

# Measuring the Legislative Design of Judicial Review of Agency Actions SUPPLEMENTARY APPENDIX

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## APPENDIX A: Coding Detail

**Table A1: Public Laws Excluded**

<b>Pub. L. Num.</b>	<b>Law Title</b>
85508	Alaska Statehood
86003	Hawaii Statehood
93198	D.C. Self Government Act
98144	Martin Luther King, Jr. Birthday
108105	Partial Birth Abortion Ban
108212	Laci and Conner's Law
109002	Class Action Fairness Act of 2005

Notes: Two laws delegate to a federal agency but have judicial review provisions that relate only to non-federal agency actions (i.e., state implementation actions). We included these laws and coded them as not specifying federal-level judicial review.

**Table A2: Judicial Review Attributes and Descriptions**

<b>Category of Review Provision</b>	<b>Judicial Review Attribute</b>	<b>Description</b>
Reviewability (Allow, Preclude, and Limit are mutually exclusive categories).	Allow	Allows for judicial review of agency actions (or specifically “does not preclude” judicial review).
	Preclude	Specifically precludes judicial review of agency actions.
	Limit	Various limited allowances for review.
Time Limits	Time Limit in Days and	Includes mention of time limits (in days) for filing for judicial review. We code no time limit at the maximum of 6 years (2190 days) and center the variable on its mean as a z-score. If review is precluded, the time limit in days is zero. We also recode these days into an ordinal three-category variable for our robustness tests such that 1 = preclusion of review (0 days of time to submit), 2 = 1-2189 days to file for review (but a specific time limit is included); 4 = No time limit is mentioned.
Venue (these are not mutually exclusive categories)	District Court	Specifically mentions a district court(s)
	Appellate Court	Specifically mentions an appellate court(s)
	D.C. Court of Appeals	Specifically mentions the D.C. Court of Appeals
	Specialized Court	Specifically mentions a specialized court, such as customs court, tax court, etc.
Scope of Review/Standards (these are not	Arbitrary and Capricious	Specifically includes the terms “arbitrary and capricious” with respect to judicial review.

mutually exclusive categories)	Substantial Evidence	Specifically includes the terms “substantial evidence” of problematic processes/decisions, or wrongdoing by agency.
	Clearly Erroneous	Specifically includes the terms “clearly erroneous,” “outside the scope of agency’s discretion,” and similar phrases.
Scope of Review/Judgement (mutually exclusive)	<i>De novo</i>	States that the court can substitute its own judgement for that of the agency.
	Question Agency	Allows the court to question agency processes and decisions, but does not allow for de novo review or deference to the agency.
	Defer	Specifically states that the court must defer to the agency or use only the agency’s findings of fact or record.
Standing (mutually exclusive)	Adversely Affected	Includes mention of adversely affected or higher levels of harm for petitioners.
	Aggrieved	A middle category of harm to petitioners, typically a catch-all for less than adversely affected, but more than low harm.
	Low level of harm	Mentions “any interested” person or other lower levels of harm to petitioners that can file for judicial review.

## **APPENDIX B: Latent Index Construction**

### **Alternative Assumptions and Specifications**

Instead of the static mixed Bayesian model reported in the main text, alternatively we could utilize a static IRT factor model, an ordered Bayesian latent model, or two-dimensional models at each level (law and agency). For our dynamic model, we could assume our time periods are each public law number, instead of each year. We consider these alternatives below, but find few differences with the models reported in the text. The attribute loadings for the IRT model are provided in Figure B1a; those for the 2-dimensional mixed factor Bayesian model (agency-level) in Figure B1b. Figure B1c excludes the time limit from our mixed Bayesian analysis, which allows us to consider the extent to which time influences our index.

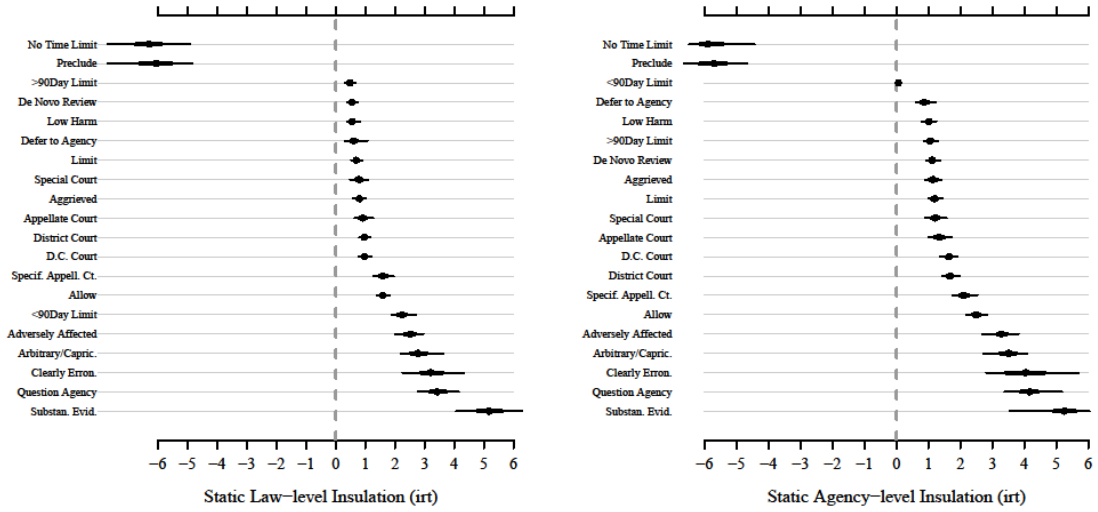
Finally, Figure B1d provides an ordinal Bayesian model at the law-level (left panel) and agency-level (right panel). These ordered models were sensitive to the operationalization of our ordered time variable and had lengthy convergence times.

Our scores have a correlation greater than 0.97 across specifications and robustness checks within a particular level (i.e., agency-section or law-section or dynamic) and greater than 0.98 across levels within a specification. The correlation between the mixed Bayesian and ordinal latent index is greater than 0.77 at the agency-level and greater than 0.98 at the law-level. The two-dimensional model has a correlation of 0.85 with our main (agency-level, static) model for the first dimension and -0.34 for the second dimension.

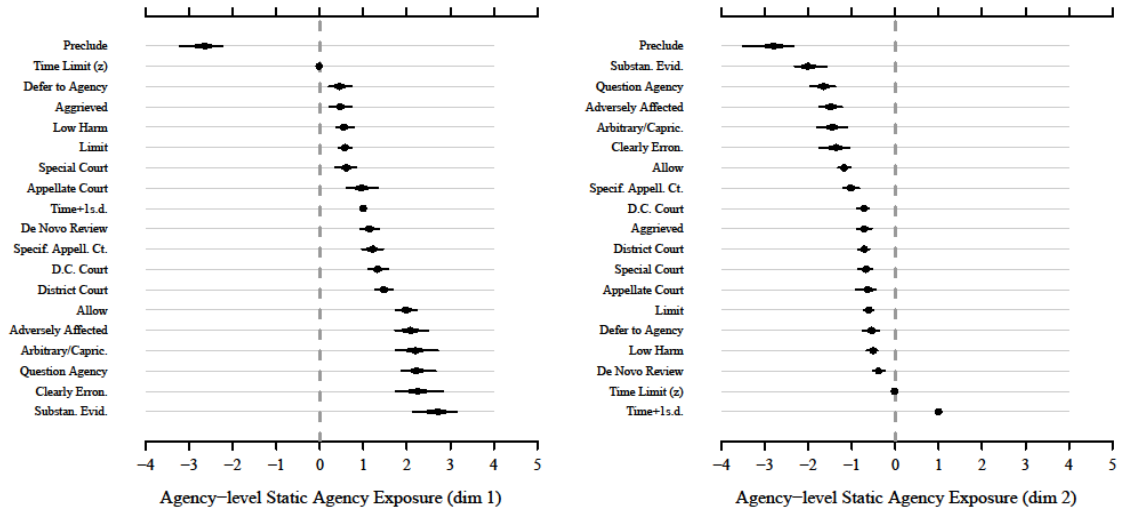
To identify our models, we constrain the attribute “Preclude” to be negative and “Allow” to be positive, along with (in models with our continuous time variable) constraining the mean of its z-score to be zero. Otherwise we leave our attributes unconstrained.

In order to test the robustness of our models to inclusion and exclusion of specific laws and sections, we (1) exclude laws with a word count less than the 25<sup>th</sup> percentile of the distribution; (2) omnibus legislation; and (3) sections of laws with policy topic codes that differ from the overall policy code of the law. We find a high degree of correlation between our original measure and each of these adjusted sets of laws (0.99, 0.98, and 0.98, respectively). Hence, we are confident that our scores are robust to either the inclusion or exclusion of these features, and that none of them are unduly driving or affecting our results. At the law level, our robustness checks included excluding various combinations of the codes for: “arbitrary and capricious,” “substantial evidence,” and “clearly erroneous.” The resulting indices with these exclusions have a correlation between 0.97-0.99. Additionally, we examined an IRT-based modeling approach at the agency-level and law-level, given our use of IRT as the foundation of the dynamic index. Also note that for the dynamic index, there is a correlation of 0.067 between the indices when we aggregate by year and 0.058 when we aggregate by public law number, suggesting the importance of a theoretical reason for a researcher’s aggregation choice.

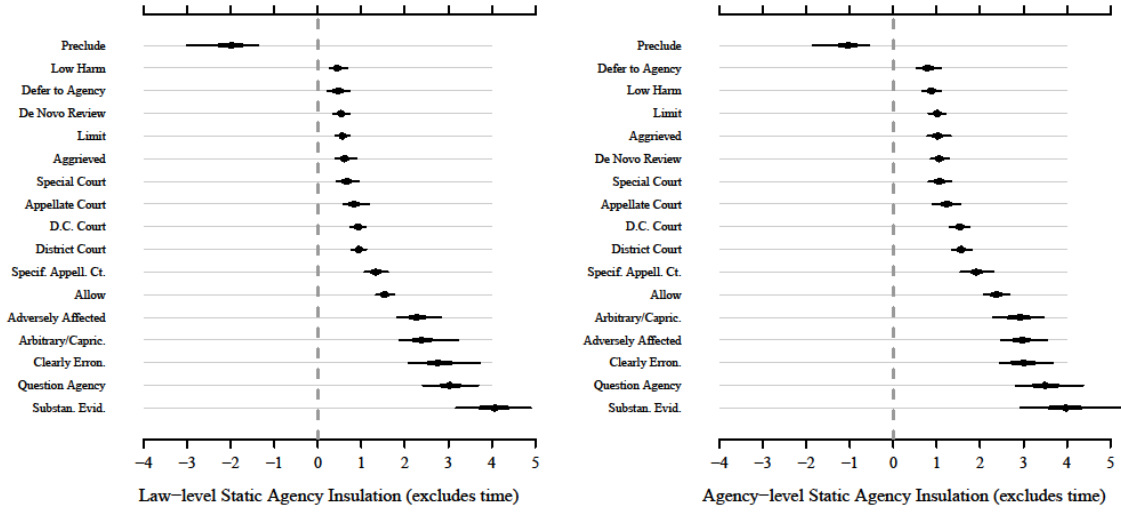
**Figure B1a: Static IRT Model Attribute Loadings**



**Figure B1b: 2-dimensional Mixed Factor Bayesian Model Attribute Loadings**



**Figure B1c: Mixed Bayesian Model Attribute Loadings for Reviewability Index, excludes Time Limits**



### Ordered Latent Model

For our ordered latent analysis, let  $i = 1, \dots, N$  represent the coded sections of significant public laws enacted from the 80<sup>th</sup> to the 114<sup>th</sup> Congress (i.e., from 1947-2016) and  $j = 1, \dots, J$  be the individual attributes we collected above that are related to judicial review of agency actions. Following Trier and Jackman (2008), we first assume that each attribute can be modeled as the probability that it is measured as present (which we recoded as a 2 for dichotomous indicators), or, for our continuous time limit in days, is present at specified categories:  $k=1, 2$ , or 3. Following from this, our model is:

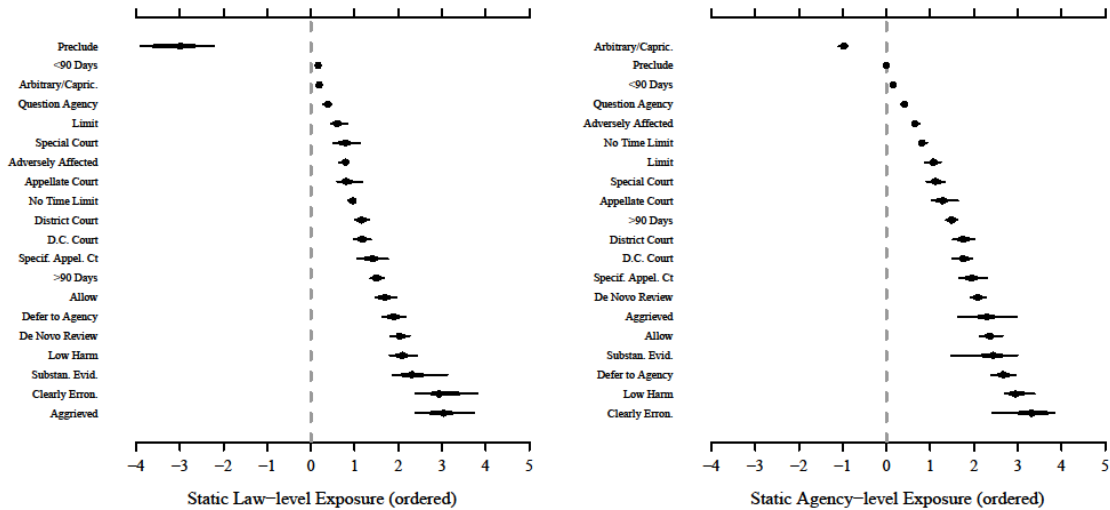
$$\Pr(y_{i,j,k} = 1) = \begin{cases} F(\lambda_{j1} - \mu_{ij}) & \text{if attribute}=1 \\ F(\lambda_{j2} - \mu_{ij}) - F(\lambda_{j1} - \mu_{ij}) & \text{if attribute}=2 \\ F(\lambda_{j3} - \mu_{ij}) - F(\lambda_{j2} - \mu_{ij}) & \text{if attribute}=3 \end{cases}$$

where  $\mu_{i,j} = x_i \beta_j$ ,  $x_i$  is a latent level of agency exposure for the section level or agency level,  $y_{i,j,k}$  is the score for the  $j^{\text{th}}$  indicator, given a cut-point for  $k$ . Our model of latent agency exposure for each section or agency, then, is a function of a matrix of factor loadings ( $\Lambda$ ) and a vector of factor scores ( $\eta_i$ ) using a probit link for  $F(\cdot)$ :

$$x_i^* = \Lambda \eta_i + \varepsilon_i.^\dagger$$

<sup>†</sup> The error term ( $\varepsilon_i$ ) is assumed to be distributed normally with mean of zero and variance of  $\Psi$ , which is assumed to be diagonal and equal to one for our dichotomous attributes. We rely on MCMCordfactanal within the MCMCpack package for R, which

**Figure B1d: Ordered Bayesian Model Attribute Loadings for Reviewability Index:**



### Dynamic Latent Model

Additionally, we considered a dynamic latent model, excluding our continuous measure of time, relying on an IRT model. Our measure of time is each year, although we find substantively similar findings using our time unit as each public law. Our unit of agency exposure is the agenc(ies) promulgating rules within each of the laws within the years. To construct our dynamic score, we use the fast estimation methods developed by Imai, Lo, and Olsmtd (2016). Imai, Lo, and Olsmtd (2016) use variational Bayesian inference that approximates posterior inference by deriving a variational Expectation-Maximization algorithm. In the traditional ideal point estimates, researchers use the observed vote of legislator  $i$  on roll call  $j$  at time  $t$  to construct the dynamic score. In our case,  $i$  denotes various agencies,  $j$  indicates the attributes we have coded for each section (preclude, allow, adversely affected, etc.), and  $t$  denotes years in the main text. Given that the algorithm can accommodate only binary variables, we create three dichotomous variables using our ordered measure of time constraints: 0,1 if there are no time constraints; 0,1 if the time constraint placed is less than 90 days; and 0,1 if the time constraint placed is greater than or equal to 90 days. We implement the proposed algorithms via the open-source R package, **emIRT**. The algorithms then create a dynamic score of agency exposure for each agency in each year.

The correlation with our static measure (agency-level) is 0.48 (disaggregating the static measure by year and agency) using informative priors (assuming agency-years that

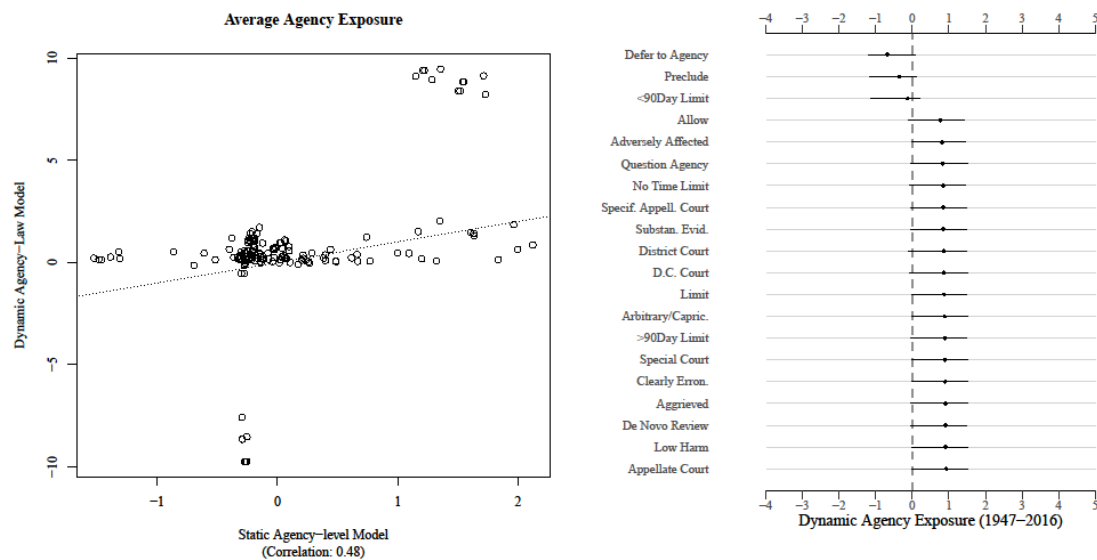
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assumes independent conjugate priors on factor loadings and factor scores and an inverse gamma prior on the error variances (as in Selin 2015 and Jackman 2009).

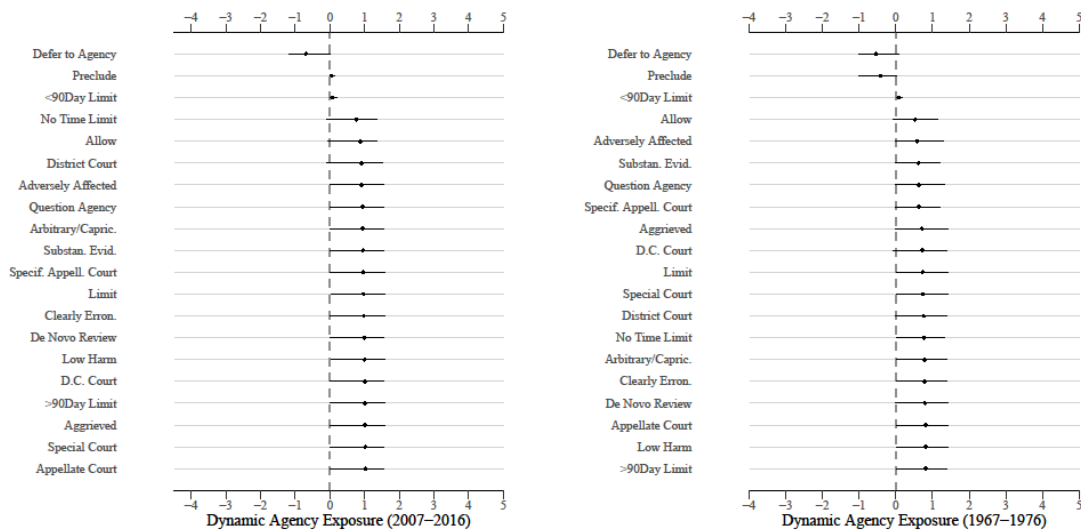
preclude are negative and agency-years that are the most positive from the static model as positive, all else are assumed to be zero) and the attribute loadings are similar to our previous measures, as indicated in Figure B1e.

We provide two-decade samples in Figure B1f to reveal similarity of loadings over time, although there is a degree of change in the point estimates for each loading's contribution (e.g., note the movement of preclusion across the x-axis). We also provide graphs of the dynamic agency exposure score over time for a sample of agencies in Figure B1g.

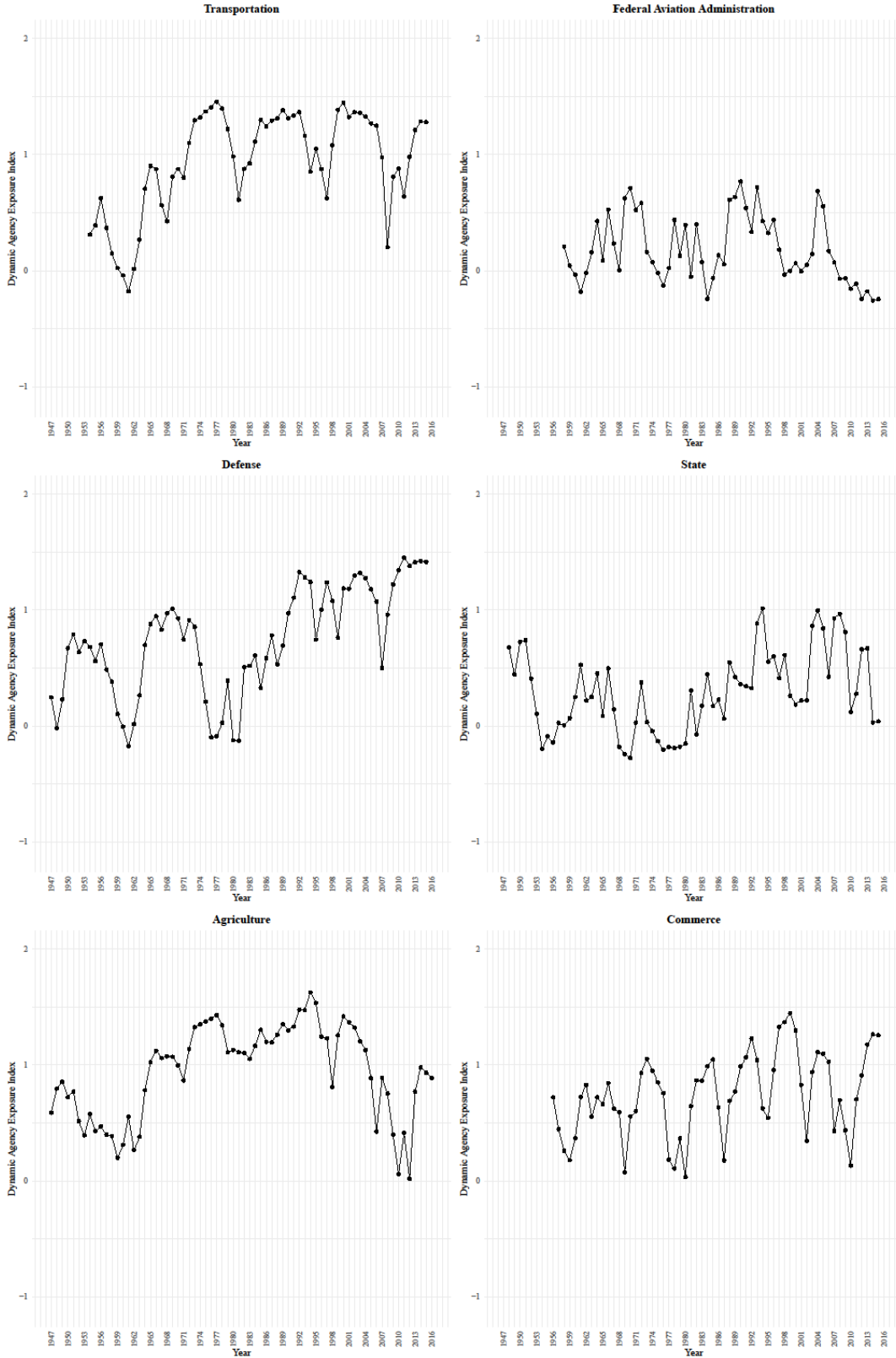
**Figure B1e: Static-Dynamic Correlation and Mean Dynamic (agency-year) Attribute Loadings**

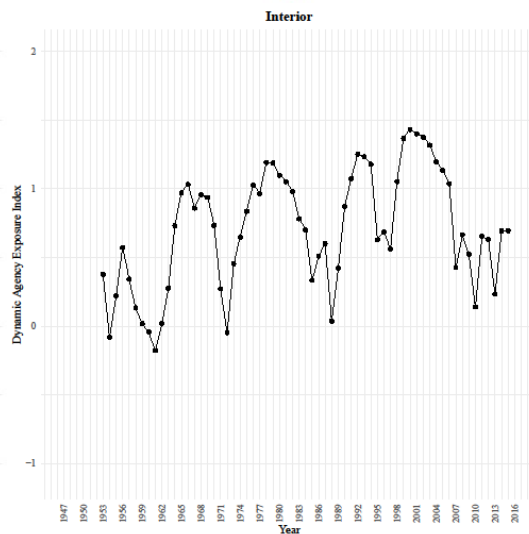
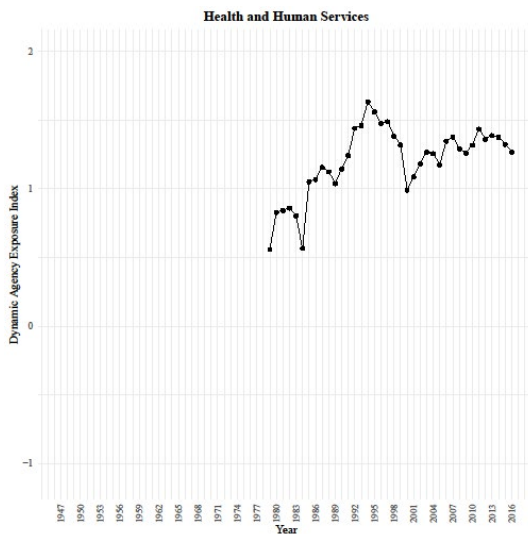
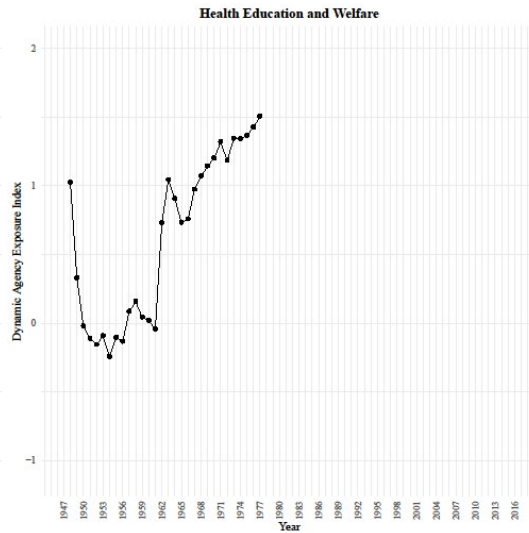
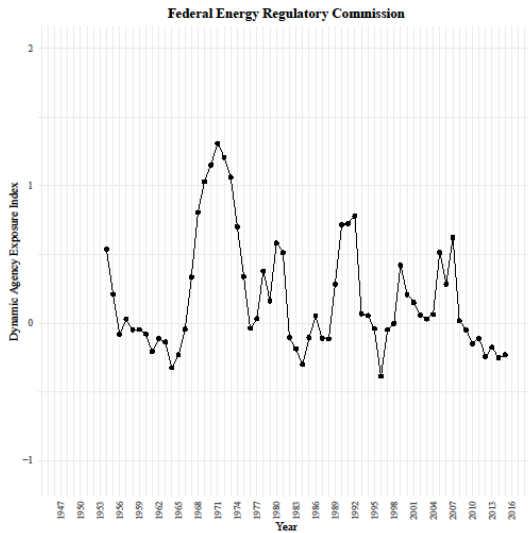
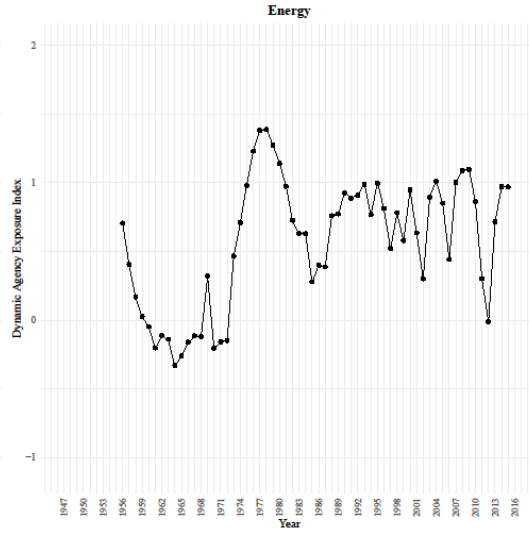
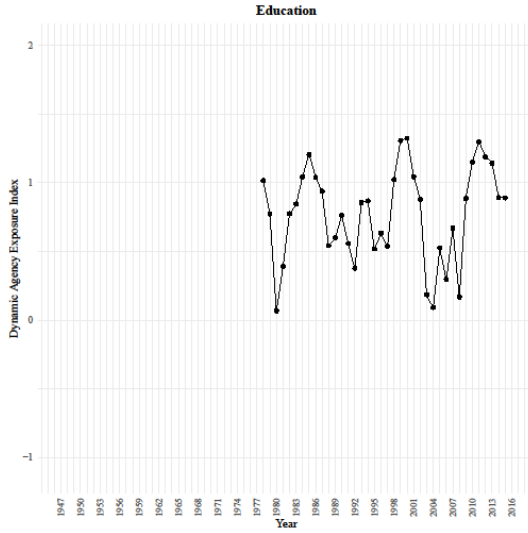


**Figure B1f: Example Years' Dynamic Attribute Loadings:**

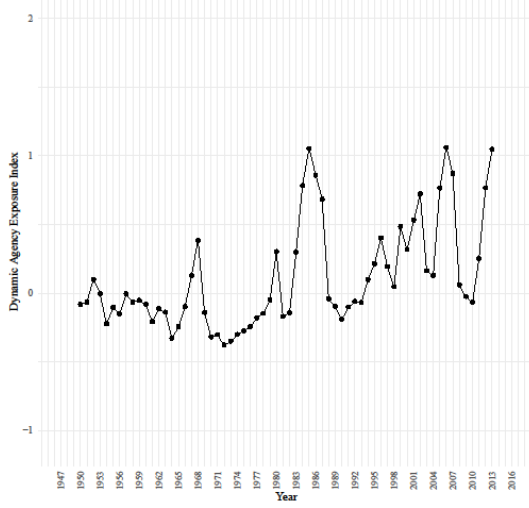


**Figure B1g: Agency Exposure over Time for a Sample of Agencies**

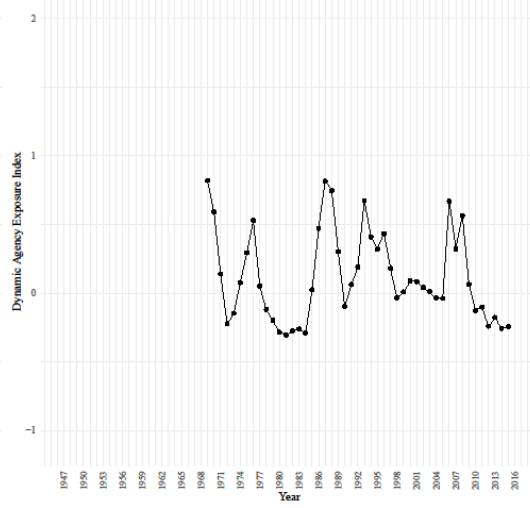




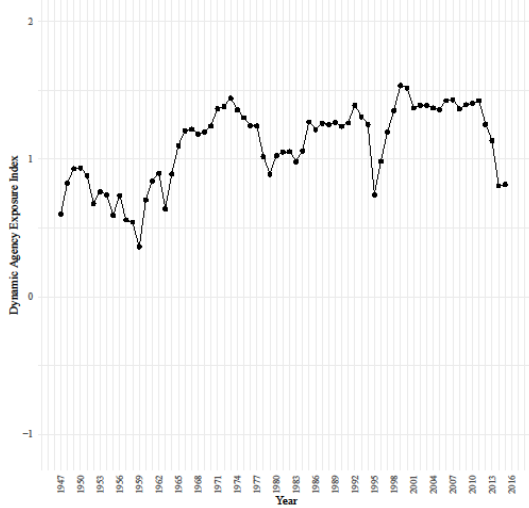
Federal Emergency Management Agency



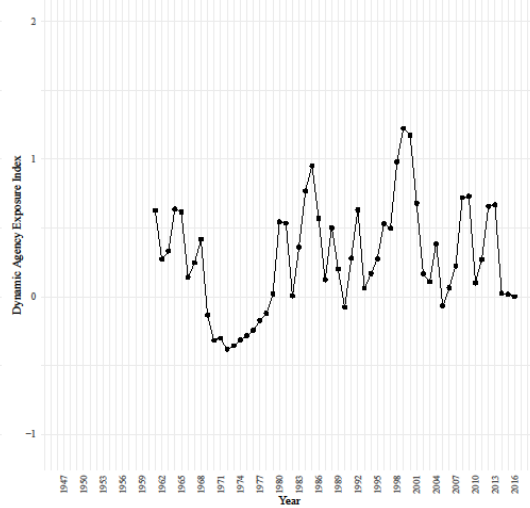
Postal Service



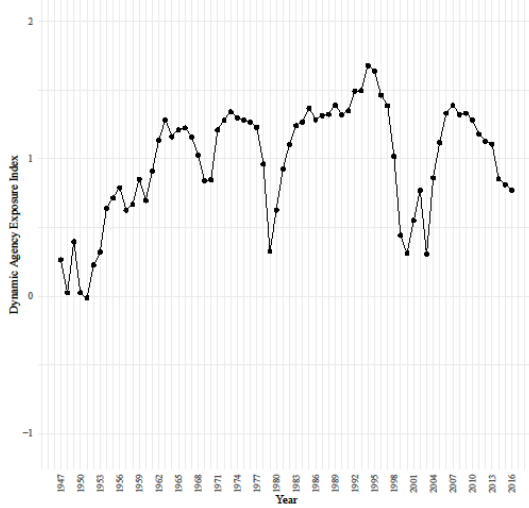
Treasury



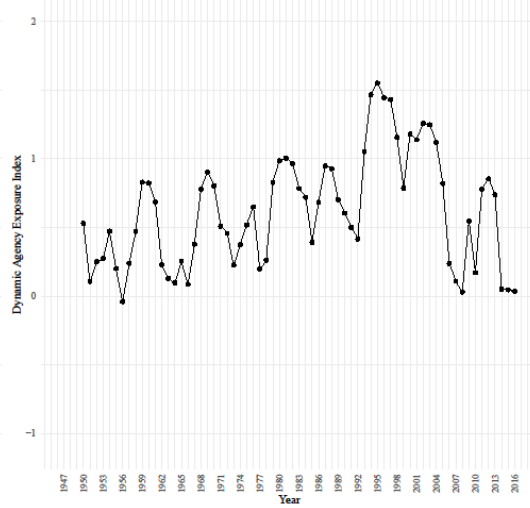
Small Business Administration



Labor



Justice



## APPENDIX C: Additional Validation

### Exposure to Judicial Review and Inter-institutional Agreement

When deciding how much exposure to judicial review to include in a law, Congress may also take into account the relative preferences of courts and the executive branch. For example, if Congress's preferences align more closely with those of the courts (i.e., a sympathetic judiciary) than with those of the executive branch, it is plausible to expect that it will increase the opportunities for judicial review. Conversely, if Congress's views are more similar to those of the executive branch than to those of the courts (i.e., a sympathetic agency), it might insulate agencies from review.<sup>‡</sup> Thus, an additional validation check of our approach is that we should expect to see an increase in our exposure scores (i.e., increased opportunities for review) when Congress is more aligned with the judiciary, and a decrease in our scores when Congress is more aligned with the executive branch.

Because no reliable, consistent, and comparable measures of ideology exists for Congress, courts, and agencies during the period we examine, we rely on political parties. In addition, we rely on the president's party, given his role as the head of the executive branch, to capture the partisan leaning of that branch. While acknowledging that these are blunt measures, we also contend that they provide good insight into whether Congress's views that match up more closely with the partisanship of the courts or the executive branch. Our measure is coded as a 1 when the partisan difference with the judiciary is smaller and a 0 when this difference with the executive branch is smaller.<sup>§</sup>

Our tests reveal a positive correlation between our separation-of-powers measure (i.e., whether the courts are closer to Congress than is the executive branch, based on party) and our agency-level index of exposure to the judiciary as well as with our dynamic index. In other words, this provides additional validation for our measure, as it is consistent with the idea that when Congress trusts the courts more, it increases opportunities for review, and when it trusts agencies more, it acts to protect those

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<sup>‡</sup> This corresponds to Shipan's (2000) concepts of *sympathetic judiciary* and *sympathetic agency*, respectively.

<sup>§</sup> More specifically and in line with many scholars operationalizing cross-institutional preferences, we use the party of the appointing president to assign a partisanship value for each judge on the D.C. Appellate Court and take the average of this value for each year in our dataset (using a -1 for Democrats and a +1 for Republicans) (e.g., in Boyd and Boldt 2017; Hubert and Copus, forthcoming). The party of the current president in each year is our proxy for the preferences of the executive branch and we average the majority party in power in each chamber of Congress to determine its preference measure (e.g., Clouser McCann 2016; Thrower 2017). We take the absolute value of the difference between Congress and the court and Congress and the executive branch and, given the measurement error in our approach, assign an indicator variable a value of zero when the difference with the executive branch is smaller and a one when the difference with the judiciary is smaller.

agencies from the courts. As our t-tests reveal, we find a statistically significant 0.096 unit increase in exposure when we move from an agency that is closer to Congress to when the judiciary is closer (approximately a 2.6% increase in our static measure and a 0.22% increase in our dynamic measure). While we hesitate to make too much of this finding, given the lack of a nuanced measure of which other institution is closer to Congress, it suggests that our measure captures the idea that when Congress has a greater partisan affinity with the courts than with agencies, it acts to increase the likelihood of review.

**Table C1: Preferences and Agency-level Exposure**

Two-Sample T-Test of Constraints			
	Agency-level exposure		Dynamic Exposure
Sympathetic Agency N=1,325	-0.073 (0.019)	Sympathetic Agency N =2,359	0.504 (0.012)
Sympathetic Judiciary N=1,195	0.024 (0.022)	Sympathetic Judiciary N =2,012	0.547 (0.023)
Difference:	-0.096 (0.029)**		-0.043 (0.025)*

Notes: Standard errors are reported in parentheses. Significance is \*\*  $p < 0.01$ .

## Supplemental Appendix References

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