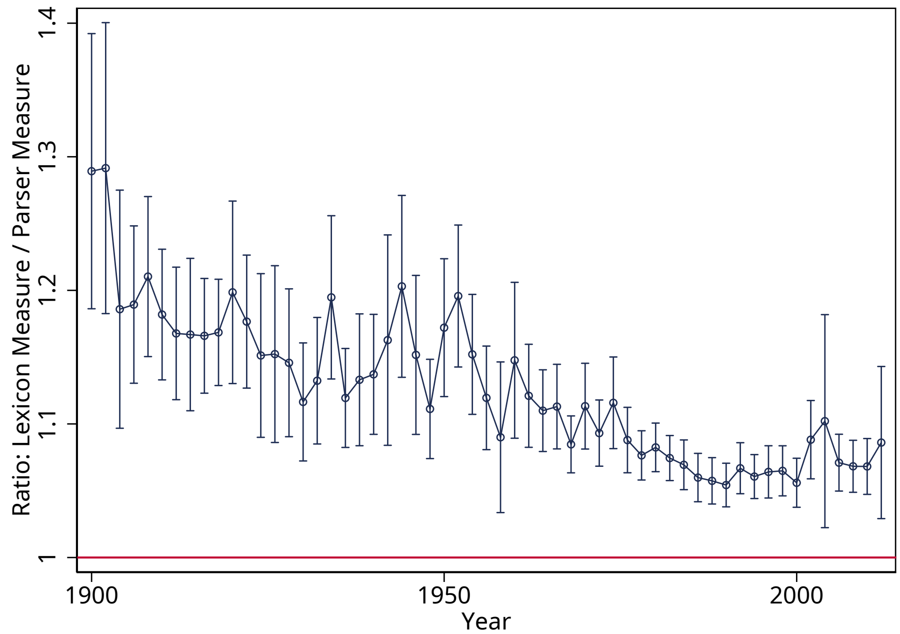
For the validation check, we follow our method and compute the number of delegations with "governor" as the subject on the U.S. state session laws corpus. This gives a count of sentences matching our extraction rule for delegations for each state and each biennium for the years 1900-2010. The lexicon-based comparison is the count of the bigrams "governor shall" and "governor will."

These measures are highly correlated, as one would expect from the similarity of the definition. However, we find that they result in different time series in our corpus. Figure **??** shows the ratio of the lexicon-based measure to the parser-based measure along with 95% confidence intervals. The figure shows that (although decreasing over time) the ratio is always statistically greater than one, suggesting that simply counting modals tends to generate false positives.

Bureaucratic Discretion in U.S. States

In recent decades, the literature on bureaucracy has focused on whether and how politicians delegate tasks to bureaucrats. In particular, 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). On a leading framework for this process, legislators can use either ex-ante or ex-post control mechanisms (Martin 1997). Ex post control mechanisms

Figure 2: Modal Counts tend to Generate False Positives



refer to backward-looking incentives, such as firing bureaucrats who fail to implement a policy correctly. Ex-ante mechanisms are more forward looking and try to structure the bureaucracy to maintain the desired policy. These include administrative procedures (McCubbins, Noll and Weingast 1987), for example, and the level of detail of legislation. Detailed laws can be used to micro-manage policy implementation (Huber and Shipan 2002). The delegation literature studies whether these two types are substitutes or complements (Huber and Shipan 2008).

We build on these ideas to analyze the introduction of an independent bureaucracy. These reforms weaken the legislators' capacity to control bureaucrats ex-post, so legislators might write more detailed legislation as a form of ex-ante control. As a set of natural experiments, we study the introduction of merit systems in the civil service in U.S. states (Volden 2002; Wood and Bohte 2004). Note that an alternative expertise model of civil service reform would predict that legislation might become less detailed, if increased professionalism among bureaucrats means they need less legislative guidance.

The first step in this analysis is to measure legislative detail, which is central in analyzing bureaucratic discretion. A leading analysis in this area is Huber and Shipan (2002), who examine variation in 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 use manual annotation to distinguish between procedural and policy language in the statutes. They argue that procedural language is less constraining than policy language because

> 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 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).

They then measure discretion quantitatively. As a baseline, they use a simple length-based measure of legislation as a proxy for the discretion left to bureaucrats: the longer the statutes, the greater the effort to reduce discretion. In addition, they look at the share of policy language, which gives less discretion.

The approach in our paper is a compromise between a length-based baseline and a hand-annotated measure like policy-vs-procedure share. On the one hand, the length of legislation alone is missing a lot of linguistic detail and treats legally relevant statements identically to boilerplate and other irrelevant text. On the other hand, the distinction between procedural and policy language is costly to annotate, somewhat subjective, and cannot be easily applied to other cases. We build at this intersection by looking 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 listed in Table 1 (delegations, constraints, permissions, entitlements).

Formally, our outcome is $\log(LegalProvisions_{st})$, the logged number of legal provisions in the statutes of state s for each biennium t. We test the effect of the introduction of an independent bureaucracy on this outcome, where more provisions means less discretion.

We analyze 50 U.S. states from 1900 to 2000. The Appendix reports some results using alternative text measures of discretion.

The estimating equation is

$$\log\left(LegalProvisions_{st}\right) = \alpha Merit_{st} + \beta X_{st} + \gamma_s + \delta_t + \phi_s t + \varepsilon_{st} \tag{1}$$

where, $Merit_{st}$ 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 trends. The state fixed effects control for time-invariant state characteristics, while year fixed effects address any factors that change over time, but not across states, such as influence from the federal level.[1] The state trends allow for confounding trends at the state level. The equation is estimated using the reghdfe Stata package (Correia 2016) and standard errors are clustered to allow serial correlation within state.

Table 2 shows the results for the fixed-effects estimates of Equation (1). The introduction of the civil service is statistically associated with higher levels of detail in legislation (Column 1). The coefficient and standard errors are robust across specifications, including state trends and controls for Divided Government (Column 2). There is no change from adding the lagged dependent variable (Column 3), addressing the issues of long-term serial correlation in state panel data documented by Caughey, Xu and Warshaw (2017). 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 of the merit system and not contemporaneously with it. The results do not change when interacting the treatment with Divided Government (Column 5), meaning that our results are not driven by the correlated changes in government structure. Finally in Column 6 we also include in the treatment variable repeals of the merit system (which occurred in 15 states from 1996), finding similar results.

[1] In particular, we can rule out influences from vertical delegation of powers from the federal to the state level. Assuming that the delegation of competences from the federal to the state level occurs at the same time for all the states, time fixed effects control for this.

Table 2: Civil Service Reform and Legislative Detail

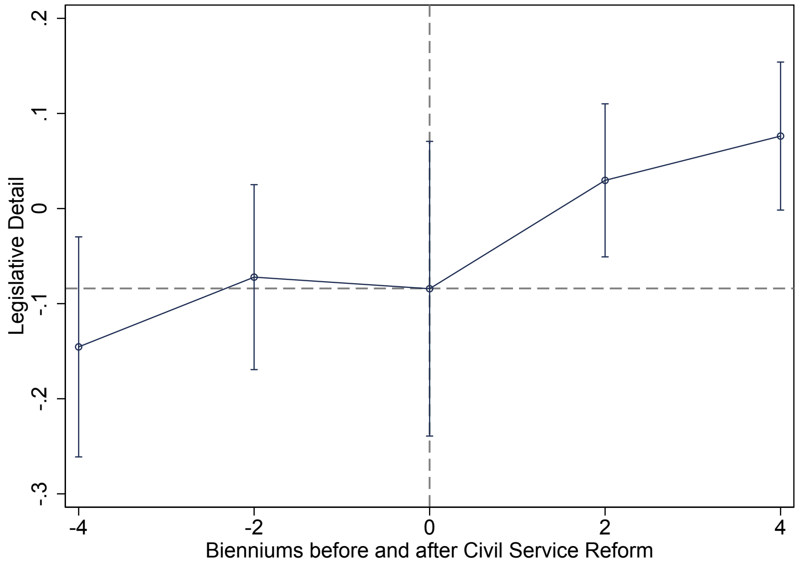
	(1) Leg Detail	(2) Leg Detail	(3) Leg Detail	(4) Leg Detail	(5) Leg Detail -Repeal
Introduction Civil Service	0.137*	0.112+	0.157*	0.147*	
	(0.0625)	(0.0643)	(0.0646)	(0.0705)	
Introduction of Drafting System	0.0755	0.111	0.0775	0.0764	0.0820
	(0.0807)	(0.0766)	(0.0804)	(0.0804)	(0.0783)
Divided Government	-0.0256	-0.0153	-0.0255	-0.0359	-0.0255
	(0.0294)	(0.0289)	(0.0288)	(0.0308)	(0.0285)
Introduction and Repeal Civil Service					0.131*
					(0.0588)
Observations	1,438	1,382	1,438	1,438	1,485
R-squared	0.838	0.814	0.838	0.838	0.838
State FE	X	X	X	X	X
Time FE	X	X	X	X	X
State-Specific Trends	X		X	X	X
Lagged DV		X			
Interaction				X	
Reform Year			X		

Notes: Column 1 shows the results for the OLS regression model with state and biennium fixed effects, time-varying controls (introduction of drafting system and divided government) and state-specific time trends. Column 2 adds the lagged dependent variable (without state-specific time trends). Columns 3 and 4 use the same specification of Column 1, but respectively add a dummy variable for the reform year and the interaction between divided government and the introduction of the merit system. Column 5 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 dynamics of this effect are illustrated in Figure 3. The event study graph plots the log provision count (residualized on state/time fixed effects and state trends, corresponding to Column 2 of Table 2), binned by biennium, for the two bienniums before and two bienniums after civil service reform. The plot suggests no pre-trend, with a significant increase in legislative detail taking place the next biennium after the introduction of an independent bureaucracy.

After the establishment of an independent bureaucracy, legislators start writing more detailed statutes. This finding is consistent with the idea that more independent bureaucrats are prone to agency drift, so legislators tend to micro-manage policy implementation. Without ex-post control mechanisms (such as firing bureaucrats at will), legislators start putting in place ex-ante control mechanisms (more detailed legislation). The data do not support the alternative professionalism model, where expert bureaucrats would require less legislative guidance.

Figure 3: Event Study Graph



Notes: Event study graph for effect of civil service reform on legislative detail. Dots give the binned mean residuals of log provision counts (vertical axis) from a regression on state fixed effects, biennium fixed effects, and state trends, binned by the bienniums before and after the reform (horizontal axis). Error spikes give 90% confidence intervals from standard errors of the mean.

An additional set of model specifications and robustness checks are reported in the Appendix, 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 delegations associated with the introduction of an independent civil service. In addition, we test whether divided government affects legislative complexity in those years where the merit system was not in place. Results 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 U.S. States

A consistent prediction from delegation models is that when preferences between principal and agent converge, more delegation will take place (e.g. Huber and Shipan 2002, 2008).

Empirical support for this prediction includes Volden (2002), who studies welfare boards in U.S. states. He finds that, when the preferences of the legislature and the governor are aligned (that is, they come from the same party), legislators tend to give governors more appointment power over welfare boards.

The work on delegation is part of the broader literature on the powers of governors, such as appointment powers, control over the budget, term limits, and so on (Beyle 1990, 2007; Krupnikov and Shipan 2012; Kousser and Phillips 2012).

Another way of analyzing delegation to governors is to look at the content of legislation that delegates powers (Huber and Shipan 2008). Epstein and O'Halloran (1999) introduce a measure of statutory executive delegation which considers two components.[2] First, the degree of authority delegated to the executive branch, measured by the proportion of provisions in a legislative act delegating policy authority. Second, the degree of constraints imposed on the executive branch, measured by the number of constraints imposed in legislation. 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.

Epstein and O'Halloran (1999) apply this measure to the delegation of powers from U.S. Congress to the president. They find less delegation under divided government. Franchino (2004) extends this analysis to delegation of powers in the European Union. He looks at the Council of Ministers (the EU's equivalent to a second legislative chamber) and finds they delegate more to the Commission (the equivalent of the executive) where Member States' preferences converge.

This previous work has computed delegation through a combination of qualitative and quantitative methods. First, they identified relevant pieces of legislation, according to some guidelines, such as previous research (Epstein and O'Halloran 1999) or the relevant jurisprudence (Franchino 2004). Second, they manually code provisions according to whether they

[2] In the original work this is referred to 'statutory executive discretion' and not 'statutory executive delegation', but in this work we use the latter to avoid confusion with the measure of discretion used in the first analysis.

grant policy discretion or not. Finally, they identify potential categories of procedural constraints and manually count their frequency in the documents. This approach has some limitations. Perhaps most importantly, it is time and resource intensive. Manual coding requires expert knowledge of the legal documents and associated legal system. The coders must go through hundreds of documents and preferably cross-validate results. In addition, manual coding requires subjective judgments on a series of important factors: which documents to sample, which statements are relevant, what the potential categories of procedural constraints look like, and so on. The method is necessarily domain-specific, which limits opportunities for clean replication.

The time and resource requirements of hand-coding legislative clauses can be ameliorated by machine learning from labeled documents. O'Halloran, Maskey, McAllister, Park and Chen (2016) is a promising example of this approach. However, machine classification does not address the issue of subjective judgments in labeling the documents. In addition, there is still the problem that documents labeled in one legal context would not be valid for machine classification in other legal contexts. We view the rule-based information extraction method and the machine learning method as complementary approaches.

In this section we aim to address some of these issues using legislative information extraction. The empirical context is legislation in U.S. states, and our outcome of interest is delegation to the governor. Following Epstein and O'Halloran (1999) and Franchino (2004), $Delegation_{st}$ to the governor of state s at biennium t is computed as

$$Delegation_{st} = \frac{D_{st}}{M_{st}} - \frac{C_{st}}{M_{st}} \cdot \frac{D_{st}}{M_{st}}, \tag{2}$$

where D_{st} is the number of delegation statements with governor as subject, M_{st} is the total number of statements in that session's legislation, and C_{st} is the number of constraint statements with governor as subject.[3] This is the delegation ratio minus the constraint ratio

[3]Note that this formula is slightly modified from that used by Epstein and O'Halloran (1999) and Franchino (2004). They compute delegation as $Y = \frac{D}{M} - \frac{C}{K} \cdot \frac{D}{M}$, where K is the number of possible constraints. The choice of K requires expert knowledge of the possible set of constraints and is not feasible

(weighted by the delegation ratio). In the Appendix, we report similar results for alternative outcome specifications that ignore constraints and/or use the number of provisions with governor as subject (rather than all provisions) as the denominator M_{st}.

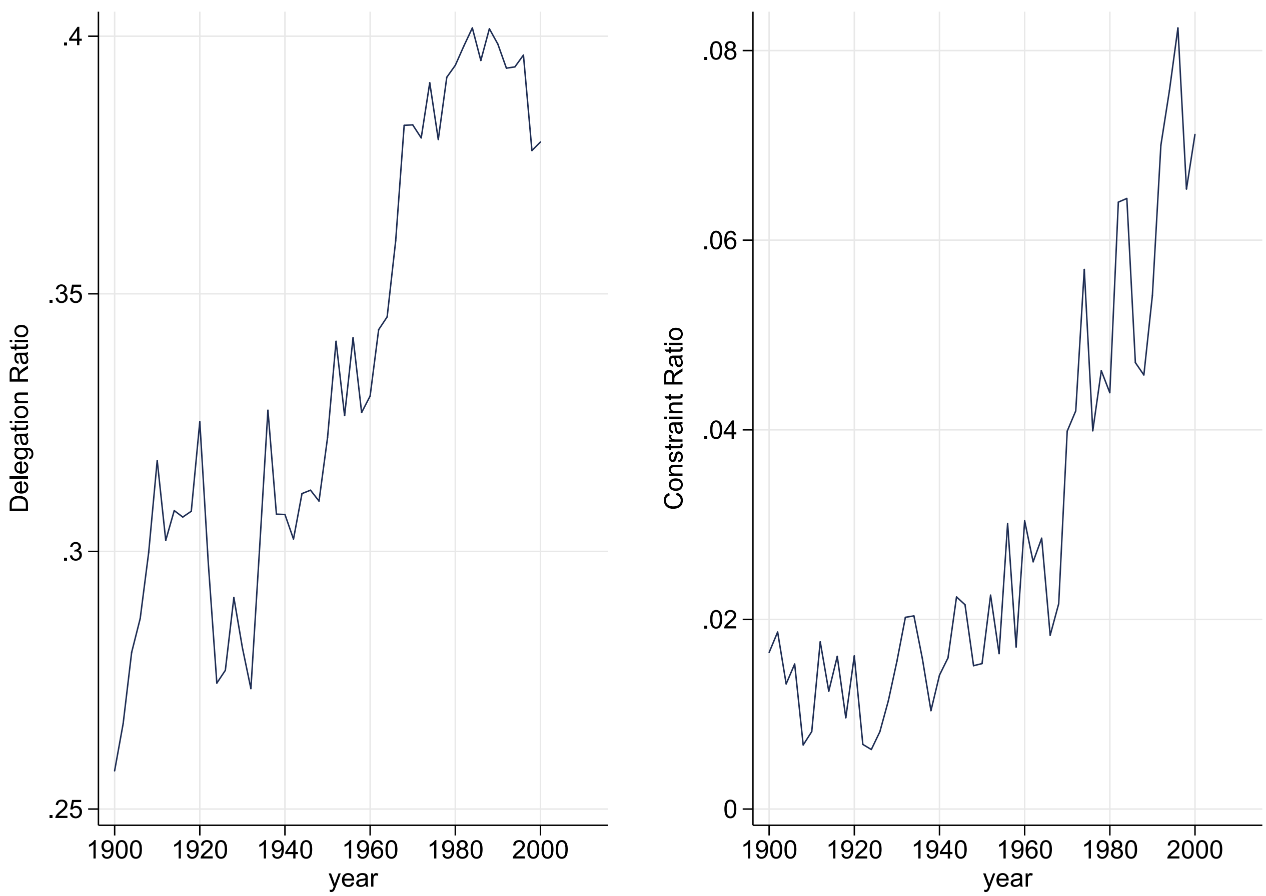
Figure **??** illustrates how these factors have evolved over time in the U.S. state session laws for the years 1900-2000. The left panel shows that the delegation ratio had a negative trend roughly until WWII, then an increase in delegation until the 1980s, and then again a decreasing trend. These trends for governors are very similar to the delegation trends at the federal level documented by Epstein and O'Halloran (1999, Fig. 5.10, p. 138). The right panel shows the evolution of the constraint ratio, which was constant until the 1950s but then began a positive trend. Again, this is similar to trends at the federal level Epstein and O'Halloran (1999, Fig. 5.11, p. 139). Moreover, these trends are broadly in line with anecdotal evidence on the powers of governors provided by the literature. Ruhil and Camões (2003) argues that the powers of governors increased after the Great Depression, while Rosenthal (1982) argues that powers became more balanced starting in the 1980s.

These descriptive statistics are promising initial support for our method. But our main inquiry is whether the previous evidence on unified government and delegation to the governor can be replicated using the new text-based measure. If our measure is valid, we would expect a positive relationship between government unity and statutory executive delegation.

To measure unified government, we use data from Klarner (2003) for the years 1935 through 2010. While we experiment with different specifications in the appendix, our preferred measure $Unified_{st}$ takes value one when a single party (Democrat or Republican) controls the governorship and both chambers of the legislature in state s during biennium t. If at least one of the three government bodies is controlled by a different party, it takes value zero.

to do in our diverse context (50 states, 100 years).

Figure 4: Average Delegation and Constraint Ratios in State Session Laws, 1900-2000



Our estimating equation is

$$Delegation_{st} = \alpha Unified_{st} + \beta X_{st} + \gamma_s + \delta_t + \phi_s t + \varepsilon_{st} \tag{3}$$

where as before, 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 trends. Controls include the introduction of the civil service because, as seen above, it affects the number of provisions in the statutes. As before, standard errors are clustered by state.

Table 3 shows the results of the fixed effects regression from Equation (3). 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. Results are robust to different specifications, including the inclusion of state time trends (Column 2), the lagged dependent variable (Column 3), and controls for civil service reform (Column 4). The preferred specification is robust to specifying the outcome as just the delegation ratio (Column 5), as well as using just governor statements (rather than all statements) as the denominator (Column 6).

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 policy preferences, the former delegate more powers to the latter. This is in line with the findings of an extensive set of previous delegation studies and hence lends support to our information extraction approach to measure executive delegation.

Conclusion

In this work, we introduce a new approach to political text analysis – instead of a bag-of-words text representation, we look at richer language representations. By looking at the lexical and syntactic features of texts, we can classify statements according to more

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

VARIABLES	(1) Exec Del	(2) Exec Del	(3) Exec Del	(4) Exec Del	(5) Del Ratio	(6) Del Ratio Gov
Unified Govt	0.0054+	0.0046+	0.0045+	0.005+	0.00678*	0.008+
	(0.003)	(0.0027)	(0.0025)	(0.0027)	(0.0031)	(0.004)
Observations	2,270	2,270	2,185	2,223	2,223	2,221
R-squared	0.396	0.464	0.434	0.463	0.529	0.328
State FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State Trends		X		X	X	X
Lagged DV			X			
Civil Service				X	X	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 Column 3 adds the lagged dependent variable. Column 4 adds the introduction of an independent civil service as control. Column 5 and Column 6 use 'Delegation Ratio' and 'Delegation Ratio Gov' as dependent variable, respectively. In all models standard errors are clustered by state. **p<.01; *p<.05; +p<.1.

refined meaning. Above, we show how to retrieve some legal provisions, namely delegations, entitlements, and constraints, from legal texts.

We illustrate the validity of this approach, by analyzing two predictions commonly accepted in the literature. First, 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. Second, the number of provisions delegating powers to the governor in U.S. state session laws is associated with government unity.

This is only one of the many potential contributions computational linguistics can make to social research. In another paper (?), we use an information extraction approach to distinguish between contingent and non-contingent clauses and test the differential effects of these types of clauses on economic growth. We find that contingent clauses, namely those provisions which cover more realizations of states of the world, have a positive effect on the economy. This is in line with a model that sees law drafting as akin to contract writing.

In future, we will 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.

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

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Syntactic Parsing

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 material 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.' [1]

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 headword 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). In the Appendix, we show an example of a dependency 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

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

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). [2] After each sentence is parsed, we match up the extracted dependency relations to our set of syntactic units for delegations, prohibitions, and so on. 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

[2] spaCy 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).

use". Below in Figure A1, we provide the dependence trees for parts of these two sentence. [3] 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.[4] 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 **??** 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'. [5]

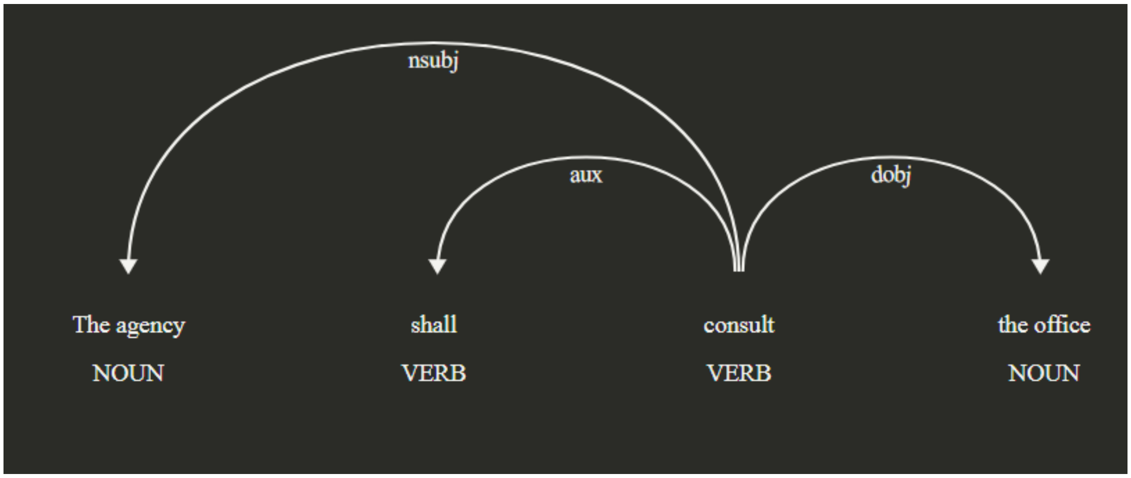
As it can be seen, the first sentence is a delegation, as it is an active and positive sentence which contain a strict modal, namely 'shall'. This is close in spirit to the 'the Agent shall act' example of delegation provided above. Conversely, the second sentence is a permission, as it is positive and 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 **??** 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

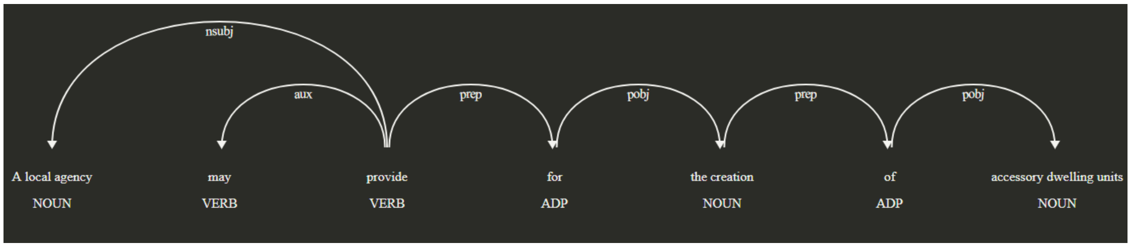
[3]This figure is taken from displaCy, a graphical interface for Spacy, the dependency parser used here.

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

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



(a) Delegation



(b) Permission

Figure 1: Dependency Parse Tree

Table 1: Example of Permission

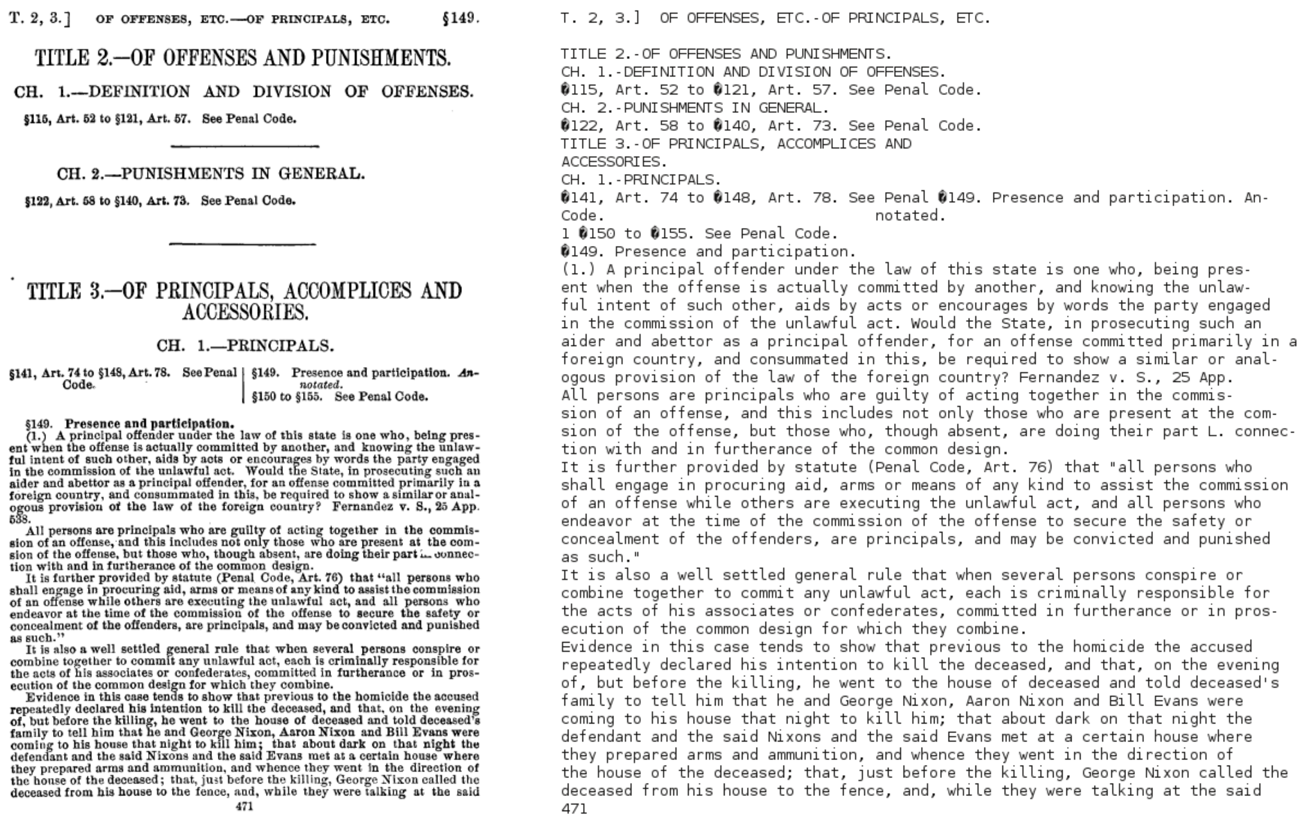
Full sentence	[...]the Governor of the State of Arkansas be authorized to designate and appoint distinguished visitors, citizens, and former citizens, who have distinguished themselves in various fields of endeavor as an Arkansas Traveler
Subject tags	'DT', 'NNP', 'IN', 'DT', 'NNP', 'IN', 'NNP'
Subject 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']

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.

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 **??** 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



T. 2, 3.] OF OFFENSES, ETC.—OF PRINCIPALS, ETC. §149.

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. 538.

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 comsion 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

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(a) Scanned Text

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T. 2, 3.] OF OFFENSES, ETC.-OF PRINCIPALS, ETC.
TITLE 2.-OF OFFENSES AND PUNISHMENTS.
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�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 �149. Presence and participation. An-
Code.                                   notated.
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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
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(b) OCR

Figure 2: Example of State Session Law

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 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

Table **??** 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 2: 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	Personnel Act adopted in 1957

Introduction of Reference and Drafting System

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 3: 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 4: 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 **??** 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 **??** show that in those years there is no effect of divided government on legislative complexity.

Table 5: The Effect of the Divided Government on the Different Types of Provisions

VARIABLES	(1) Entitlement	(2) Entitlement	(3) Entitlement	(4) Constraint	(5) Constraint	(6) Constraint	(7) Permission	(8) Permission	(9) Permission	(10) Delegation	(11) Delegation	(12) Delegation
Introduction Civil Service	0.985**	0.132*	0.143*	1.284**	0.0899	0.106+	1.109**	0.145*	0.157**	0.896**	0.134+	0.146*
	(0.0714)	(0.0619)	(0.0584)	(0.0765)	(0.0701)	(0.0624)	(0.0734)	(0.0562)	(0.0510)	(0.0711)	(0.0720)	(0.0647)
Constant	7.449**	-6.185**	-4.058**	5.535**	-8.658**	-6.201**	6.943**	4.589**	5.688**	7.871**	-5.055**	-2.817*
	(0.0376)	(0.932)	(1.085)	(0.0403)	(1.229)	(1.291)	(0.0387)	(1.008)	(1.396)	(0.0374)	(0.975)	(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
State-Specific Trends		X	X		X	X		X	X		X	X
Controls		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 6: 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	-0.00556	0.00573
	(0.0577)	(0.0664)	(0.0710)
Constant	8.631**	-0.102	190.8
	(0.0142)	(72.36)	(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.

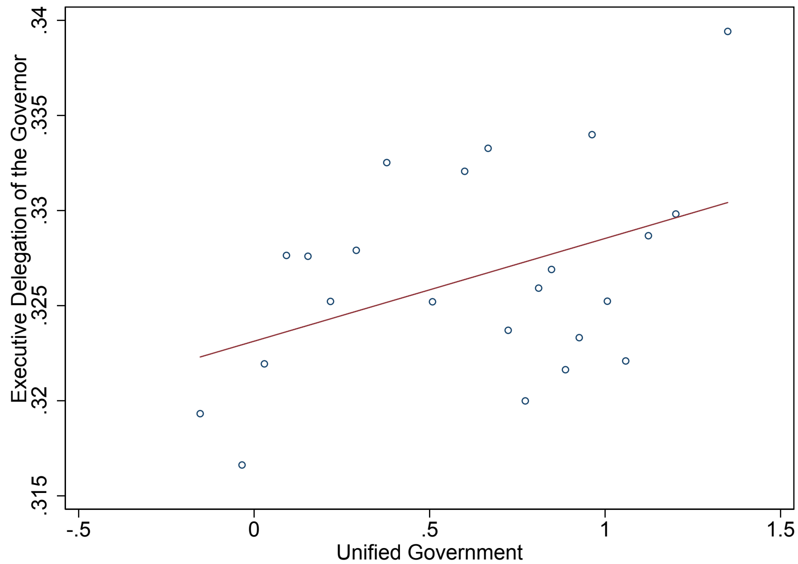
Executive Delegation in US States

Descriptive Statistics

Table 7: Descriptive Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Unified Government	2,311	0.630	0.483	0	1
Delegation Ratio Gov	3,985	0.754	0.160	0	1
Delegation Ratio	2,497	0.336	0.0784	0	0.596
Constraint Ratio	2,497	0.0295	0.0504	0	0.298
Executive Delegation	2,497	0.325	0.0722	0	0.532

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



Robustness Checks

Figure **??** 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. And we can see that it is not driven by outliers.

Table **??** and Table **??** shows the results with 'Delegation Ratio' (D_i/M) and 'Delegation Ratio Gov' (D_i/M_i) as dependent variable, respectively.

Table 8: Effect of Unified Government on the Delegation Ratio

VARIABLES	(1) Delegation Ratio	(2) Delegation Ratio	(3) Delegation Ratio
Unified Government	0.00774*	0.00689*	0.00679*
	(0.00384)	(0.00266)	(0.00305)
Constant	0.334**	0.336**	0.777**
	(0.00240)	(0.0338)	(0.0387)
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.

Table 9: Effect of Unified Government on the Delegation Ratio Gov

VARIABLES	(1) Delegation Ratio Gov	(2) Delegation Ratio Gov	(3) Delegation Ratio Gov
Unified Government	0.00897+	0.00806+	0.00803+
	(0.00520)	(0.00420)	(0.00435)
Constant	0.789**	0.0991	0.298**
	(0.00325)	(0.0758)	(0.0600)
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.

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