Online Supporting Information

Legislative Capacity and Credit Risk

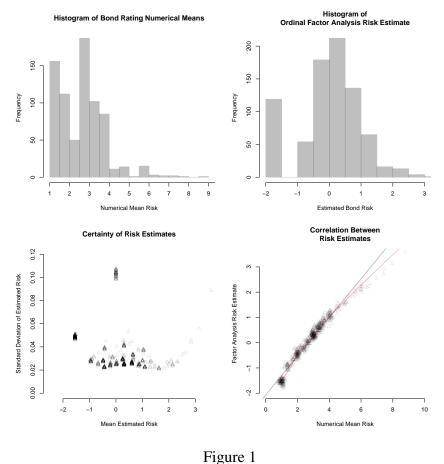
David Fortunato
Assistant Professor
Department of Political Science
Texas A&M University
fortunato@tamu.edu

Ian R. Turner
Assistant Professor
Department of Political Science
Yale University
ian.turner@yale.edu

In this online appendix we provide further information to support analysis in the main text of the article. **Section 1** provides a description of the risk estimates employed in the main text. We also provide empirical results that utilize the numerical mean of the bond ratings as the predictor, rather than the estimated risk used in the main text. **Section 2** provides alternative specifications for robustness, as well as a more thorough treatment of the two-stage model.

1 Description of risk estimates

Figure 1 compares our factor analysis derived risk estimates to the numerical means of the bond ratings and also shows the distribution of the error estimates across these estimates. The correlation between the two measures is quite high and, indeed, as the next section shows, results of a model using the numerical mean as the dependent variable deliver the same substantive results that we present and discuss in the main text. We also note the outlier error estimates in the lower left pane of the figure — these are estimates from 11 states, the 10 non-issuing states, thus omitted from the main analysis, and Arizona, which does issue bonds, but was nonetheless unrated by two of the ratings houses for a large portion of our data.



riguic i

Table 1 estimates the model presented in the main text, but substitutes the numerical mean

of the bond ratings for the estimated risk dependent variable (used in the main text). The recovered effects are of largely the same magnitude and similarly robust.

Mean	(SE)
1.548	(0.526)
2.523	(0.859)
0.063	(0.038)
1.215	(1.025)
0.088	(0.074)
1.409	(0.423)
0.080	(0.029)
-0.302	(0.062)
3.812	(4.255)
0.251	(0.217)
-0.056	(0.069)
0.063	(0.123)
-0.262	(0.339)
0.426	(0.274)
-0.333	(0.348)
6	33
0.2	295
	1.548 2.523 0.063 1.215 0.088 1.409 0.080 -0.302 3.812 0.251 -0.056 0.063 -0.262 0.426 -0.333

Table 1: FGLS Estimates of Numerical Average of State Credit Risk.

2 Alternative model specification

In this section we present several different specifications and estimations of the statistical model presented in the main text. The point here is to assure readers that the evidence we recover in support of our theoretical arguments is firmly "in the data" and not an artifact of model choice. We begin by presenting an OLS model estimated with panel-corrected standard errors following Beck and Katz (1995). This model produces substantially smaller error estimates for nearly every covariate — typically doubling the ratio of the parameter to error estimate, found in Table 2.

Table 3 gives the results of the main text model with the addition of a one-year lag on the dependent variable to demonstrate that the results are robust to explicitly modeling auto-correlation in the dependent variable — only about 0.04 posterior draws on the Squire Index parameter are

Intercept -0.949 (0.148) Squire Index 2.905 (0.265) Divided Government 0.166 (0.067) Historical Turnover 4.049 (1.406) ACIR Lax 1.188 (0.072) Term Limits 0.161 (0.049) Unemployment Rate 0.124 (0.046) Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150) Revenue 0.011 (0.105)
Squire Index 2.905 (0.265) Divided Government 0.166 (0.067) Historical Turnover 4.049 (1.406) ACIR Lax 1.188 (0.072) Term Limits 0.161 (0.049) Unemployment Rate 0.124 (0.046) Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
Divided Government 0.166 (0.067) Historical Turnover 4.049 (1.406) ACIR Lax 1.188 (0.072) Term Limits 0.161 (0.049) Unemployment Rate 0.124 (0.046) Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
Historical Turnover 4.049 (1.406) ACIR Lax 1.188 (0.072) Term Limits 0.161 (0.049) Unemployment Rate 0.124 (0.046) Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
ACIR Lax 1.188 (0.072) Term Limits 0.161 (0.049) Unemployment Rate 0.124 (0.046) Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
Term Limits 0.161 (0.049) Unemployment Rate 0.124 (0.046) Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
Unemployment Rate 0.124 (0.046) Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
Income -0.345 (0.036) Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
Average Tax Burden 0.478 (1.529) Spending 0.242 (0.150)
Spending 0.242 (0.150)
-r
Revenue 0.011 (0.105)
Debt -0.031 (0.114)
Revenue Limit -0.413 (0.065)
Spending Limit 0.264 (0.059)
Debt Restriction -0.145 (0.056)
N 640
R^2 0.335

Table 2: OLS Estimates of Numerical of State Credit Risk with Panel-Corrected Standard Errors.

less than zero. Of course, our focus is modeling cross-sectional variation in general obligation bond risk, rather than within-unit changes over time, making this specification a poor match to our theoretical argument. Nonetheless, it is encouraging that our hypothesized relationship is still present at traditional levels of significance.

Table 4 gives the parameter estimates resulting from a model interacting capacity with our other specified sources of political uncertainty: divided government, historical turnover patters, and term limits. The divided government and historical turnover interactions wash out, but the interaction with term limits produces a robust positive relationship, while substantially reversing the direction of the term limits constituent term and leaving the Squire Index parameter virtually unchanged. Our substantive interpretation of this result is that term limits may increase market uncertainty and therefore increase a state's riskiness, but these effects may only manifest in the presence of a high capacity legislature that offers the resources necessary to convert the turnover in membership yielded by term limits into a corresponding turnover in policy.

Table 5 gives the parameter estimates resulting from a model interacting capacity with only term limits — the models used to generate the effects given in Figure 3 from the main text.

In Table 6 we assess the data dependence of our results via non-parametric bootstrap. We

Covariate	Mean	(SE)
Intercept	-0.162	(0.010)
Lagged Risk	0.925	(0.012)
Squire Index	0.192	(0.111)
Divided Government	0.007	(0.019)
Historical Turnover	0.032	(0.522)
ACIR Lax	0.059	(0.046)
Term Limits	0.002	(0.024)
Unemployment Rate	0.026	(0.009)
Income	-0.011	(0.012)
Average Tax Burden	0.644	(0.961)
Spending	-0.075	(0.077)
Revenue	-0.001	(0.063)
Debt	0.075	(0.038)
Revenue Limit	-0.050	(0.037)
Spending Limit	0.048	(0.030)
Debt Restriction	0.009	(0.037)
N	6	00
R^2	0.8	875

Table 3: FGLS Estimates of State Credit Risk with Lagged Risk Estimate

Covariate	Mean	(SE)
Intercept	-0.972	(0.441)
Squire Index	2.156	(0.739)
Divided Government	0.064	(0.056)
Historical Turnover	3.182	(1.856)
Term Limits	-0.141	(0.111)
ACIR Lax	1.110	(0.343)
Unemployment Rate	0.061	(0.020)
Income	-0.243	(0.049)
Average Tax Burden	3.634	(3.541)
Spending	0.170	(0.174)
Revenue	-0.016	(0.056)
Debt	-0.049	(0.097)
Revenue Limit	-0.182	(0.278)
Spending Limit	0.118	(0.217)
Debt Restriction	-0.274	(0.283)
Squire X Divided Government	-0.096	(0.241)
Squire X Historical Turnover	-13.931	(8.496)
Squire X Term Limits	1.146	(0.419)
N_{2}	64	
R^2	0.2	71

Table 4: FGLS Estimates of State Credit Risk with Interactions.

randomly sample (with replacement) 160 observations — just 25% of our total sample — and estimate our model via linear regression, take 100 posterior samples and record the results. These distributions are summarized in Table 6. We employ OLS, rather than the more standard time-series models because the sampling procedure often yields observation duplicates. Roughly 98% of the

Covariate	Mean	(SE)
Intercept	-0.797	(0.447)
Squire Index	1.740	(0.701)
Term Limits	-0.146	(0.115)
Divided	0.041	(0.032)
ACIR Strictness	0.527	(0.985)
Historical Turnover	1.119	(0.347)
Unemployment Rate	0.062	(0.021)
PC Income	-0.249	(0.052)
Tax Rate	3.058	(3.639)
PC Spending	0.190	(0.180)
PC Revenue	-0.028	(0.057)
PC Debt	-0.043	(0.100)
Revenue Limit	-0.220	(0.279)
Spending Limit	0.131	(0.218)
Debt Restriction	-0.306	(0.287)
Squire X Term Limits	1.237	(0.436)
N	6	40
R^2	0.2	276

Table 5: FGLS Estimates of State Credit Risk with Term Limits Interaction.

Covariate	Mean	(SE)
Intercept	-0.929	(0.917)
Squire Index	2.903	(1.028)
Divided Government	0.171	(0.197)
Historical Turnover	3.580	(4.957)
Term Limits	0.168	(0.242)
ACIR Lax	1.225	(0.441)
Unemployment Rate	0.119	(0.106)
Income	-0.352	(0.122)
Average Tax Burden	0.226	(8.666)
Spending	0.554	(1.346)
Revenue	-0.086	(1.095)
Debt	-0.183	(0.970)
Revenue Limit	-0.398	(0.365)
Spending Limit	0.262	(0.284)
Debt Restriction	-0.119	(0.358)
N	1	60
$\bar{R^2}$	0.4	402

Table 6: OLS estimate summaries from non-parametric bootstrap assessing data dependence.

models yield support at the p < 0.05 level and far less than 1% of the posterior draws are negative. This suggests that our results are robust to changes in the sample.

Two-stage model

There are two issues, discussed in the main text of the manuscript, that warrant the estimation of a two-stage model. First, the majority of our variation is cross-sectional, however, a great deal of our power comes from repeated years. Second, there is a fairly high level of correlation between our variable of interest, capacity, and other non-institutional predictors of credit risk. This correlation is mapped in Figure 2, which shows a fairly strong, positive correlation between the Squire Index and several economic variables. It is possible that those correlations may be making for odd (i.e., sign-flipped) or biased estimates of our focal variable. Though we believe the probability of this is low, particularly given the strong bivariate relationship between capacity and risk, we would be remiss in not accounting for this covariance.

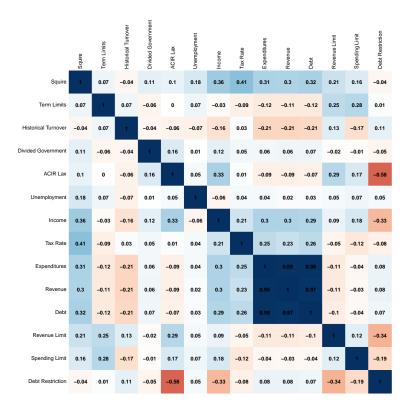


Figure 2

Here, we estimate two-stage models that attempt to account for both of these concerns. First, for each of our forty states, we model risk as a function of the parameters that vary over time:

divided government, turnover, unemployment, income, tax rate, spending, revenue, and carried debt—the same variables that also covary with capacity. The results of the first stage models are given in Figure 3, which plot the distributions of t-scores for each covariate, for each state, from all draws of the credit risk estimates. The individual plots are quite small by necessity, but they can be zoomed in on until clear when being viewed electronically.

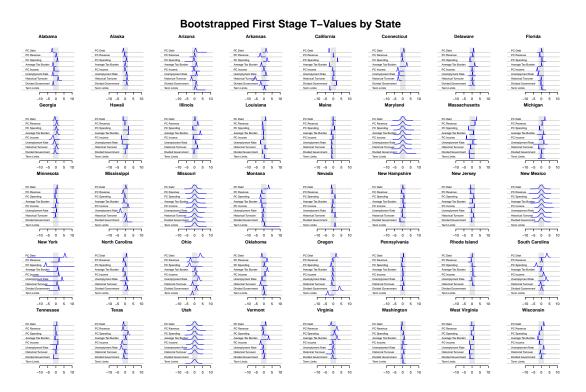


Figure 3

After running through the first stage we then predict, for each state, its typical credit risk holding all of those time-varying parameters constant. These predictions then become the dependent variable in a second model that estimates the impact of factors that vary predominantly cross-sectionally: legislative capacity, ACIR, revenue and spending limits, and constitutional debt restrictions. We take the mean of the capacity estimates, but the remaining factors do not vary over time. The results of these second models are given in Table 7 and the results are remarkably consistent with those presented in the main text.

We can go a step further and assess the sample dependence of these results by randomly sam-

Covariate	Reduced	Full
Intercept	-0.699	-0.991
	(0.298)	(0.547)
Squire Index	3.798	3.612
	(1.276)	(1.314)
ACIR Lax		1.079
		(0.621)
Revenue Limit		-0.127
		(0.502)
Spending Limit		0.159
		(0.398)
Debt Restriction		0.216
		(0.520)
Observations	40	40
\mathbb{R}^2	0.189	0.281

Table 7: Second stage results from two-stage modeling of state credit risk.

pling (with replacement) 40 observations, estimating the model, and repeating 1,000 times. From each of these models we drew 100 posterior samples and then plotted them in Figure 4. As the figure shows, over 94% of the draws are in the predicted direction, which, given the difficulty of the test, we interpret as very strong support for our central hypothesis, and good evidence that the results are not being driven by outliers in the data.

Bootstrapped Parameter Estimates

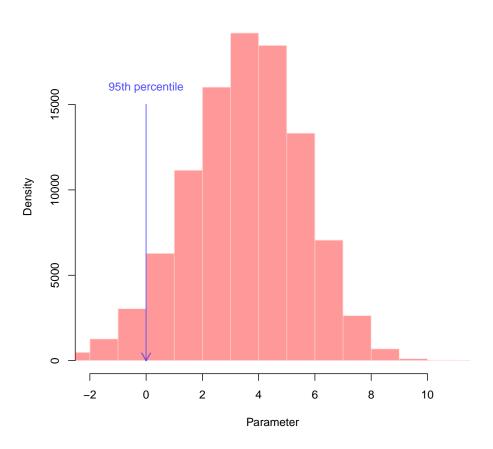


Figure 4

References

Beck, Nathaniel and Jonathan N. Katz. 1995. "What to Do (and Not to Do) with Time-Series Cross-Section Data." *American Political Science Review* 89(3): 634–647.