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Using Deep and Active Learning Classifiers to Identify Congressional Delegation to Administrative Agencies: Supplemental Information

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Supplemental Information for:
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1 Dataset Details

As discussed in Section 4, our data is partitioned into labeled and unlabeled components, and these are also split into training, validation, and testing partitions. In performing this splitting, we ensured that all titles/versions from the same bill were apportioned to the same subset. This is important, because different bill versions frequently had a plurality, if not majority, of their bill sections stay unchanged throughout the process. By segregating bills invariant of bill version, we prevented over-fitting on these (essentially) duplicate sections.

Table 1: Splits of our Dataset into Training, Validation, and Test Subsets

| | # of Bill Sections | | | # of Bill Numbers | | |
|-----------|--------------------|--------|--------|-------------------|------|------|
| | Train | Val. | Test | Train | Val. | Test |
| Labeled | 1228 | 483 | 387 | 510 | 127 | 159 |
| Unlabeled | 82,061 | 21,483 | 34,072 | 4188 | 1047 | 1308 |

We randomly divided the bills in our labeled data into training, validation, and test using proportions of 65%, 15%, and 20%, respectively. The remaining bills from the 110th Congress were also apportioned into training, validation, and test using the same proportions. The number of bills (by bill number) and number of examples (e.g. bill section) are provided in Table 1.

2 Convolutional Neural Network Specification

For the results presented in this paper, we use the CNN architecture described here with 64 filters each of sizes $\{1, 2, 3, 4, 5\}$. We choose a word embedding dimension of $d = 300$, and our dataset yields a vocabulary size of 5775 words. Our first MLP hidden layer has 64 neurons, while the second has 32. To train our model, we optimize the parameters using the Adam optimizer (Kingma & Ba 2014) with a learning rate of 0.0001 and batch size of 64 bill sections. The loss to minimize is the binary cross-entropy loss, with bill sections labeled according to whether they delegate authority or not. We allow the model to train for 13 epochs, and regularize the model using Dropout (Srivastava *et al.* 2014) in the MLP with a drop-rate of 15%.

Additional model specification details for both the CNN and active learner are available at: <https://github.com/gspell/deep-active-learning-congressional-delegation>

3 Baseline Specification

We describe here the baseline models to which we compare against the convolutional neural network for text classification. These models use term-frequency, inverse-document frequency (tf-idf) text representations of text, and over tf-idf features we compare three different classifiers: a linear support vector machine (SVM)¹, an L1-penalized logistic regression (LASSO), and random forest. In all cases, the baselines were implemented using the `sklearn` package in Python.

For a tf-idf word frequency representation, each document (bill section) is represented as a high-dimensional vector $\mathbf{v}_d \in \mathbb{R}^{|V|}$ where V is the vocabulary of the dataset. The elements of this vector are determined by:

$$\text{tf-idf}_{t,d} = \text{tf}_{t,d} \times \log \frac{N}{\text{df}_t} \quad (1)$$

where $\text{tf}_{t,d}$ is the number of times the word t occurs in the document d (the *term frequency*), df_t is the number of documents the word t occurs in the dataset (*document frequency*), and N is the total number of documents in the dataset. Before performing this text transformation, we used the standard set of preprocessing techniques for text classification tasks: removed punctuation, removed numbers, removed symbols, reduced to lower case, removed stop words, and stemmed and tokenized to unigrams.²

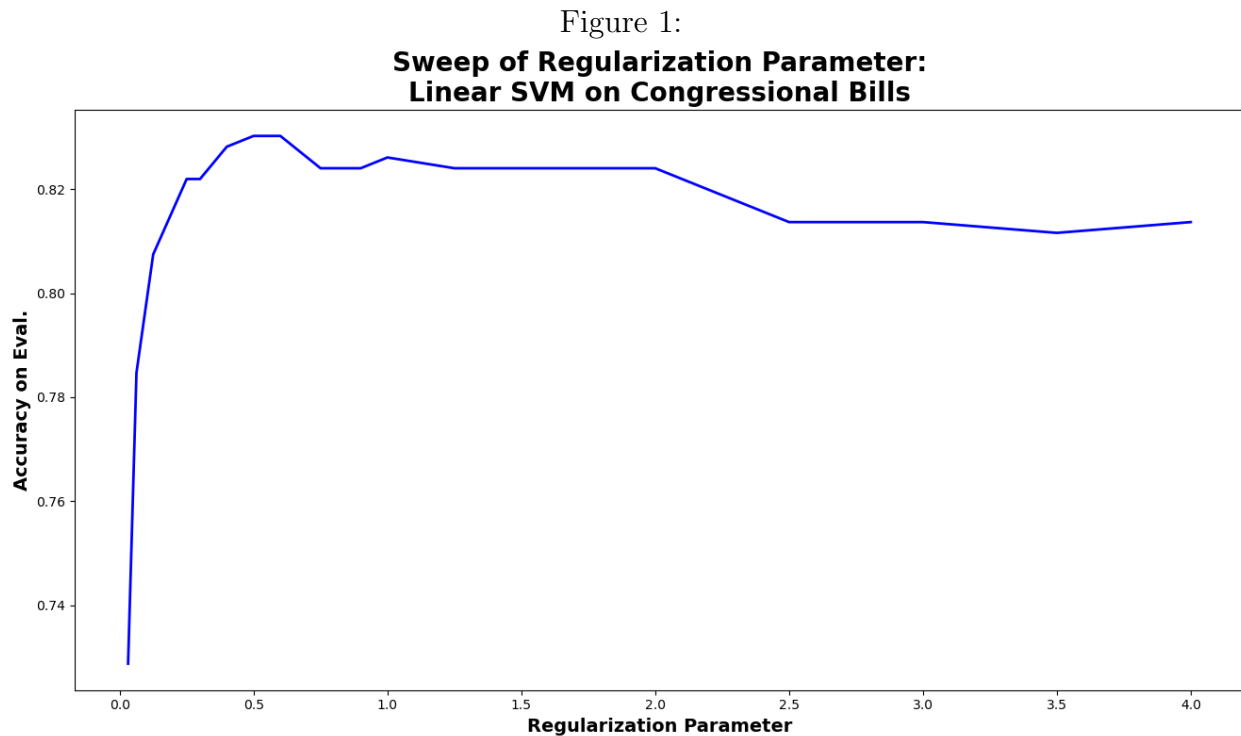
With the documents in a word-frequency vector-space, the SVM separates the data by class by learning a hyperplane as a decision boundary between high dimensional points, each of which has a class label associated with it. The distance between this hyperplane and the closest points of both classes (the *support vectors*) is defined to be the margin; for an SVM, the decision boundary is chosen to be the hyperplane for which the margin is maximized (Tong & Koller 2001; Grimmer & Stewart 2013).

¹See Miller *et al.* (2019) for another example of this method with active learning

²We sought to minimize assumptions when doing this, keeping in mind the concerns raised by Denny & Spirling (2017)

3.1 SVM Regularization

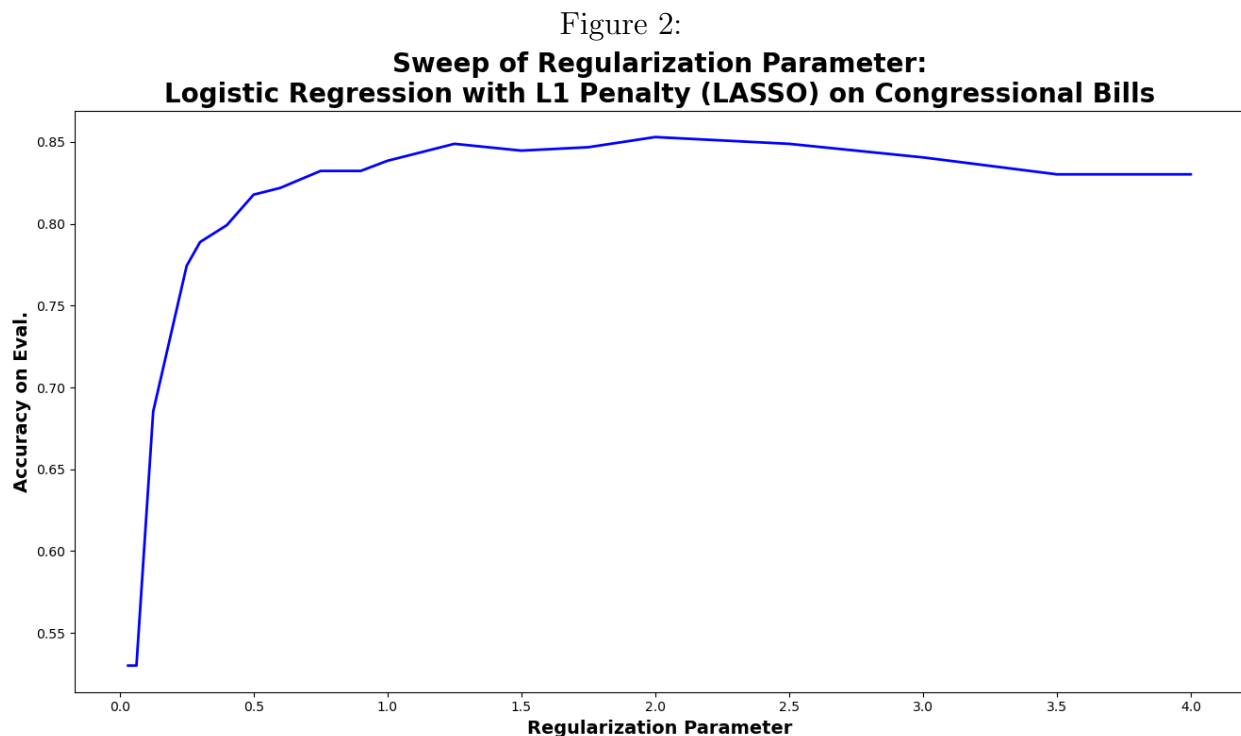
SVMs are typically optimized to solve a problem that allows — but penalizes — misclassified examples. This penalty serves as a regularizer for the model, with the weight of the penalty (inversely) modulating regularization. To demonstrate the SVM baseline’s robustness to choice of this regularization parameter, we evaluated its performance on the validation set of Congressional bill sections for a range of parameter values, plotted in Figure 1. We find that the performance is moderately consistent across regularization values within the range, and for the results presented in the paper we use the typical “default” regularization with a linear SVM: $C = 1$.



Accuracy on validation set of bill sections for a range of regularization parameter values. Note that the SVM formulation gives that regularization is inversely proportional to the parameter value — smaller values exhibit more regularization.

3.2 LASSO Regularization

For an L1-penalized logistic regression (LASSO), the regularization parameter determines how strongly the L1 penalty is weighted against the classification objective. As with the SVM baseline, we demonstrate the LASSO baseline’s robustness to choice of this regularization parameter by evaluating its performance on the validation set of Congressional bill sections for a range of parameter values, plotted in Figure 2. We find that performance is moderately consistent across regularization values with the range, and for the results presented in the paper we use the typical “default” regularization of $C = 1$.

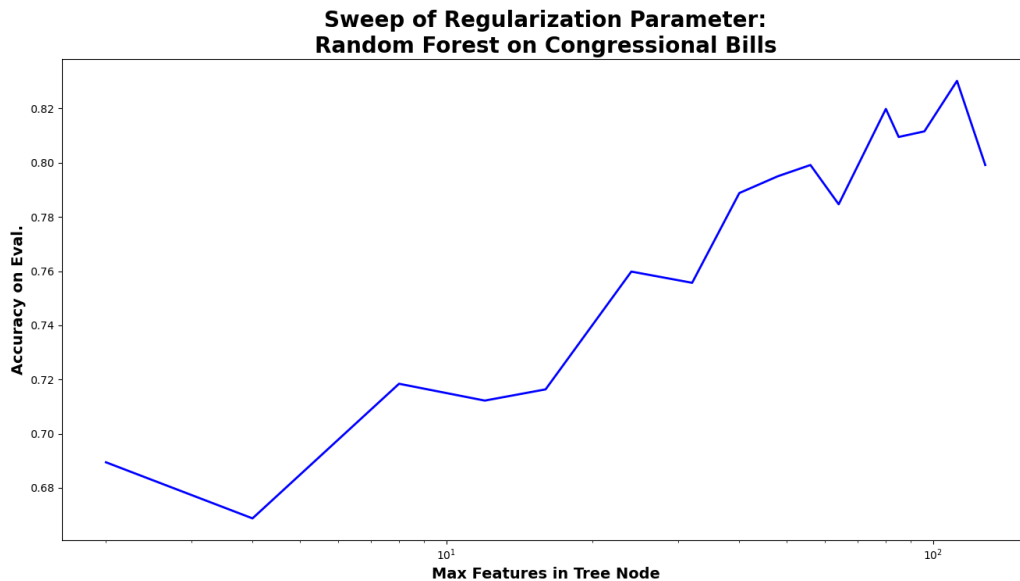


Accuracy on validation set of bill sections for a range of regularization parameter values. Note that the LASSO formulation (in `sklearn`) gives that regularization is inversely proportional to the parameter value — smaller values exhibit more regularization

3.3 Random Forest Regularization

Because a random forest classifier is an *ensemble* method, rather than a linear classifier like LASSO and SVM, its regularization is less straightforward than our other two baselines. Here, we treat the number of features in each tree-node as a parameter that may be chosen by the user, similarly to a regularization parameter. The sweep over that parameter choice is presented in Figure 3. Again, we opt for the *sklearn* default, which occurs at $n = 85$, and note that this is before the drop in performance demonstrated in Figure 3 after $n = 100$.

Figure 3:



Accuracy on validation set of bill sections for a range of parameter values for the maximum number of features in each tree-node of the random forest classifier.

4 Word Embeddings

In the methods section of the main paper, we described word embeddings as distributed representations of words as vectors. We mentioned there that unsupervised training of word embeddings is typically accomplished by predicting the incidence of words given local context words; one of these methods is the now popular Skip-Gram model that forms the basis for the `word2vec` software from Google (Mikolov *et al.* 2013). In Figure 4, we show a visualization of word embeddings learned for the Congressional corpus using `word2vec`. The visualization is obtained by projecting the high-dimensional ($d = 300$) word embeddings to two dimensions using the t-distributed stochastic neighbor embedding (t-SNE) method (van der Maaten & Hinton 2008). We do not initialize using pre-trained embeddings, but instead we randomly initialize and train them as free parameters of the model (For a thorough discussion of the trade-offs in using custom or pre-trained embeddings in political science research, see Rodriguez & Spirling 2021).

Figure 4 reveals that some words of interest appear reasonably “close” together in the center-right to bottom-right sectors of the word cluster: “Education,” “Treasury,” “Defense,” “Energy,” “Veterans” – all of which are cabinet level departments. Additionally, in the bottom-left sector of the cluster, words such as “regulations,” “program,” “projects,” and “activities” appear near each other, all of which are words that may be associated with agencies performing some task that has been delegated to them. These observations offer evidence that learning word embeddings should improve underlying classification accuracy. We note that we performed this analysis as a validating investigation of our data, but for training our classification models, we opt to randomly initialize our word embeddings and let them be fully trained as parameters of the model.

Figure 4: T-SNE graph of Word Embeddings Learned on corpus of 110th Congressional bills



T-SNE graph (without axes) showing Word Embeddings Learned on 110th Congressional Bills Corpus reduced to two dimensions. Distance between words corresponds to proximity found in the corpus.

5 Summary Statistics for Bills

Below are the summary statistics for each of the variables that appear in models in Section 6, as well as the various DVs used throughout this paper.

Table 2: Summary Statistics for All Bills

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|-------------------------------|--------|-------|----------|-----|----------|----------|-----------|
| Number of Delegating Sections | 28,906 | 3.249 | 16.113 | 0 | 0 | 2 | 403 |
| Congress | 28,906 | 110.5 | 0.499 | 110 | 110 | 111 | 111 |
| Number of Referrals | 28,906 | 1.447 | 0.840 | 0 | 1 | 2 | 13 |
| Report out of Committee | 28,906 | 0.266 | 0.442 | 0 | 0 | 1 | 1 |
| Pass Chamber | 28,906 | 0.291 | 0.454 | 0 | 0 | 1 | 1 |
| Number of Sections | 28,906 | 8.974 | 35.493 | 1 | 2 | 6 | 1,166 |
| Number of Words | 28,906 | 7,416 | 34,511 | 10 | 403 | 4,355 | 1,162,520 |
| Number of Agencies | 28,906 | 1.298 | 3.982 | 0 | 0 | 1 | 124 |
| Delegation Ratio | 28,906 | 0.278 | 0.298 | 0 | 0 | 0.500 | 1.000 |

Table 2 summarizes all 28,906 distinct bills over these two Congresses. It is worth noting the distribution of number of delegating sections, which has a mean of 3.249 and a standard deviation of 16.113, which is consistent with the use of a negative binomial count model. Though it isn't explicitly stated in the table, it is also clear that there are many bills that do not delegate authority at all (42.3%), similarly motivating the use of the zero-inflated negative binomial model from Section 6 of the main paper.

Table 3: Summary Statistics for All Laws

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|-------------------------------|-----|--------|----------|-------|----------|----------|---------|
| Number of Delegating Sections | 816 | 6.923 | 36.255 | 0 | 0 | 2 | 403 |
| Congress | 816 | 110.5 | 0.498 | 110 | 110 | 111 | 111 |
| Number of Referrals | 816 | 1.810 | 0.936 | 1 | 1 | 2 | 11 |
| Report out of Committee | 816 | 0.571 | 0.495 | 0 | 0 | 1 | 1 |
| Pass Chamber | 816 | 1.000 | 0.000 | 1 | 1 | 1 | 1 |
| Number of Sections | 816 | 18.930 | 80.889 | 1 | 2 | 7 | 1,076 |
| Number of Words | 816 | 13,962 | 62,472 | 192 | 286 | 2,459 | 730,463 |
| Number of Agencies | 816 | 2.819 | 9.407 | 0 | 0 | 1 | 119 |
| Delegation Ratio | 816 | 0.145 | 0.201 | 0.000 | 0.000 | 0.304 | 1.000 |

Table 3 is the same as Table 2, but only covers the 816 versions of bills that become

law (hence the lack of variance on the Pass Chamber variable). It is worth noting that only a little over half of all bills that become law get reported out of committee: this is because modern Congresses are more likely to bypass committees altogether and move bills the leadership wants to pass directly to the floor (those interested should read Bendix 2016; Curry & Lee 2020, for a more thorough discussion of this phenomenon). It is also worth noting that bills that become law tend to delegate more than those bills that fail along the way, and they reference more agencies on average.

Table 4: Summary Statistics for All Bills that Delegate

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|-------------------------------|--------|--------|----------|-------|----------|----------|-----------|
| Number of Delegating Sections | 16,629 | 5.648 | 20.923 | 1 | 1 | 4 | 403 |
| Congress | 16,629 | 110.5 | 0.499 | 110 | 110 | 111 | 111 |
| Number of Referrals | 16,629 | 1.535 | 0.965 | 0 | 1 | 2 | 13 |
| Report out of Committee | 16,629 | 0.303 | 0.460 | 0 | 0 | 1 | 1 |
| Pass Chamber | 16,629 | 0.294 | 0.456 | 0 | 0 | 1 | 1 |
| Number of Sections | 16,629 | 13.894 | 46.108 | 1 | 2 | 9 | 1,166 |
| Number of Words | 16,629 | 12,136 | 44,868 | 68 | 1,189 | 7,971 | 1,162,520 |
| Number of Agencies | 16,629 | 2.045 | 5.096 | 0 | 2 | 3 | 124 |
| Delegation Ratio | 16,629 | 0.484 | 0.235 | 0.004 | 0.333 | 0.571 | 1.000 |

Our final summary table only looks at the 16,629 bills that delegate authority. Table 4 is particularly relevant to Section 6.3, since we limit the agency counting models to just those that delegate authority. Again, the distribution on the number of agencies variable is consistent with a negative binomial model.

6 Information about Delegated Agencies

In this section we provide extra information about the agencies identified in Section 6.3 of the main paper. The agencies were identified using a list of agencies from Richardson *et al.* (2018) and were matched to a delegating section. Table 5 shows the top 20 agencies from the 110th and 111th Congresses.

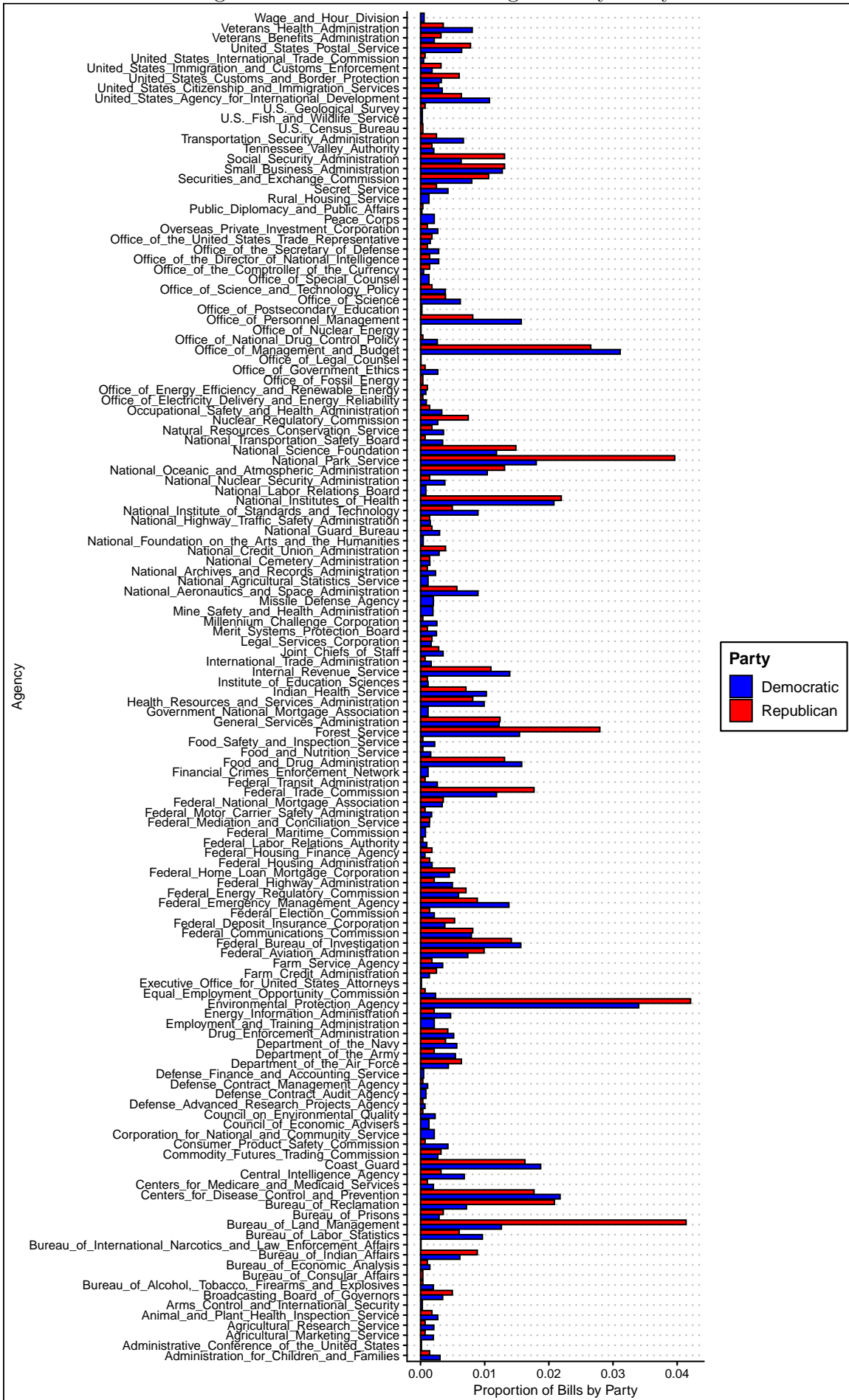
Table 5: Top Agencies Delegated To

| Rank | 110 th Congress | | 111 th Congress | |
|------|--|-------|--|-------|
| | Agency | Total | Agency | Total |
| 1 | Department of Defense | 807 | Department of Defense | 655 |
| 2 | Environmental Protection Agency | 627 | Environmental Protection Agency | 584 |
| 3 | Department of Justice | 581 | Office of Management and Budget | 572 |
| 4 | Department of Homeland Security | 551 | Department of Health and Human Services | 473 |
| 5 | Office of Management and Budget | 529 | Department of Justice | 471 |
| 6 | Department of State | 528 | Department of Homeland Security | 453 |
| 7 | Department of Health and Human Services | 495 | Department of Energy | 401 |
| 8 | Department of Veterans Affairs | 464 | Department of the Interior | 388 |
| 9 | Department of Energy | 454 | Department of Veterans Affairs | 367 |
| 10 | Department of Labor | 384 | Centers for Disease Control and Prevention | 346 |
| 11 | Department of the Interior | 383 | Department of Commerce | 341 |
| 12 | National Park Service | 382 | Coast Guard | 335 |
| 13 | Centers for Disease Control and Prevention | 366 | Department of State | 335 |
| 14 | National Institutes of Health | 364 | Department of Labor | 334 |
| 15 | Department of Commerce | 337 | National Park Service | 324 |
| 16 | Coast Guard | 319 | National Institutes of Health | 285 |
| 17 | Forest Service | 309 | Department of Agriculture | 268 |
| 18 | Bureau of Land Management | 305 | Department of Transportation | 261 |
| 19 | Department of Agriculture | 296 | Office of Personnel Management | 254 |
| 20 | Department of the Treasury | 282 | Forest Service | 253 |

Top Agencies delegated to by Congress. Total is number of bills they are delegated to.

Figure 5 is a compliment to Figure 4 from the main paper, and includes information on all the non-cabinet agencies and the proportion of bills delegated to them by members of each party.

Figure 5: Non-Cabinet Level Agencies by Party



7 Alternative Specifications for Models

In this section, we provide a model robustness check to the models from Table 4 from the main paper. In that section, we use a zero inflated negative binomial regression to model number of delegating sections per bill. Here, we construct the delegation ratio, which takes the number of sections that delegate authority to an administrative agency and divide it from the total number of sections. It is a widely used measure of overall legislative discretion (Epstein & O’Halloran 1999; Anastasopoulos & Bertelli 2020).

Table 6: Beta Regression on Delegation Ratio

| | DV: Delegation Ratio | | | |
|-------------------------------|----------------------|----------------------|----------------------|----------------------|
| | All Bill Versions | | | Laws |
| | Model 1 | Model 2 | Model 3 | Model 4 |
| Number of Referrals | 0.092*** (0.008) | 0.083*** (0.008) | 0.119*** (0.009) | 0.094** (0.037) |
| Unified Gov? | -0.017 (0.013) | -0.026* (0.013) | -0.029** (0.013) | -0.045 (0.071) |
| Republican | | -0.158*** (0.015) | -0.165*** (0.015) | -0.115 (0.093) |
| Sponsor Chair of Committee | | 0.050** (0.024) | 0.059** (0.025) | 0.337*** (0.091) |
| Sponsor Chair of Subcommittee | | 0.070*** (0.022) | 0.060*** (0.022) | 0.303*** (0.100) |
| Report out of Committee | | | 0.221*** (0.020) | |
| Pass Chamber | | | -0.298*** (0.020) | |
| Constant | -1.011*** (0.015) | -0.961*** (0.017) | -0.983*** (0.017) | -1.921*** (0.094) |
| N | 28910 | 28910 | 28910 | 816 |
| R-squared | 0.006 | 0.013 | 0.023 | 0.060 |
| Log Likelihood | 12248.280 | 12326.490 | 12443.800 | 800.682 |

***p < .01; **p < .05; *p < .1

Table 6 shows the results from the 4 different beta regressions (a beta regression is used because the DV is a ratio). The estimates are all consistent with the count portion of the

ZINB model from the paper, with differently scaled coefficients and standard errors, but consistent effects.

8 Robustness of Delegation Measure

Below we include a series of robustness checks to compare our main result with alternative specifications.

Table 7 replicates Table 4 from our main paper, but exclude commemorative legislation, as defined by the Congressional Bills project <http://www.congressionalbills.org/>. Though we expect the zero-inflated negative binomial model we use will take care of commemorative bills – modeling those as zeros in our process – this eliminates any possibility that those non-substantive bills influence our final results. Besides excluding commemorative bills, the regressions are identical to the models run in Table 4.

What we find in Table 7 is that the results are essentially identical to the main paper models that do not exclude commemorative bills, especially when one looks at the results that are focused on the count of delegatory sections. The general takeaway on the substance of the binary model remain largely the same, though the magnitude of the coefficients in the models here are larger, indicating a clearer selection process.

The next table, Table 8, replicates the delegation ratio table from earlier in the appendix, 6, but focuses only on Mayhew’s significant laws—detailed in Mayhew (1991) and used in Epstein & O’Halloran (1999) and Farhang & Yaver (2016). This can be thought of as a closer replication of Epstein & O’Halloran (1999), in that it limits itself to only the 26 laws from the 110th and 111th Congresses that Mayhew identified as significant. Given the small number of observations, any estimated effect is going to be noisy.

As we see in Table 8, there aren’t a lot of significant effects. In fact, because Mayhew’s significant laws is limited to bills that became laws, we lose some of the interesting process story that was described in the main paper. What we still find, interestingly enough, is a story on unified vs. divided government that is not very clear; the coefficient on unified

Table 7: Zero-Inflated Negative Binomial Model of Number of Delegating Sections: No Commemorative Bills

| | All Bill Versions | | | Laws |
|---|----------------------|----------------------|----------------------|----------------------|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| Number of Delegating Sections: Negative Binomial | | | | |
| Number of Referrals | 0.113*** (0.009) | 0.112*** (0.009) | 0.139*** (0.009) | 0.094* (0.048) |
| Number of Bill Sections | 0.032*** (0.0005) | 0.030*** (0.0005) | 0.030*** (0.0005) | 0.012*** (0.001) |
| Unified Gov? | -0.057*** (0.017) | -0.067*** (0.017) | -0.064*** (0.017) | -0.166 (0.132) |
| Sponsor Chair of Committee | | 0.210*** (0.027) | 0.155*** (0.027) | 0.530*** (0.152) |
| Sponsor Chair of Subcommittee | | 0.141*** (0.025) | 0.114*** (0.025) | 0.411** (0.160) |
| Republican | | -0.191*** (0.022) | -0.201*** (0.021) | -0.545** (0.246) |
| Report out of Committee | | | 0.415*** (0.023) | |
| Pass Chamber | | | -0.385*** (0.024) | |
| Delegation: Logit | | | | |
| Number of Referrals | -0.631*** (0.113) | -0.600*** (0.106) | -0.830*** (0.157) | -0.237 (0.375) |
| Number of Bill Sections | -1.359*** (0.062) | -1.336*** (0.061) | -1.333*** (0.063) | -0.879*** (0.218) |
| Unified Gov? | -0.068 (0.081) | -0.055 (0.082) | -0.070 (0.083) | -0.625 (0.460) |
| Sponsor Chair of Committee | | 1.103*** (0.142) | 1.066*** (0.148) | 1.074** (0.486) |
| Sponsor Chair of Subcommittee | | 0.557*** (0.130) | 0.585*** (0.132) | 0.111 (0.559) |
| Republican | | 0.159* (0.094) | 0.167* (0.096) | -1.183 (0.877) |
| Report out of Committee | | | -0.155 (0.126) | |
| Pass Chamber | | | 0.301** (0.151) | |
| N | 24756 | 24756 | 24756 | 545 |

***p < .01; **p < .05; *p < .1

government is still negative, albeit neither statistically significant nor as large as the total set of bills.

Table 8: Beta Regression on Delegation Ratio for Mayhew’s Significant Laws

| | Delegation Ratio | | | |
|-------------------------------|----------------------|----------------------|----------------------|----------------------|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| Number of Referrals | 0.079*** (0.025) | 0.079*** (0.025) | 0.088*** (0.026) | 0.068 (0.066) |
| Unified Gov? | -0.077 (0.138) | -0.077 (0.138) | -0.107 (0.139) | -0.105 (0.358) |
| Sponsor Chair of Committee | | | 0.060 (0.139) | 0.551 (0.354) |
| Sponsor Chair of Subcommittee | | | 0.102 (0.185) | -0.161 (0.507) |
| Report out of Committee | | | 0.125 (0.149) | |
| Constant | -1.042*** (0.142) | -1.042*** (0.142) | -1.159*** (0.187) | -1.217*** (0.429) |
| N | 158 | 158 | 158 | 26 |
| R-squared | 0.054 | 0.054 | 0.060 | 0.145 |
| Log Likelihood | 55.998 | 55.998 | 56.591 | 9.223 |

***p < .01; **p < .05; *p < .1

Our next robustness check compares the results of our models in our main paper using our measure of delegation with models using number of words as an alternative measure of delegation. This is, in many ways designed as a one-to-one comparison with the length measure proposed by Huber & Shipan (2002). We otherwise mimic the parameters from our other models, though for these models we use the log of total words of statute as our DV and model this with OLS.

We see the results of these regressions in Table 9. The major effects reported in the paper and in the robustness checks above remain consistent, though the coefficient on unified government is somewhat more positive than when using our measurement of delegation.

The final robustness check included here combines the previous two: what if we only look at Mayhew’s Significant Laws and use the word count based measure? What do our results look like under those circumstances? This most closely adheres to what is more widely done in studies of delegation.

Table 9: Using number of words as an alternative measure of delegation

| | log(Words) | | | |
|-------------------------------|---------------------|----------------------|----------------------|----------------------|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| Number of Referrals | 0.470*** (0.011) | 0.391*** (0.011) | 0.494*** (0.012) | 0.350*** (0.059) |
| Unified Gov? | -0.022 (0.019) | -0.033* (0.018) | -0.043** (0.018) | 0.018 (0.111) |
| Sponsor Republican | | -0.363*** (0.021) | -0.383*** (0.021) | -0.458*** (0.144) |
| Sponsor Chair of Committee | | 1.137*** (0.033) | 1.174*** (0.033) | 1.555*** (0.144) |
| Sponsor Chair of Subcommittee | | 0.651*** (0.030) | 0.645*** (0.030) | 0.886*** (0.157) |
| Report out of Committee | | | 0.448*** (0.026) | |
| Pass Chamber | | | -0.747*** (0.027) | |
| Constant | 6.595*** (0.021) | 6.644*** (0.022) | 6.601*** (0.022) | 6.061*** (0.139) |
| N | 28906 | 28906 | 28906 | 816 |
| R-squared | 0.056 | 0.131 | 0.153 | 0.239 |
| Adj. R-squared | 0.056 | 0.130 | 0.153 | 0.235 |

*** p < .01; ** p < .05; * p < .1

The results are presented in Table 10. We find significant differences in this model on the unified government variable than to all the other models presented in this paper and the appendices, finding a positive and significant effect of unified government on delegatory scope. This is evidence, we believe, that it is a function of both the oddities of the measure itself—using length as a proxy for discretion—and the selection bias induced by only looking at significant laws that promotes this effect. This allows us to reconcile the results presented in this paper with Shaffer (2020) on the one hand, and Epstein & O’Halloran (1999); Farhang & Yaver (2016) on the other.

Table 10: Using number of words as an alternative measure of delegation on Mayhew’s Significant Laws

| | log(words) | | | |
|-------------------------------|---------------------|---------------------|---------------------|---------------------|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| Number of Referrals | 0.276*** (0.049) | 0.276*** (0.049) | 0.320*** (0.049) | 0.207 (0.132) |
| Unified Gov? | 0.625** (0.265) | 0.625** (0.265) | 0.543** (0.252) | 0.485 (0.699) |
| Sponsor Chair of Committee | | | 0.967*** (0.253) | 1.098 (0.687) |
| Sponsor Chair of Subcommittee | | | 0.416 (0.337) | −0.079 (0.964) |
| Report out of Committee | | | 0.772*** (0.271) | |
| Constant | 9.587*** (0.269) | 9.587*** (0.269) | 8.590*** (0.333) | 9.554*** (0.818) |
| N | 158 | 158 | 158 | 26 |
| R-squared | 0.178 | 0.178 | 0.282 | 0.219 |
| Adj. R-squared | 0.167 | 0.167 | 0.259 | 0.070 |

***p < .01; **p < .05; *p < .1

9 Delegation Coding Instructions

Here is the instruction sheet handed out to each person doing the hand labeling for the supervised learning task. We oversaw 4 different coders working on this, but every single hand labeling was checked by one of the authors of the paper.

Figure 6: Delegation Hand coding Sheet

Specifics of Delegation Coding:

When we think of congressional delegation to administrative agencies, we have to keep two things in mind as we code the sections:

First, is Congress acting upon an administrative agency? This will include all references to

- The Secretary of _____
- The Administrator
- The Commission[er]
- Head of the _____ agency
- The Administration
- Office of _____
- Attorney (or Surgeon) General
- Corporation (sometimes)

Among others. Most often, if Congress is referring to a governmental entity (with the exception of organizations already within Congress, which they should make obvious, things like appropriations committee, etc.) it is an administrative agency. We make an exception for delegating to the Courts or the President, because those are coequal branches, and therefore the rules governing them are more complex.

Second, what are they asking the agency to do? In general, Congress delegates authority by asking an agency to:

- Administer a task
- Collect information
- Write new regulations
- Hire people
- Report to Congress
- Delegate authority to sub-agencies or outside of government
- Make or distribute an award

Among others. These are the big picture tasks as broadly defined. They are not delegating authority if they are appropriating money, or if they are referencing actions already taken.

These two concepts are most often linked with conjunctions:

Shall, must, may, is required to, should, will, etc.

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