Partisanship or Policy? A Text-as-Data Study of Institutional Complexity in American Law

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Abstract

How do legislators allocate policymaking authority? Formal allocation of power is often framed as a *preference-based* problem. Under unified government, legislators should favor efficient implementing arrangements, while under divided government they should favor complex systems that optimize oversight. By contrast, I argue that this relationship is conditioned by the *importance* of the policy problem under consideration. To test this proposition, I propose a novel language- and network-based measurement strategy, which I use to measure institutional complexity in American law enacted from 1993-2014. I find that high-visibility legislation passed under divided government is more complex than similar legislation passed under unified government. For lower-visibility legislation - which forms the bulk of all law passed by Congress - this difference vanishes. These findings both challenge existing work on formal institutional design and contribute to the burgeoning literature on "submerged" bipartisan collaboration over policy content in American politics.

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1 Introduction

How do legislators allocate policymaking authority? As any would-be lawyer knows, statutes, constitutions, and other formal legal texts establish relationships between actors, describing who can do what, when, and to whom. Debates over these allocation-of-authority decisions have clear policy implications, and often occupy a high-profile position in public discourse. For a concrete example, consider the Patient Protection and Affordable Care Act (ACA). As a core part of Barack Obama's first-term agenda, the ACA represented a sweeping overhaul of the American healthcare system, which expanded availability of public and private insurance plans and empowered regulators to implement an wider set of health insurance regulations. Supporters argued that these changes would protect consumers by empowering expert administrators, while detractors worried that the ACA placed undue authority with unelected bureaucrats. The discussion surrounding so-called "death panels" offers a immediate example of this latter set of concerns. Though fantastical, the fear that government regulators might be given unchecked authority to control end-of-life decision-making for Medicare patients resonated with voters, and represented one of the most durable talking points in the entire ACA debate (Oberlander 2012).

Political scientists and legal scholars have generally framed allocation-of-authority decisions like these in *partisan* terms. When the executive's policy preferences are aligned with those of the legislature (and are likely to remain so in the future), legislators are more willing to pass simple "framework"-style legislation involving one or a few implementing actors and straightforward decision-making rules. By contrast, when legislative and executive preferences diverge, legislators tend to favor complex institutional structures with many implementing actors, which provide greater oversight opportunities by fragmenting decision-making authority. This pattern, some authors suggest, helps explain the slow-moving and haphazard policymaking patterns that characterize the American federal bureaucracy. Because divided government is common in the United States, American law often contains fragmented administrative structures that slow bureaucratic action and encourage intervention by courts (see, e.g. Moe 1990b; Moe and Caldwell 1994; Kagan 2009).

However, recent scholarship on minority-party influence over Congressional lawmaking calls this logic into question. Despite increasingly polarized voting patterns in Congress, minority-party lawmakers are often able to influence the content of the final legislative product, both through small-scale amendments and by attaching their preferred bills wholesale as "hitchhikers" to other legislative vehicles (Wilkerson *et al.* 2015; Casas *et al.* 2018). Findings like these motivate the basic puzzle of this paper: if the lawmaking process is more collaborative than previously realized - and has remained collaborative as voting patterns have become increasingly polarized - under what conditions does divided/unified government affect downstream institutional complexity? Are previous findings regarding the relationship between political preferences and complexity of formal institutions generally applicable, or do they depend on the characteristics of the issues and policy areas under consideration?

In this paper, I suggest that the answer to this puzzle lies in the *importance* of the law under consideration. Since institutional design is a costly process, we should only expect lawmakers to exert the effort required to implement their policy preference through legal language on issues which are particularly salient to their public or elite constituents. In other situations, characteristics of the issues and policy problems under consideration should dominate partisan concerns. Because previous studies have almost exclusively examined "important", high-salience bills, the existing literature overstates the influence of partisan divisions on downstream institutional design choices.

To test this proposition, I offer a novel language-based conceptualization and measurement scheme designed to quickly and easily measure the complexity of institutional structures contained in legal texts. Conceptually, I argue that formal legal texts are best viewed as *relational* documents, which describe which actors can do what, when, and to whom. I then propose and implement a neural network-based approach designed to extract these "implementing networks" from legislative texts, which I validate both qualitatively and in out-of-sample quantitative tests. I then use this measurement approach to study patterns of institutional complexity in a dataset consisting of nearly all enacted American laws passed from 1990-2014, rather than simply the "significant" ones from the period. As predicted, I find that high-salience bills passed under unified government tend to be more complex than those passed under unified government. By contrast, their lower-salience counterparts passed under unified and divided government are indistinguishable. These findings challenge the existing literature on formal allocation of authority and contribute to the growing literature on bipartisan collaboration in the American lawmaking process.

2 The Causes of Institutional Complexity

2.1 Institutional Complexity as Bureaucratic Oversight

When a policymaker writes a formal legal document - such as a constitution, law, or administrative regulation - that policymaker must choose between a range of possible implementing structures. At one extreme, she could create a complicated, interconnected institutional system, which involves many actors in a particular policy area and requires agreement among them to reach a particular policy decision. At the other, she could write a simple "framework" document, which allows one or a few actors to unilaterally make decisions in a given policy area. Farhang and Yaver (2016) succinctly describe this quality - which they term *fragmentation* - as the extent to which a law

> [divides] implementation authority over a larger number of distinct actors, over a larger number of different agencies, and [gives] multiple actors the authority to perform the same function with respect to the same statutory provisions.

The choice between a simple, streamlined implementing structure and a fragmented, diffuse one is consequential. By splitting policymaking authority among several actors, lawmakers reduce implementing efficiency and limit implementer discretion, but offer more opportunities for outside groups to monitor and intervene into the policymaking process. Streamlined implementing structures, by contrast, offer a more efficient policymaking process but fewer oversight opportunities.

To explain variation in institutional complexity, most empirical work on formal institutional design focuses on *partisanship-based* explanations. As Moe (1990a; 1990b; 2012) and Moe and Caldwell (1994) argue, complex implementing structures are not *ex ante* desirable. From a policy standpoint, complicated power-sharing arrangements curtail administrative flexibility, reduce implementer responsiveness, and promote policy gridlock. Worse, complex implementing structures are costly to create. If a lawmaker wants to design a complicated institutional structure involving many implementing actors with the purpose of accomplishing a particular policy goal, she will need to devote a substantial quantity of time and attention to the institutional design process. For example, she might need to carefully research the existing legal and administrative landscape, interview expert interest group and agency leaders, and design incentives, evidentiary rules, and decision-making procedures to encourage bureaucrats to reach favorable policy decisions. Thus, at least in the abstract, policymakers should prefer "framework" legislation that offers one or a few implementing actors substantial discretionary authority.

Here, Moe's "politics of structural choice" intervenes. Whenever policymaker and implementer possess different substantive preferences - for example, during periods of divided government - institutional complexity becomes more attractive for legislative actors. By creating overlapping decision-making processes that involve a larger number of implementers, lawmakers can slow the rollout of undesirable policy programs and generate new opportunities for "fire alarm"-style oversight from interest groups and the courts (McCubbins and Schwartz 1984; Kagan 2009; Farhang 2010). Institutional complexity, from this standpoint, provides a means for members of Congress to passively check the administrative state, even after members of the current majority coalition lose control of the formal tools of Congressional oversight.

This framework produces a natural set of predictions. Based on this logic, when the executive and legislative branches share similar interests, the implementing structures contained in a given legal document should be *simpler*. In other words, fewer actors should be named by the law, and decisions articulated by the law should require approval from fewer implementers. Of course, policy and political context matter too; for example, majority-party lawmakers might favor simpler implementing structures under unified government, but might nevertheless create complicated decision-making structures in defense or macroeconomics bills, which frequently address policy problems that cut across many administrative departments. However, these intercept-type shifts aside, based on this framework we should expect executive/legislative preference disagreements to produce more complex decision-making structures at a rate that is roughly constant no matter the policy area or political context.

2.2 The Costs of Complexity

Though this partisanship-based framework is appealing and influential, it has received surprisingly mixed empirical support. On the positive side, studies of historically "important" legislation in the US Congress (Epstein and O'Halloran 1999; Farhang and Yaver 2016) and the European Community (Franchino 2004, 2007) have each reported the predicted positive relationship between preference disagreement and institutional complexity. By contrast, Huber *et al.* (2001) and Huber and Shipan (2002) report the opposite relationship in the context of American state-level healthcare legislation.[1] de Figueiredo Jr (2002) and Bendor and Meirowitz (2004) argue that this result is due to the fleeting nature of unified government in contemporary American politics, which incentivizes majority lawmakers to "insulate" new programs from future political opponents through directive language and complex institutional structures. Whatever the reason, these findings suggest that the relationship between partisanship and formal institutional design is at least more complicated than the logic I describe above.

The partisanship-based formal institutional design framework is also at odds with a

[1]In particular, these authors find a negative relationship between preference disagreement and statute length (a proxy for legal detail) in states with sufficiently professionalized legislatures, and a null relationship otherwise.

growing body of work on minority-party influence over Congressional lawmaking. Though voting patterns in Congress have becoming increasingly polarized over the last several decades, recent studies have found that minority-party lawmakers retain substantial influence over the *content* of legislation. For example, Wilkerson *et al.* (2015) demonstrate that, though the Affordable Care Act received zero Republican votes, as much as 25% of its substantive content was drawn from bills originally proposed by Republicans in the same Congressional session. Similarly, Casas *et al.* (2018) find that majority-party "hitchhiker" bills - or, those bills which are proposed as independent laws but enacted as part of an unrelated bill - are only 25-50% more likely than their minority-party counterparts to pass, compared with a 200-300% estimated difference for majority-party complete bill proposals. Though findings like these tell us relatively little about the characteristics that make minority-party proposals successful, they do suggest that minority-party lawmakers exert a surprising level of influence over the content of legislation, even during periods of unified government.

To unite these literatures, I argue that a key missing element in existing work is the *importance* lawmakers assign to a given law. As I note above, institutional design is a costly process. If a policymaker wants to design a complex policy structure with the intention of accomplishing a policy objective, she needs to research the institutional and legal context and consult with experts to accomplish her objective. As a result, *institutional complexity is not equally appealing in all situations*. Rather, lawmakers will be more willing to exert the energy required to create a complex implementing structure to the extent that they view the policy problem addressed by a given law as a *high-priority* issue.

For the purposes of this paper, by "high-priority" I refer to those issues that capture publicly-expressed attention from lawmakers' public and elite constituents and partisan stakeholders. Of course, issues can capture public attention for a variety of reasons. For example, periodic negotiations like those over the Farm Bill create predictable spikes in public attention to agricultural policy, while exogenous shocks like the 2008 Financial Crisis create more erratic spikes in public attention to banking and macroeconomics. But, whatever the source, increased public attention to a problem should prompt politicians to examine that problem more closely, and should render lawmakers more willing to craft complex implementing solutions.

Crucially, we should also expect the "importance" of the policy problems contained in a law to condition the relationship between partisanship and institutional complexity. Again, because institutional design is costly, lawmakers should be differentially motivated by preference disagreement when addressing low-salience policy problems compared with their higher-salience counterparts. When addressing lower-priority issues, politicians have little incentive to carefully design implementing structures that implement their preferred policy outcomes. In these cases, legislators should be more willing to accept content proposals (and accompanying institutional design suggestions) from minority-party lawmakers, which mutes the effect of executive-legislative preference disagreements on downstream institutional design choices. By contrast, when addressing high-salience policy problems the relationship between preference disagreements and downstream institutional complexity should be large and positive, since politicians should be more willing to use institutional complexity as a tool of bureaucratic control.

This heterogeneous incentive structure helps explain some of the mixed findings reported by previous studies on formal institutional design. As I note above, depending on the context under consideration, various studies have reported positive, negative, or null relationships between preference disagreements and various measures of legal complexity. Authors like de Figueiredo Jr (2002) and Bendor and Meirowitz (2004) argue that these findings are actually due to a countervailing incentive structure; in particular, because unified government is rare in contemporary American politics, majority lawmakers are incentivized to "insulate" new programs through directive language and complex institutional structures. However, if institutional design costs render complexity more attractive as a means of constraint in some cases than others, an alternative explanation is *selection.* As I discuss in the following section, existing empirical studies of formal institutional design focus on either a small set of historically "significant" legislation or on laws that concentrate on a single policy area. As a result, if lawmakers place a higher priority on some policy areas and issues than others, results reported by existing studies may be inflated or otherwise inaccurate.

2.3 Measurement Limitations as Theoretical Constraints

Before continuing, it is worth pausing to consider the reasons why "importance"-type effects have not been explored in the existing literature. After all, an extensive body of work in the bounded rationality (Baumgartner *et al.* 2009; Baumgartner and Jones 2015) and broader public policy literatures (e.g. May and Jochim 2013) suggests that we should only expect legislators to actively reconsider the existing institutional and policy regime in a particular domain in response to a major exogenous disruption. Based on these ideas, we should expect partisan preferences to have a disproportionate impact on the content of legislative proposals when lawmakers are considering high-salience problems, as opposed to their more day-to-day counterparts.

The reason for this gap, I suggest, is simple: *measuring text-based distribution of authority is difficult.* Even for experts, parsing legal texts is difficult and labor-intensive. To underscore the extent of this measurement challenge, consider Farhang and Yaver (2016)'s recent study. In their paper, the authors read and coded some 24,000 pages of legislative text in order to produce data on some 366 "historically significant" laws passed from 1947 to 2008. Though heroic, hand-coding protocols like these are impractical to apply beyond the relatively small corpus these authors examine. As a result, most existing studies of formal institutional design patterns have been forced to limit the scope of their work, either by focusing on single policy areas (e.g. Huber and Shipan 2002) or (more commonly) by focusing on high-salience, "important" legislation (e.g. Epstein and O'Halloran 1999; Farhang and Yaver 2016).

Limitations like these are problematic in at least two respects. First, from a descriptive standpoint, the labor-intensive nature of textual data collection efforts means that we know very little about the content of most legislation, even in an institution as well-studied as the US Congress. Most laws enacted by Congress are not the kinds of high-profile and transformative legislative actions that receive the bulk of scholarly attention. For example, take Mayhew (1991)'s list of "significant" legislation, an extended version of which forms the sample used by Farhang and Yaver (2016). For the period from 1989-2008, Mayhew's list contains some 63 pieces of legislation, compared with compared with 4,186 total laws passed during the period. Of course, not all of these enactments were impactful; approximately one-quarter (1,018) are relatively trivial "commemorative" bills, which established monuments or symbols designed to commemorate noteworthy people or places in US history. The remaining three-quarters are highly heterogeneous, ranging from technical, procedural bills[2] to impactful, transformative legislation. For a concrete example, consider the Enhanced Partnership with Pakistan Act (2009).[3] This bill authorized some $1.5 billion in yearly defense-related aid to the government of Pakistan from 2010-2014. Though not significant enough to make lists like Mayhew's, the Enhanced Partnership with Pakistan Act nevertheless involved substantial financial outlays and represented an important shift in US-Pakistan relations. Unfortunately, measurement limitations like those I describe above mean that we know almost nothing about the prevalence or content of these important but not "historically significant" laws.

Second - and perhaps more importantly - measurement and data limitations like those I describe inhibit our ability to test key outstanding theoretical claims. The focus on high-profile legislation common in existing work would be less problematic if public salience was unrelated to downstream institutional design choices, or to key predictor variables such as the presence of divided or unified government. Unfortunately, as I describe in the previous section, features of the policy areas and policy issues addressed by a given law are likely both to directly influence its institutional content and to condition the relationships between

[2]E.g. Pub. L. 108-306, "To provide an additional temporary extension of programs under the Small Business Act and the Small Business Investment Act of 1958 through September 30, 2004, and for other purposes".

[3]Public Law No. 111-73.

standard preference-related variables and the institutional structures favored by legislative actors. As a result, without a more scalable measurement approach, we cannot speak more generally about lawmaking patterns beyond the "high-profile" datasets studied in existing work.

3 Using Implementing Networks to Measure Institutional Complexity

To address this measurement challenge, in this section I present a novel network- and language-based conceptualization of formal institutional power, which I use to develop a scalable measure of formal institutional complexity. In social science research, a common way to study the power relationships contained in a document is to study the *relational* statements that document contains. For example, Franzosi *et al.* (2012) use a semi-automated method to study portrayals of agency and victimhood in newspaper accounts of lynching episodes in the American South. Among other findings, this analysis reveals a surprisingly strained relationship between law enforcement officials and white lynching mobs, who targeted sheriffs and deputy sheriffs for violence in nearly half of all lynching episodes. In political science, a notable example of this kind of approach is GDELT (Leetaru and Schrodt 2013), which mines news accounts for subject/action/object triples corresponding to international events.

This approach is similarly helpful in the legal setting. Among other functions, legal texts articulate power relationships, describing who can do what, when, and to whom. As a result, a reasonable way to conceptualize a law, contract, or constitution is to view it as a *network* of institutional relationships. The "nodes" in this network represent actors involved in the execution of powers outlined in the text, while the "edges" represent the relationships between them. Depending on the scope of the document, these relationships might be directed or undirected, and might include simple connection types or more complex ones. To take an example familiar to most Americans, the US Constitution provides the House and the Senate joint authority over "legislative Powers herein granted"[4] (an undirected relationship) while empowering the Senate alone to offer "Advice and Consent"[5] to the President over treaties, and judicial/executive appointments (a directed relationship). By collecting and combining all such entities and relational ties, we can construct an "implementing network" for the US Constitution, which describes the set of formal institutional relationships envisioned by the document. We can then use this representation to construct measures of downstream quantities of interest such as the overall complexity of the network, which I turn to in §4.

Besides its conceptual and measurement advantages, a relational conceptualization of formal power also helps to pinpoint the technical challenges involved in studies of this kind. At their most fundamental level, networks are constructed from *entities* (the actors involved in the network) and *edges* (the ties between them). Treating formal legislative texts as implementing networks implies two natural tasks: in particular, what is the set of implementing actors named in a particular legal document, and what are the relationships between them? As I show in the following subsections, both of these quantities can be extracted in a straightforward, scalable fashion using natural language processing methods.

3.1 Entity Extraction

To construct an implementing network for a particular legal text, the first challenge is to identify the set of actors named by that text. In political science, perhaps the most common approach to this problem is a dictionary-based system (see, e.g. Leetaru and Schrodt 2013), in which the entities of interest are pre-identified using a dictionary generated by expert researchers. This approach produces few false negatives, but misses a large number of items of interest, since generating a comprehensive named entity dictionary is impractical in most situations. By contrast, general-purpose machine learning approaches - which rely on lexical and grammatical information to make tagging decisions - usually capture most entities of interest, but will also include irrelevant entries such as the names of people or

[4] U.S. Const. Art I, §1.
[5] U.S. Const. Art II, §2.

places (Manning *et al.* 2014). For the purposes of this paper, I therefore opt for a customized machine learning approach, which splits the difference between these two alternatives by leveraging expert-generated lists of government entities to train a specialized named entity recognition model.

To collect training data for this method, I used a three-step procedure. First, using Wikipedia and US government sources, I built a custom dictionary ($n = 1,346$) of common federal US government entities, which includes executive-branch agencies and departments, Congressional committees, and government-sponsored enterprises.[6] Second, I scraped, cleaned,[7] and split into sentences[8] all non-appropriations bills included in legislation enacted from 1993-2014.[9] Third, for each sentence, I conducted a simple string search for each entity contained in the entity dictionary, and tagged any entities found using a standardized per-token tagging scheme (see Table 1 for an example).[10] This process left me with some 90,711 sentences containing at least one named entity, which formed the training set for the tagging model I employed.

As a tagging model, I use a long short-term memory (LSTM) neural network, which is a common approach in modern natural language processing work.[11] Broadly, LSTMs are a type of recurrent neural network, which allow the tagging decision for each individual token to be influenced both by characteristics of the token and by characteristics and tagging predictions

[6]In particular, I first scraped names from usa.gov, the Federal Register, or one of five Wikipedia sources: specifically, the lists of federal agencies, defunct federal agencies, House committees/subcommittees, Senate committees/subcommittees, and joint committees. I then removed common prefixes and suffixes from these items (e.g. "United States"; "USA"), and stripped names of states and national governments (e.g. "Texas"; "California"; "Federated States of Micronesia") from the list. As an additional quality control measure, an undergraduate research assistant read a random sample of 1,000 sentences, and supplemented this list with a series of additional missing items.

[7]In order to maintain parity between the LSTM training set and the testing and prediction sets, I used identical preprocessing steps for both training and prediction. See §4.1 for a description of the cleaning procedure used for each document.

[8]Using the pretrained Punkt sentence tokenizer, available via NLTK.

[9]As defined using Casas *et al.* (2018)'s data. This dataset includes both enacted legislation and "hitch-hiker" bills (independently-proposed bills included as amendments to other enacted legislation).

[10]Since some named entities are substrings of others - for example, compare "Secretary of Defense" with "Assistant Secretary of Defense" - before searching each sentence I ordered the named entity dictionary from longest tag to shortest, to ensure that the longest present named entity would be tagged first.

[11]E.g. language modeling (Sundermeyer *et al.* 2012) and part of speech tagging (Huang *et al.* 2015; Plank *et al.* 2016).

Table 1: Sample training example

Token	Tag
Funds	O
herein	O
appropriated	O
to	O
the	O
Department	B-MISC
of	I-MISC
Defense	I-MISC
for	O
construction	O
shall	O
be	O
available	O
for	O
hire	O
of	O
passenger	O
motor	O
vehicles	O
.	O

Sample training example, formatted according to a modified version of the CoNLL2003 format. Military Construction Act 1992 §102. For original text see the corresponding congress.gov page.

for "adjacent" data points. This approach creates a recursive, context-sensitive prediction structure ideal for analyzing textual data and other sequentially-organized information. For the purposes of this paper, I specifically rely on the bidirectional CRF-LSTM neural network architecture proposed by Lample *et al.* (2016) and Ma and Hovy (2016).[12]

How well does this custom-trained LSTM approach perform? Since the purpose of using a machine learning approach for named entity recognition is to capture named entities not already known to the researcher, the most relevant (and stringent) performance test would be one in which we assess the model's ability to recover *unseen entities* not available during training. In order to assess the model's performance in this scenario, I therefore

[12] As implemented in Tensorflow and Python in the tf_ner library. This implementation is slightly different from the one outlined in the two papers I cite in-text; for details, see the accompanying documentation. See Appendix A.3 for details regarding parameter settings and training.

conducted a five-fold cross-validated predictive accuracy study. First, I randomly split my entity dictionary into five equally-sized sets of entity names. For each set, I then identified all sentences exclusively containing entities from the set in question, and used these sentences to form a held-out test set. I then trained a model using sentences containing entities from the remaining four groups, and calculated precision, recall, and F1 scores for the held-out test set.[13] Finally, I repeated this process for each group, and averaged the performance statistics to produce the final set of results.

Assessed according to these metrics, the LSTM model I employ achieved a cross-validated F1 score of 0.817, with a cross-validated precision of 0.904 and recall of 0.743. These values are comparable to or higher than those reported elsewhere in the literature; for example, Augenstein *et al.* (2017) report an overall F1 score of 0.507 for entity recognition on unseen named entities, averaged across three modeling approaches and 19 standard benchmarking datasets. For the standard CoNLL datasets - which contain newswire text that is relatively similar to the language I examine in this paper - these authors report F1 scores of 0.844 and 0.871. Overall, then, the performance results I report match state-of-the-art performance on standard testing datasets, and represent a strong basis from which to work.

3.2 Relation Extraction

Compared with entity extraction, relation extraction is a more difficult problem. Identifying a particular word or phrase as a named entity involves analyzing some data about that word or phrase (and perhaps its local context), and reaching a classification decision. By contrast, analyzing the *relationship* between two entities involves analyzing the entities, their local context, and any words or phrases which might encode information regarding their relationship. Worse still, relationships between actors are highly heterogeneous; for example, in a particular piece of legislation, two agencies might be given joint veto authority

[13] Defined as $F1 = \frac{2PR}{P+R}$, $P = \frac{TP}{TP+FP}$ and $R = \frac{TP}{TP+FN}$, where P and R denote precision and recall, $T(P|N)$ denote the count of true positive/negative examples correctly classified and $F(P|N)$ denote the counts of true positive/negative incorrectly classified.

over the implementation of a policy program, or a court might be assigned to oversee and approve an agency's actions. Pre-specifying these relationship types and locating examples of each is a difficult problem, and is likely impractical when applied to a large corpus.

Fortunately, studying institutional complexity - my focus in this paper - does not require a detailed typology of relationship types. Institutional structures are complex to the extent that they include more actors in a particular policy area and create a denser network of decision-making structures that connect those actors. Though this definition might be enriched by a more nuanced definition of actor types or relationships, simply counting the number of actors and the relationships between them still reveals useful information on my key construct of interest. For both practical and theoretical purposes, I therefore focus on an abstract tie type, which is similar to that identified by Farhang and Yaver (2016). In particular, I define a tie between two actors as an instance in which two actors are *assigned to implement the same policy program.*

Drafting guidelines for American legislation make these kinds of relationships relatively easy to identify. As noted in the drafting guide for the US Consolidated Code, the "basic unit" of federal US law is the *section*.[14] Laws are often further subdivided into ordered list elements of various types, but *sections* are intended to be stand-alone units that are roughly comparable in substantive scope. As a result, if we observe that two actors are co-mentioned in a section of a law, we can reasonably conclude that those two actors share authority over the policy area under consideration in that section. Without a sharper definition of the relationships under consideration, we cannot draw strong conclusions about the nature of the connections between these actors, but we can draw general conclusions about the complexity of the implementation structure envisioned by the law in question.

[14] http://uscode.house.gov/detailed_guide.xhtml

3.3 Constructing Implementing Networks

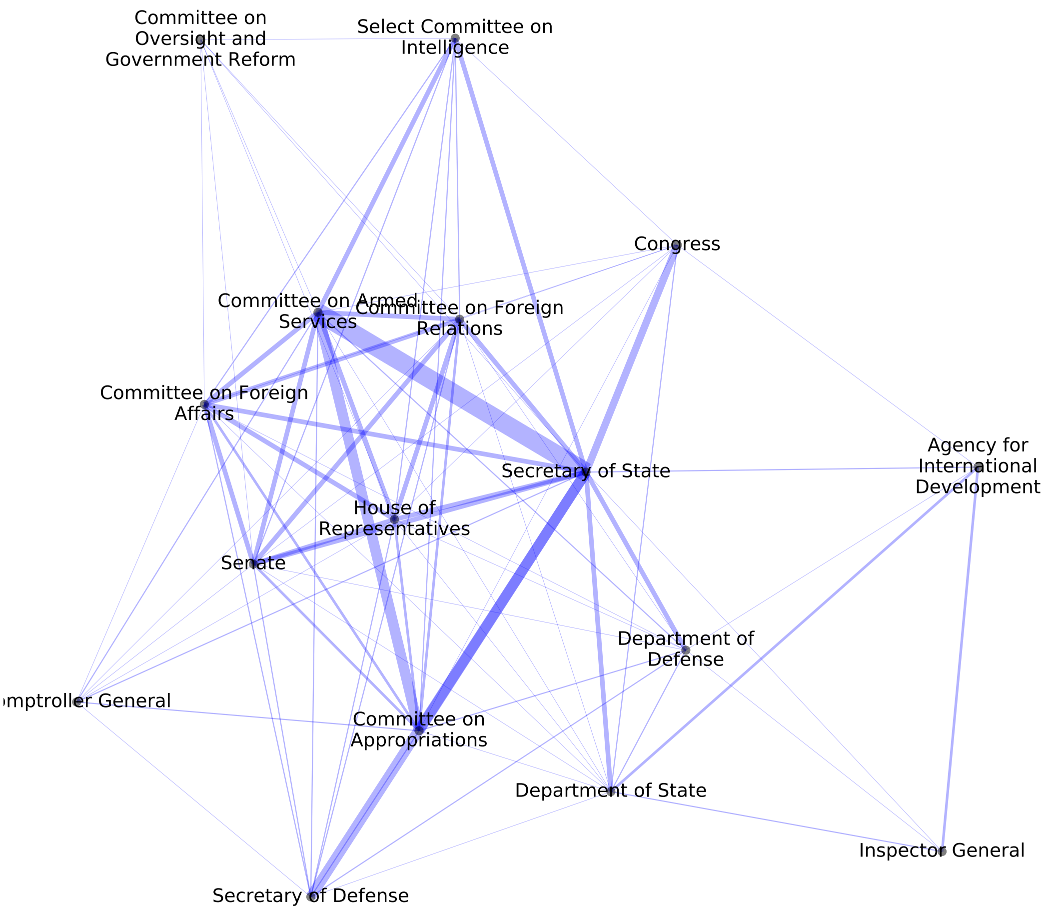
Put together, the named entity and relation extraction approaches I describe offer a simple three-step implementing network construction procedure. First, I split each text into sections[15] and extracted entities from each second using the pre-trained LSTM model described in §3.2. Second, I drew an edge between any set of entities that co-occur in a given section. This process yields a distinct implementing network for each bill, which can be used both to describe the bill's institutional content and to calculate bill-level quantities of interest like institutional complexity.

To illustrate this process, I provide a sample output from the Enhanced Partnership with Pakistan Act of 2009 (Pub. L. 111-73). The Enhanced Partnership with Pakistan Act was a relatively straightforward foreign aid bill intended to provide military and developmental assistance to the Government of Pakistan. The law authorized the President to provide $1.5 billion in non-military aid from 2010-2014, and provided additional military aid conditional on a certification process implemented by the Secretary of State.[16] Unusually for a defense-oriented bill, the law gave the State Department substantial authority over defense-related aid allocations (Epstein and Kronstadt 2013). As shown in Figure 1, these features are clearly visible in the law's implementing network. The law contains a central cluster consisting of the Secretary of State, the Secretary of Defense, and several Congressional actors. Quantitative assessments of node importance reinforce this visual message; as measured by eigenvector centrality, the Secretary of State is the most central actor in this network (eigenvector centrality of 0.45), followed by the the Committee on Armed Services (0.39), the Committee on Appropriations (0.32), and the Committee on Foreign Relations (0.29). These figures roughly track with qualitative summaries of the bill's content, lending this representation a substantial degree of face validity.

[15] Using the constitute_tools regular expression parser. This parser separates each document according to a given set of organizational headers (e.g. titles; sections), while maintaining the internal hierarchy of each document. See Appendix A.1 and A.2 for details and sample parsed text.

[16] Enhanced Partnership with Pakistan Act of 2009, §203.

Figure 1: Implementing network, Enhanced Partnership with Pakistan Act of 2009.



Line density is approximately proportional to the number of ties between each node. Node placement is random, but is loosely related to node centrality.

4 Institutional Complexity in American Law

Throughout this paper, my key theoretical contention is that the relationship between executive/legislative preference disagreement and institutional complexity should be positive on publicly visible, "important" legislative proposals, and null otherwise. To investigate this hypothesis, I used Casas *et al.* (2018)'s hitchhiker bills dataset to construct a comprehensive dataset of bill texts (and accompanying metadata) included in laws passed from 1993-2014 ($n = 6,109$).[17] This dataset includes both independently-enacted bills and separately-proposed "hitchhiker" laws that were eventually included in enacted legislation. As Casas *et al.* (2018) demonstrate, many bills proposed by members of Congress that fail to pass are later included as "hitchhikers" onto future enacted bills.[18] Because these "hitchhiker" bills are drafted and proposed separately from the laws of which they become part, we should expect their content to be primarily influenced by the characteristics of lawmakers who originally proposed them. In order to enable these kinds of comparisons, I therefore isolated the text of each "hitchhiker" bill from the enacted bill in which it was eventually included, and treated these "hitchhikers" as distinct units.[19]

Before proceeding, I conducted some simple preprocessing steps on each document. For each text, I first stripped headers, footers, and editor's notes (e.g. date of passage; legislative history; transcription notes). I then split each law text into sections, and removed

[17] This dataset excludes two types of bills: specifically, "commemorative" laws, and appropriations and budget bills. As defined by the Congressional Bills Project, "unimportant" laws include "commemorative" laws and laws which transfer small quantities of land between government entities, and are therefore unlikely to include allocation-of-authority language. Appropriations and budget bills are also unlikely to include allocation-of-authority language, but for different reasons. Because these bills are primarily designed to disburse funds to various agencies and governmental entities, most of their language is devoted to detailed descriptions of fundraising allocations, rather than to the powers and duties of governmental entities. As a result, I retain "hitchhiker" bills that eventually became part of an appropriations or budget bill (since these "hitchhikers" are usually unrelated to the budgeting and appropriations processes), but remove appropriations and budget bills themselves from the dataset.

[18] Usually, as a separate title or chapter of the enacted law.

[19] In particular, for bills identified by Casas *et al.* (2018) as "hitchhiker", I compared each section of the hitchhiker to each section of the final "target" bill. I then removed all sections from the target bill that shared at least 95% of their tokens with a section from the hitchhiker and differed in length by no more than 5%.

sections containing tables of contents, short titles, and related non-legally binding language.[20] Finally, for all remaining sections I removed section titles and bill common names from each section's text.[21] Because bill names often contain the names of the administrative agencies or institutions whose jurisdiction they affect, these names are a common source of false positive named entity results.[22]

4.1 The Dependent Variable: Network Complexity

As I describe in §2.1, the formal implementing structures contained in a given text are *complex* to the extent they grant a larger number of actors overlapping responsibility over execution of a particular policy program. In the network context, the most plausible operationalization of this quantity is the *average degree* of the network. We can interpret this quantity as the average number of instances in which a given actor is coinvolved with other actors in the implementation of a particular policy program.[23] To calculate this value, I use the procedure I describe in §3 to extract a distinct implementing network for each bill, and simply calculate an average degree statistic for each bill.

Some basic descriptive information for this variable is provided in Figure 2. As this plot suggests, the average degree measure is both widely dispersed and zero-inflated, with a maximum of 639 and some 1,174 observations (approximately 20% of the overall dataset) with an average degree value of zero. Moreover, some 1,813 bills (approximately 30% of the dataset) contain zero named entities, leaving them with an undefined average degree value and reducing the final dataset to $n = 4,296$ observations.

Both of these features are unsurprising from a theoretical standpoint. In the context of this project, I expect to encounter two kinds of bills: an "administrative" type, which increases, decreases, or otherwise modifies the jurisdiction of one or more governmental

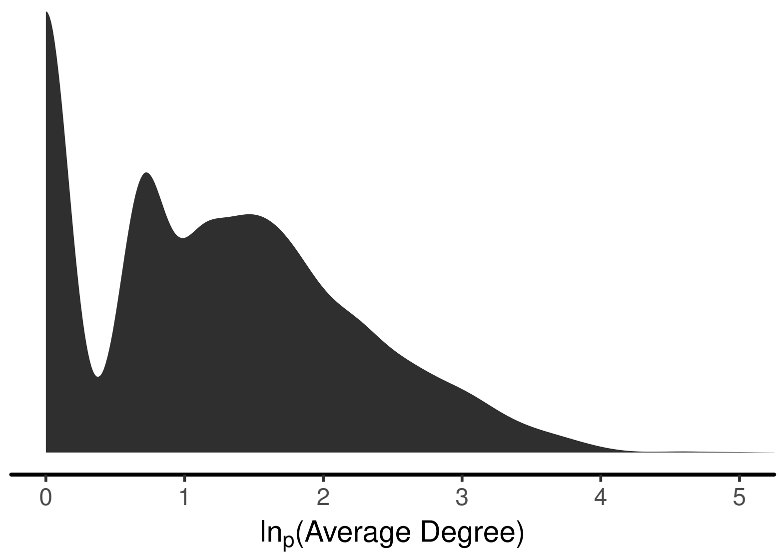
[20] In particular, I removed all sections containing any of the terms "Short Title", "Table of Contents", "Finding", "Purpose", "Definition".

[21] Using the Cornell Legal Information Institute's list of common law names.

[22] For example, the Poison Control Center Enhancement and Awareness Act (Pub. L. 106-174).

[23] Formally, the degree of a node in a real-valued network refers to the sum of all edge weights connected to that node. The average degree simply represents the average degree value over all nodes in the network.

Figure 2: Density plot, per-bill average degree value.



Density plot, log-plus-one transformed average degree value ($n = 4,296$). Bills with undefined average degree values not displayed.

actors, and a "non-administrative" type, which consists of short, technical bills that do not alter the jurisdiction of any actor.[24] Bills of the "non-administrative" type likely follow a different data-generating process than the one I focus on in this paper, which I address from a technical standpoint in the modeling discussion in §4.4.

4.2 Predictor Variables

Based on the expectations I describe in §2, my key predictor variables are the presence of executive-legislative preference disagreement and the public importance of a given law. To operationalize executive-legislative preference disagreement, I use a simple binary indicator, which consists of a dummy variable indicating whether the same party controlled both the executive and legislative branches at the time that the bill was passed.[25] For bill importance,

[24] E.g. Pub. L. 108-306, "To provide an additional temporary extension of programs under the Small Business Act and the Small Business Investment Act of 1958 through September 30, 2004, and for other purposes." This bill simply extends authorization for existing provisions of the Small Business Investment Act of 1958, and therefore provides no modifications to existing administrative jurisdiction.

[25] See Appendix B for descriptive statistics on all predictor variables.

I follow Volden and Wiseman (2014) and use a binary indicator denoting whether the bill in question was mentioned in the CQ Almanac's year-end summary of Congressional activity. Though coarse, this measure offers a useful indicator for the "importance" of the policy concerns contained in a given bill, at least to the elite consumers of CQ's publications. I then include an interaction between these two indicators. Based on the framework I present in §2.2, the unified government coefficient should be approximately zero and the interaction coefficient should be negative. By contrast, the coefficient on the "importance" variable should be positive in all situations, since legislators should be more willing to invest in institutional complexity on issues that receive heightened public attention no matter the political circumstances.

Besides these variables, I also included a series of other individual- and bill-level controls. For the bill-level variables, I first included a random intercept term corresponding to the Congressional Bills Project's 20 bill-level policy codes. This variable is intended to capture policy area-specific institutional design patterns, and should be larger for more complex policy areas (e.g. macroeconomics or defense) and smaller in simpler ones (e.g. public lands). I also included a binary variable indicating whether the bill in question was a "hitchhiker" or an independently enacted bill, and a predictor corresponding to the square root of the number of cosponsors in each bill. Since hitchhikers are by definition subsets of other bills, we should likely expect these bills to be shorter and simpler than independently enacted bills on average, leading to a negative coefficient estimate.[26] Cosponsorship, by contrast, is intended to capture the "importance" of a bill within Congress. I broadly expect the relationship between cosponsorship levels and institutional complexity to be positive; however, since cosponsorship incentives are heterogenous across bill types and policy areas, the magnitude of this coefficient may not be large.[27]

[26] Excluding "hitchhikers" entirely from the model also leaves other model estimates substantively unaffected. See Appendix C.2.4 for details.

[27] In particular, as Sinclair (2016) notes, since important and time-sensitive bills often bypass the ordinary lawmaking process the authors of these bills may not have the time to gather a substantial number of cosponsors. For an instructive example, contrast the Patient Protection and Affordable Care Act (Pub. L. 111-148) with the American Reinvestment and Recovery Act (Pub. L. 111-5). Though both bills received

For individual-level predictors, I included an binary variable indicating whether the proposing member was part of the chamber majority, and continuous variables corresponding to the DW-NOMINATE and squared DW-NOMINATE score of the proposing member. Since members of the majority by definition control at least one chamber of Congress, they have both a greater incentive and a greater ability to engage with the administrative state, making them more willing to author complex bills containing detailed decision-making structures. For the DW-NOMINATE variable, more liberal members tend to be more willing to engage with and enact bills modifying the jurisdiction of the administrative state; as a result, we should expect the coefficient estimate on this variable to be negative. Squared DW-NOMINATE, by contrast, is intended to capture member extremism (see, e.g. Theriault and Rohde 2011, for similar usage). As with cosponsorship, the relationship between extremism and complexity is less clear. If institutional complexity does function as a means of political control, we might expect extremists on both sides to be more skeptical than centrists, leading to a positive coefficient estimate. However, again, the magnitude of this coefficient may not be particularly large.

4.3 Modeling

To model patterns of institutional complexity within this dataset, I use a Bayesian gamma regression model with a hurdle component. We can loosely treat this model as a two-step model, in which we first estimate a logistic regression to determine whether a given observation is zero or non-zero and further estimate a gamma regression for the non-zero observations (since the dependent variable is continuous and strictly positive).[28] Within both components of the model, I estimate separate intercepts and coefficients for each of the eight predictor variables included in the model. For additional flexibility, I partially pool the

substantial public attention and the latter passed by substantially larger margins than the former, the former bill had 40 cosponsors while the latter had only 9. This difference likely reflects the speed with which the bailout bill was enacted, compared with the more measured process for the Affordable Care Act.

[28]See Appendix C.1 for details regarding model specification, estimation, convergence diagnostics, and posterior predictive checks.

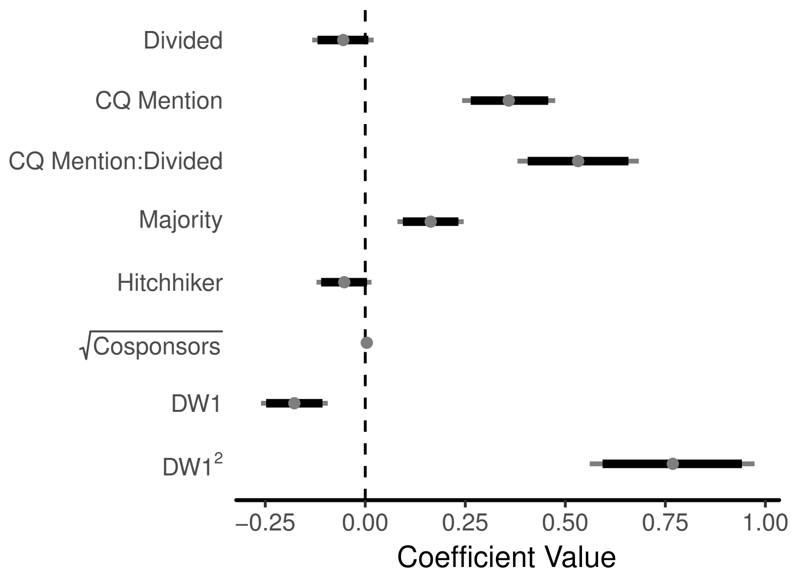
intercepts by policy area in both the hurdle and gamma regression components of the model to capture policy area-specific effects.

The motivation for this modeling structure follows directly from my theoretical expectations. The hurdle model I employ is an example of a mixture model, in which we treat the dependent variable as a mixture of two distinct latent "types". In the context of this project, I expect to encounter two kinds of bills: a "standard" type, which increases, decreases, or otherwise modifies the jurisdiction of one or more governmental actors, and a "non-administrative" type, which does not alter the jurisdiction of any actor.[29] Laws of this kind are likely to follow a different data-generating process than other bills contained in my dataset. The hurdle component of the model separates these two bill types, allowing me to estimate separate coefficients for each of my predictors and each bill type.

As I note in §4.2, one disadvantage to using the average degree of each bill's implementing network as a dependent variable is that it leaves bills with zero named entities with an undefined value on the dependent variable. As a robustness measure, I therefore follow Farhang and Yaver (2016) and calculate the *number of unique entities* named by each bill as an alternate measure of institutional complexity. This measure is less conceptually precise, but is defined for all bills, allowing me to incorporate all observations into the models I present in §5. Like Farhang and Yaver (2016) I find that these two measures are highly related (correlation of $r = 0.91$ between log-plus-one transformed versions of each variable), and I draw essentially identical substantive conclusions using both sets of variables (see Appendix C.2.5 for details).

[29] E.g. Pub. L. 108-306, "To provide an additional temporary extension of programs under the Small Business Act and the Small Business Investment Act of 1958 through September 30, 2004, and for other purposes." This bill simply extends authorization for existing provisions of the Small Business Investment Act of 1958, and therefore provides no modifications to existing administrative jurisdiction.

Figure 3: Top-level coefficient estimates, gamma regression model.



Grey dots indicate posterior mean values. Dependent variable is the average degree of each bill's implementing network ($n = 4,296$). Thick lines indicate 90% credible intervals, and thin lines indicate 95% credible intervals. Positive estimates indicate that an increase in a given coefficient increases bill complexity. Intercept suppressed for readability.

5 Results

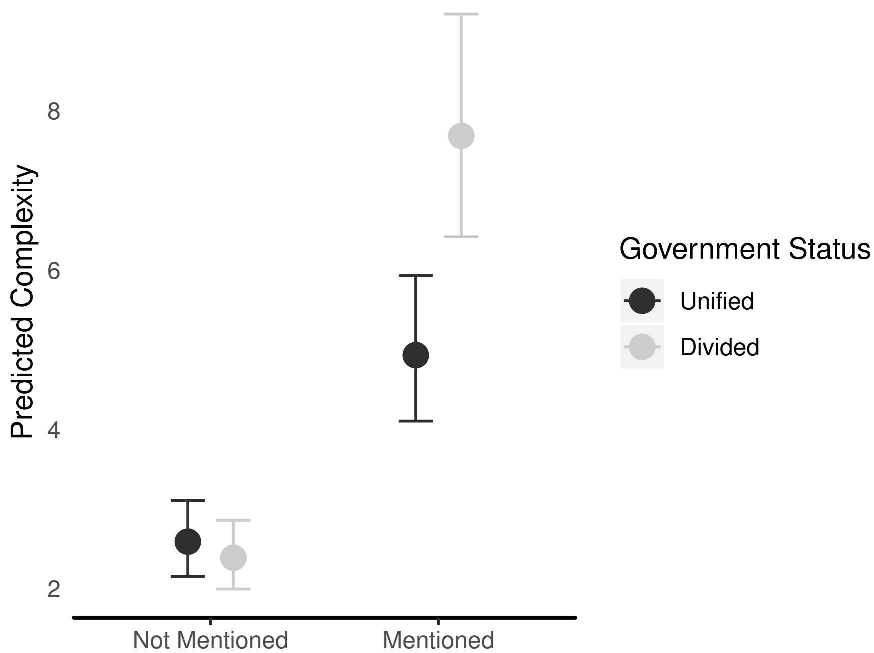
Top-level coefficients for the gamma regression model component - which models the complexity of "standard" bills that actually modify administrative authority - are given in Figure 3.[30] As predicted, the effect of divided/unified government is strongly conditioned by bill significance. For non-"significant" bills - as measured by mention in CQ's year-end summary - the coefficient on the divided government indicator is small and possesses the opposite sign predicted in the literature. By contrast, "significant" bills passed under divided government are substantially more complex than their unified-government counterparts. Also as predicted, "significant" bills contain consistently more complex implementing structures than their "non-significant" counterparts, no matter the background political context.

These findings offer substantial support for the hypotheses I present in §2. Like other authors, I find that executive/legislative preference disagreements are associated with increased

[30]For brevity, I relegate coefficient estimates for the hurdle model to Appendix C.2.1.

institutional complexity; however, this effect is almost entirely constrained to "important" laws that receive attention from legislators' constituents. As shown in Figure 4, for high-salience legislation the effect of executive/legislative preference disagreement is substantial: "important" bills passed under unified government are over 50% more complex than their divided-government counterparts. But, outside of this context, this difference essentially vanishes. This finding complicates findings presented elsewhere in the formal institutional design literature, and suggests that institutional design choices outside of high-salience issues are primarily driven by characteristics of the substantive policy problem under consideration.

Figure 4: Marginal effects plot, divided government/CQ mention interaction.



Margins plot, showing predicted values for the four conditions in the divided government/CQ mention interaction. Dependent variable is the average degree of each bill's implementing network ($n = 4,296$). Dots show posterior means, while lines show 95% credible intervals. All other predictors in the model were fixed at zero.

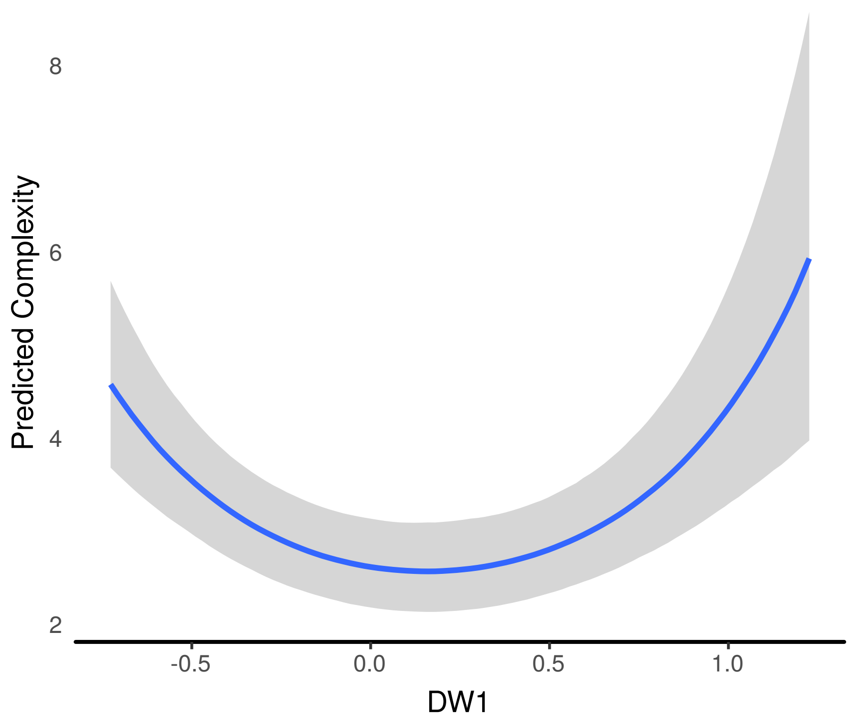
Most of the secondary expectations I present in §4.3 are also supported. As predicted, members of the majority tend to pass bills containing more complex implementing structures, which suggests that these members tend to be willing to draft bills addressing more complicated policy problems. Similarly, "hitchhiker" laws tend to be less complex than independently-passed laws, though the coefficient estimate is small and the 95% posterior credible interval crosses zero. Perhaps more surprisingly, the coefficient on the consponsorship variable is essentially zero, which suggests that cosponsorship patterns are essentially unrelated to institutional design choices. However, as I show in the hurdle model results in Appendix C.2.1, bills that receive more cosponsors are more likely to be of the "administrative" than the "non-administrative" type. Based on these results, we can infer that members are more inclined to cosponsor substantial bills that affect administrative jurisdiction rather than vacuous or highly technical legislation.

The relationship between individual-level ideology and institutional complexity also largely matches my expectations. Both DW-NOMINATE coefficient signs match the expectations I describe in §4.3. However, because the coefficient on the squared term is much larger than the base-level term, the substantive contribution of the base-level ideology variable is relatively small. As shown in Figure 5, for a given DW-NOMINATE magnitude, liberals (members with negative scores) tend to propose somewhat more complex bills than conservatives, but the difference between centrists and extremists on either side is substantially larger than the left-right differential. One possible explanation for this result relates to skepticism of the administrative state; since extremists are less likely to favor status quo policies than moderates, they may be more willing to enact laws containing more complex implementing structures designed to constrain the administrative state. However, further work is needed to test this proposition.[31]

Finally, the policy area predictions I offer in §4.3 are also at least partially supported. As shown in Figure 6, all else equal public lands bills tend to contain noticeably simpler implementing structures than essentially all other policy areas. This pattern is intuitive; public lands bills often involve small transfers of property between government institutions

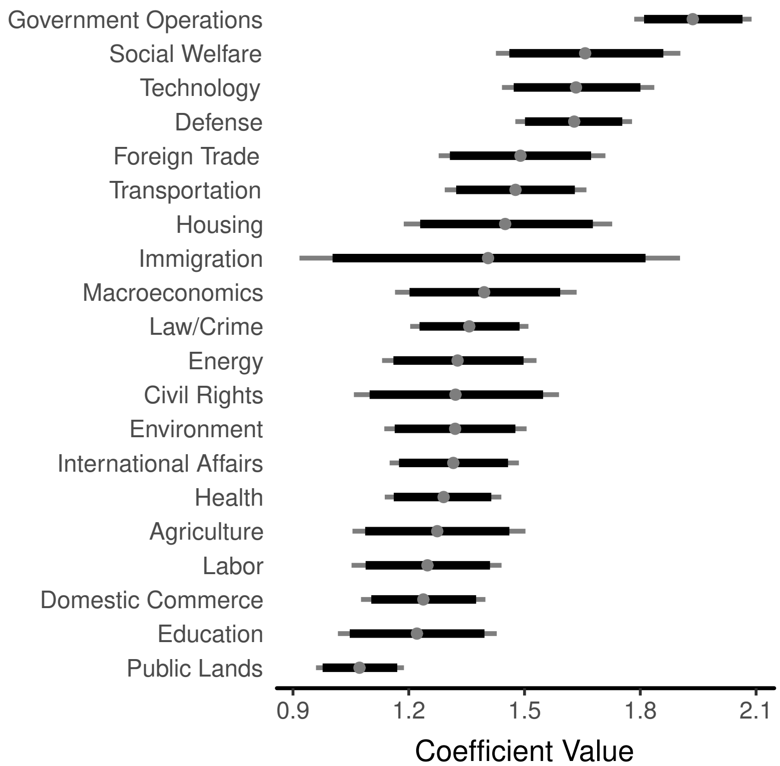
[31] As I show in Appendix C.2.2, when the squared DW-NOMINATE variable is excluded from the model the corresponding coefficient estimate for the raw DW-NOMINATE variable drops to essentially zero. Substituting the DW-NOMINATE variable for an indicator denoting the party to which the proposing member belongs offers a similar conclusion, suggesting that this finding is robust to measurement and model specification choices. However, in all cases, coefficient estimates for other variables in the model are essentially unaffected.

Figure 5: Marginal effects plot, DW-NOMINATE score of proposing member.



Margins plot, showing predicted values across various levels of the proposing member's DW-NOMINATE score. Dependent variable is the average degree of each bill's implementing network ($n = 4,296$). All other predictors in the model were fixed at zero.

Figure 6: Intercept values by policy area, gamma regression model.



Intercept values, gamma regression model. Coefficient estimates are based on a partially pooled intercept term. Dependent variable is the average degree of each bill's implementing network ($n = 4,296$).

or small modifications in land regulation or oversight, rather than large-scale modifications of the administrative state. The top end of the scale also fits with existing knowledge, though findings are more mixed. Government operations and defense, for example, are classic high-complexity policy areas, which implicate a variety of different policy concerns and necessarily involve a large number of government agencies in their implementing process. However, outside of these relatively clear examples, policy area does not appear to have a strong effect on downstream institutional design decisions.

6 Conclusion

Overall, this paper offers two primary contributions. From a theoretical standpoint, I argue that formal institutional design decisions are frequently unaffected by the background partisan context. In existing political science scholarship, institutional design choices - and particularly the *complexity* of formal institutions - are often treated as purely political tools, which legislators manipulate based on partisan circumstances. By contrast, I demonstrate that this relationship only holds for high-visibility, "important" legislation. Outside of this context, institutional complexity is primarily a function of the policy issues under consideration, rather than the partisan context. These findings dovetail with a growing literature on "submerged" bipartisan collaboration over the *content* of legislation (e.g. Wilkerson *et al.* 2015; Casas *et al.* 2018), and support a more optimistic portrayal of Congressional lawmaking than is often provided in the academic and popular presses.

To test this theory, I rely on a novel language- and network-based measurement strategy, which offers a straightforward, scalable way to extract information on formal institutional design choices. As I note in §2.3, extracting information on institutional design choices from legal texts is highly labor-intensive, which has prevented previous studies from moving beyond samples focused on single policy areas or "historically significant" legislation. By contrast, the method I present in this paper - which relies on both modern machine natural language processing methods and case-specific knowledge regarding Congressional drafting procedures - offers a more scalable alternative, which enables me to test the theoretical framework I present in this paper. Better still, the conceptualization and measurement strategy I employ is adaptable to other legal contexts, offering a useful tool for researchers interested formal institutional design patterns beyond the national-level American setting.

The results in this project offer a number of directions for future research. Within the domain of American legislation, comparing enacted legislation to proposed but unpassed bills offers opportunities understand the sources of institutional complexity in a direct fashion, both at an individual and an institutional level. The measurement framework I present also offers opportunities to other relevant quantities of interest in this setting, such as the centrality of particular actors over time or the frequency with which particular administrative agencies are called upon to collaborate on policy implementation. More broadly, though the application in this paper is restricted to American national-level legislation, the framework and tools I present are broadly applicable to legal documents from state governments or governments from outside the United States. As a result, the measurement approach I propose offers opportunities to study institutional design patterns in different social and political contexts and under different systems of government.

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