Non-linear effects of government spending shocks in the US. Evidence from state-level data (Technical Appendix).

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Abstract

Technical Appendix

1 Estimation

The mixed frequency threshold panel VAR is defined as:

$$Z_{it} = \left(c_{1,i} + \sum_{j=1}^{P} b_{1,i,j} Z_{it-j} + \sum_{j=1}^{Q} d_{1,i,j} X_{t-j} + u_{it}\right) S_{it} + \left(c_{2,i} + \sum_{j=1}^{P} b_{2,i,j} Z_{it-j} + \sum_{j=1}^{Q} d_{2,i,j} X_{t-j} + u_{it}\right)(1 - S_{it}) \tag{1}$$

where $S_{it} = 1 \iff z_{it-d_i} \leq z_i^*$.
The covariance of errors is defined as

$$\begin{aligned} var\left(u_{it}\right) = \Sigma_{it} &= S_{it} \odot \Sigma_{1i} + (1 - S_{it}) \odot \Sigma_{1i} \\ \Sigma_{1i} &= A_{1i}^{-1} H_{1i} A_{1i}^{-1\prime} \\ \Sigma_{2i} &= A_{2i}^{-1} H_{2i} A_{2i}^{-1\prime} \end{aligned}$$

where A_{1i}, A_{2i} are lower triangular and $H_{1i} = diag\left(h_{1i}\right), H_{2i} = diag\left(h_{2i}\right)$ are diagonal matrices with the variances of the orthogonal shocks $\left(h_{1i} = [h_{1i}^{(1)}, .., h_{1i}^{(N)}], h_{2i} = [h_{2i}^{(1)}, .., h_{2i}^{(N)}]\right)$ on the main diagonal. Here $\odot$ denotes element by element multiplication

1.1 Priors

Collect the slope coefficients in the following $\bar{K} \times 1$ vectors $\beta_{1,i} = vec\begin{pmatrix} b_{1i,1} \\ . \\ . \\ b_{Pi,1} \\ . \\ d_{Pi,1} \end{pmatrix}$ and $\beta_{2,i} = vec\begin{pmatrix} b_{1i,1} \\ . \\ . \\ b_{Pi,1} \\ . \\ d_{Pi,1} \end{pmatrix}$. Denote the vectorised non-zero and non-one elements in A_{1i}, A_{2i} as a_{1i}, a_{2i}. The model assumes the following hierararchical priors

$$\begin{aligned} p\left(\beta_{1,i} | \bar{\beta}_1, \lambda_1\right) \tilde{} N\left(\bar{\beta}_1, \lambda_1 \Lambda_i\right) \\ p\left(\beta_{2,i} | \bar{\beta}_2, \lambda_2\right) \tilde{} N\left(\bar{\beta}_2, \lambda_2 \Lambda_i\right) \end{aligned}$$

where $\bar{\beta}_1$ and $\bar{\beta}_2$ are the (weighted) cross-sectional average coefficients in the two regimes and Λ_i is set according to the Minnesota procedure. The parameter λ controls the degree of pooling in the model. As $\lambda \to 0$ the heterogeneity across states declines. In order to set the variances Λ_i, we use dummy observations as in Banbura *et al.* (2010a), setting the overall prior tightness parameter to 1. Note that we use a Minnesota type prior for the average coefficients $\bar{\beta}_1$ and $\bar{\beta}_2$. Following Banbura *et al.* (2010b) we implement the prior via dummy observations. The overall prior tightness of this prior is set as $\tau = 0.1$.

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The prior for λ_1, λ_2 is assumed to be inverse Gamma:$p(\lambda_k)\tilde{}IG(S_0, V_0)$ where $S_0 = 0$ and $V_0 = -1$ and $k = 1, 2$. As discussed in Gelman (2006), this prior corresponds to a uniform prior on the standard deviation.

Similarly, a hierararchical prior is set for a_{1i}, a_{2i}:

$$p(a_{1,i}|\bar{a}_1, \delta_1)\tilde{}N(\bar{a}_1, \delta_1 \Xi_i)$$
$$p(a_{2,i}|\bar{a}_2, \delta_2)\tilde{}N(\bar{a}_2, \delta_2 \Xi_i)$$

where $\bar{a}_1$ and $\bar{a}_2$ are weighted cross-sectional averages and Ξ_i equals a matrix with $10 \times abs(a_{i,ols})$ on the main diagonal. $a_{i,ols}$ represents the non-zero and non-one elements of preliminary estimate of the contemporaneous impact matrix obtained via OLS. The degree of pooling is controlled by δ.

The prior for δ_1, δ_2 is assumed to be inverse Gamma:$p(\delta_k)\tilde{}IG(s_0, v_0)$ where $s_0 = 0$ and $v_0 = -1$ and $k = 1, 2$.

We assume a normal prior for the intercepts: $p(c_K)\tilde{}N(c_0, \Lambda_C)$ where Λ_C is a diagonal matrix with 10,000 on the main diagonal. The prior for h_{1i}, h_{2i} is inverse Gamma with mean h_0 where h_0 is an estimate of the average variance of the error terms obtained using OLS estimation of the VAR for each state using a preliminary estimate of G_{it}.[1] The variance of this prior is set to $v_{h_0}^2$ where this equals 0.1 for $i = 1$ and is set to 10 for the remaining shocks. In other words, we have a relatively tight prior for variance of the shock to G_{it}.

1.2 Gibbs Sampling Algorithm

The Gibbs algorithm is based on Jarocinski (2010), Chen and Lee (1995) and Schorfheide and Song (2015). It draws from the following conditional posterior distributions (Ξ^* denotes all remaining parameters):

The following steps are repeated for state $i = 1, 2..., 50$.

1. $G(\beta_{1,i}|\Xi^*)$. This conditional posterior is normal: $N(M, V)$ where

$$V = \left((\lambda_1 \Lambda_i)^{-1} + \Sigma_{1i}^{-1} \otimes x'_{1,i} x_{1,i}\right)^{-1}$$
$$M = V\left((\lambda_1 \Lambda_i)^{-1} \bar{\beta}_1 + \Sigma_{1i}^{-1} \otimes x'_{1,i}(y_{1,i} - c_{1,i})\right)$$

where $y_{1,it}$ and $x_{1,it}$ denote the left and the right hand side of the VAR model for country i with data selected for regime 1, i.e. over periods when $S_{it} = 1$. The number of observations in the regime are denoted by $T_{1,i}$.

2. $G(c_{1,i} \backslash \Xi^*)$. The conditional posterior is normal: $N(m, v)$ where

$$v = \left(\Lambda_C^{-1} + \Sigma_{1i}^{-1} \otimes \tilde{x}'_{1,i}\tilde{x}_{1,i}\right)^{-1}$$
$$m = v\left(\Lambda_C^{-1} c_0 + \Sigma_{1i}^{-1} \otimes x'_{1,i} vec\left(y_{1,i} - x_{1,i}\tilde{\beta}_{1,i}\right)\right)$$

where $\tilde{x}_{1,i} = 1_{T_{1,i} \times 1}$ and $\tilde{\beta}_{1,i}$ denotes $\beta_{1,i}$ reshaped to be comformable with $x_{1,i}$.

2. $G(a_{1i} \backslash \Xi^*)$. Denote the residuals in regime 1 as $E_{1,it} = y_{1,i} - y_{1,i}\tilde{\beta}_{1,i} - c_{1,i}$. Then the model in regime 1 can be written as $A_{1i}E_{1,it} = H_{1i}^{1/2} U_{1,it}$ where $U_{1,it}$ is $N(0, 1)$. This is a system of linear equations. The kth equation is $E_{1,it}(k) = -\alpha E_{1,it}(-k) + H_{1i}^{1/2}(K) U_{1,it}(k)$ where k in the parenthesis denotes the kth column while $-k$ denotes columns 1 to $k - 1$ and α denotes the relevant elements of a_{1i}. The draw from this conditional posterior thus requires drawing the coefficients of a series of linear regressions. As is well known, the conditional posterior is normal with mean and variance M^* and V^* :

$$M^* = \left(\left(\delta_1 \Xi_i^{(k)}\right)^{-1} + \frac{1}{H_{1i}(k)} E_{1,it}(-k)' E_{1,it}(-k)\right)^{-1} \left(\left(\delta_1 \Xi_i^{(k)}\right)^{-1} \bar{a}_1^{(k)} + \frac{1}{H_{1i}(k)} E_{1,it}(-k)' E_{1,it}(k)\right)$$
$$V^* = \left(\left(\delta_1 \Xi_i^{(k)}\right)^{-1} + \frac{1}{H_{1i}(k)} E_{1,it}(-k)' E_{1,it}(-k)\right)^{-1}$$

Note that the superscript (k) denotes the fact that priors corresponding to the parameters of the kth equation are used.

3. $G(h_{1i} \backslash \Xi^*)$. As discussed in step 3, the model in regime 1 can be written as $A_{1i}E_{1,it} = \tilde{U}_{1,it}$ where $\tilde{U}_{1,it}\tilde{}N(0, h_{1i})$. As the prior is parameterised in terms of mean h_0 and standard deviation v_{h0}, it is convenient to draw the precision $\frac{1}{h_{1i}}$ using the Gamma distribution. Note that $\frac{1}{h_{1i}} \sim \mathcal{G}(a, b)$ where $a = \frac{\nu_1}{2}$, $b = \frac{2}{s_1}$. The parameters of this Gamma density are given by $\nu_1 = \nu_0 + T_{1,i}$ and $s_1 = s_0 + \tilde{U}'_{1,it}\tilde{U}_{1,it}$. s_0 can be calculated as $2h_0\left(1 + \frac{h_0^2}{v_{h0}^2}\right)$ while $\nu_0 = 2\left(2 + \frac{h_0^2}{v_{h0}^2}\right)$ and $T_{1,i}$ is the length of the sample in regime 1 for state i

[1] This preliminary estimate is obtained via a Mixed Frequency Bayesian VAR estimated for each state separately. This model contains annual government spending and employment for each state and a set of US wide variables (GDP, federal government spending, federal taxes, GDP deflator and the treasury bill rate).

5. $G(\beta_{2,i}|\Xi^*)$. The form of the conditional posterior is as defined in step 1.

4. $G(c_{2,i}|\Xi^*)$. The form of the conditional posterior is as defined in step 2.

5. $G(a_{2,i}|\Xi^*)$. The form of the conditional posterior is as defined in step 3.

6. $G(h_{2,i}|\Xi^*)$. The form of the conditional posterior is as defined in step 4.

9. $G(z_i^*|\Xi^*)$. The threshold value is drawn using a Metropolis Hastings step. We draw candidate value of $z_{i,new}^*$ from $z_{i,new}^* = z_{i,old}^* + \Psi_i^{1/2}\epsilon$, $\epsilon \sim N(0,1)$. The acceptance probability is given by $F\left(Z_{it}\left|z_{i,new}^*, \Xi^*\right.\right)/F\left(Z_{it}\left|z_{i,old}^*, \Xi^*\right.\right)$, where $F(.)$ denotes the posterior density: $F\left(Z_{it}\left|z_i^*, \Xi^*\right.\right) \propto f\left(Z_{it}\left|z_i^*, \Xi^*\right.\right)p\left(z_i^*\right)$ where $f(.)$ is the likelihood function of the VAR model for country i. Note that the likelihood function is simply the product of the likelihood in the two regimes. The scale Ψ_i is chosen to ensure that the acceptance rate is between 20% and 50%.

7. $G(d_i|\Xi^*)$. Chen and Lee (1995) show that the conditional posterior for d is a multinomial distribution with probability $f\left(Y_t\left|d_i, \Xi^*\right.\right)/\sum_{d_i=1}^{d_{i,\max}} f\left(Y_t\left|d_i, \Xi^*\right.\right)$, where $d_{i,\max}$ denotes the maximum delay allowed for.

8. $G(G_{it}|\Xi^*)$. Conditional on the remaining parameters for state i, the model has a linear state space representation with observation equation:

$$\tilde{Z}_{it} = \tilde{H}_t\tilde{\beta}_t + \tilde{V}_t,$$
$$var\left(\tilde{V}_t\right) = \tilde{R}_t$$

where $\tilde{Z}_i = \begin{pmatrix} na & Y_{i1} & E_{i1} \\ na & Y_{i2} & E_{i2} \\ na & . & . \\ G_{i4}^a & . & . \\ na & . & . \\ na & . & . \\ na & . & . \\ G_{i8}^a & . & . \\ . & . & . \\ . & Y_{iT} & E_{iT} \end{pmatrix}$, $\tilde{\beta}_t = \underbrace{\begin{pmatrix} G_{it} \\ Y_{it} \\ E_{it} \\ . \\ . \\ . \\ G_{it-P-1} \\ Y_{it-P-1} \\ E_{it-P-1} \end{pmatrix}}_{N_s \times 1}$ and:

$$\tilde{H}_t = \underbrace{\begin{pmatrix} 0_{1\times N_s} & \\ I_{N-1} & 0_{(N-1)\times(N_s-N+1)} \end{pmatrix}}_{N\times N_s} \text{ if } \tilde{Z}_i(1) = na$$

$$\tilde{H}_t = \begin{pmatrix} 0.25 & 0 & 0 & 0.25 & 0 & 0 & 0.25 & 0 & 0 & 0.25 & 0 & 0 \\ I_{N-1} & 0_{(N-1)\times(N_s-N+1)} & & & & & & & & & & \end{pmatrix} \text{ if } \tilde{Z}_i(1) \neq na$$

$$\tilde{R}_t = diag\begin{pmatrix} 1e10 & 0 & 0 \end{pmatrix} \text{ if } \tilde{Z}_i(1) = na$$

$$\tilde{R}_t = diag\begin{pmatrix} 0 & 0 & 0 \end{pmatrix} \text{ if } \tilde{Z}_i(1) \neq na$$

The transition equation is given by

$$\tilde{\beta}_t = \tilde{\mu}_t + \tilde{F}\tilde{\beta}_t + \tilde{U}_t$$

where:

$$\tilde{\mu}_t = \begin{pmatrix} c_{1i} + \sum_{j=1}^{Q} d_{1i,j}X_{t-j} \\ 0_{(N_s-N)\times 1} \end{pmatrix} \text{ if } S_{it} = 1$$

$$\tilde{\mu}_t = \begin{pmatrix} c_{2i} + \sum_{j=1}^{Q} d_{2i,j}X_{t-j} \\ 0_{(N_s-N)\times 1} \end{pmatrix} \text{ if } S_{it} = 2$$

and $\tilde{F}$ denotes the VAR coefficients in regime 1 $b_{1i,j}$ in companion form with $var\left(\tilde{U}_t\right)$ given by Σ_{1i} in companion form when $S_{it} = 1$. When the system is in regime 2, $\tilde{F}$ denotes the VAR coefficients in regime 2 $b_{2i,j}$ in companion form with $var\left(\tilde{U}_t\right)$ given by Σ_{2i} in companion form. With the model in state-space form, the Carter and Kohn (2004) algorithm is used to draw the state vector and obtain a draw for G_{it} from its conditional posterior.

This completes the loop across states.

11. $G\left(\lambda_1 \backslash \Xi^*\right)$. The form of the conditional posterior is inverse Gamma with scale parameter $\sum_{i=1}^{M}\left(\beta_{1,i}-\bar{\beta}_1\right)\Lambda_i^{-1}\left(\beta_{1,i}-\bar{\beta}_1\right)'+$ S_0 and degrees of freedom $\left(M\times\bar{K}\right)+V_0$

12. $G\left(\lambda_2 \backslash \Xi^*\right)$. The form of the conditional posterior is as defined in step 11.

13. $G\left(\bar{\beta}_1 \backslash \Xi^*\right)$. By the Bayes Theorem, $G\left(\bar{\beta}_1 \backslash \beta_1,\lambda_1\right)\propto p\left(\beta_1 \backslash \bar{\beta}_1,\lambda_1\right)p\left(\bar{\beta}_1\right)$ with $\beta_1=[\ \beta_{1,1},\beta_{1,2},..,\beta_{1,50}]$ denoting the coefficients for each state. This density is normal as $p\left(\beta_1 \backslash \bar{\beta}_1,\lambda_1\right)$ is normal and a product of the normal priors for each i. This density is given by $N\left(\bar{M},\bar{V}\right)$:

$$\bar{V}=\left(V_{\bar{\beta}}^{-1}+\frac{1}{\lambda_1}\sum_{i=1}^{M}\Lambda_i^{-1}\right)^{-1}$$

$$\bar{M}=\bar{V}\left(V_{\bar{\beta}}^{-1}\bar{\beta}_0+\frac{1}{\lambda_1}\sum_{i=1}^{M}\Lambda_i^{-1}\beta_{1,i}\right)$$

where the prior is defined as $p\left(\bar{\beta}_1\right)\tilde{}N\left(\bar{\beta}_0,V_{\bar{\beta}}\right)$ with the mean and variance of this prior implied by the dummy observations described above.

14. $G\left(\bar{\beta}_2 \backslash \Xi^*\right)$. The form of the conditional posterior is as defined in step 13 above.

15. $G\left(\delta_1 \backslash \Xi^*\right)$. As in step 11, this conditional posterior is inverse Gamma with scale parameter $\sum_{i=1}^{M}\left(a_{1,i}-\bar{a}_1\right)\Lambda_i^{-1}\left(a_{1,i}-\bar{a}_1\right)'+$ s_0 and degrees of freedom $\left(M\times\left(\frac{N\times(N-1)}{2}\right)\right)+v_0$

16. $G\left(\delta_2 \backslash \Xi^*\right)$. The form of the conditional posterior is as defined in step 15 above.

17. $G\left(\bar{a}_1 \backslash \Xi^*\right)$. The form of the conditional posterior is as defined in step 13 assuming a flat prior for $\bar{a}_1$. The conditional posterior is normal $N\left(\bar{m},\bar{v}\right)$ where:

$$\bar{v}=\left(\frac{1}{\delta_1}\sum_{i=1}^{M}\Xi_i^{-1}\right)^{-1}$$

$$\bar{m}=\bar{v}\left(\frac{1}{\delta_1}\sum_{i=1}^{M}\Xi_i^{-1}a_{1,i}\right)$$

18. $G\left(\bar{a}_2 \backslash \Xi^*\right)$. The form of the conditional posterior is as defined in step 17 above.

1.3 Convergence

The inefficiency factors for key parameters of the model are presented in Figure 1. These are reasonably low in most cases. Given the heavily parameterised nature of the model, these provide some evidence for convergence.

2 Further Results

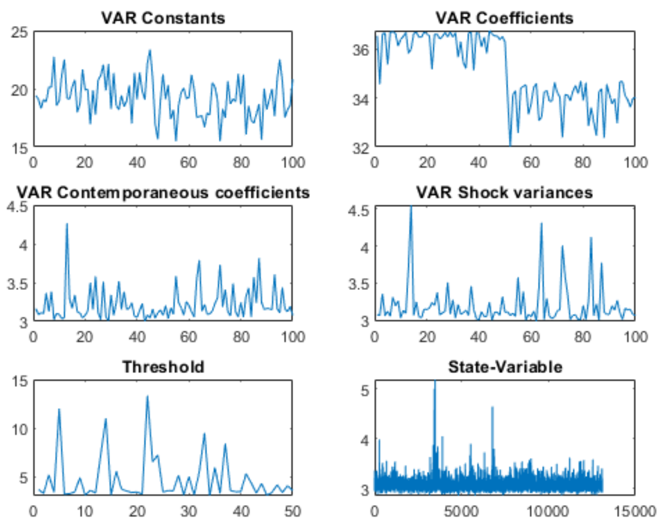

Figure 1: Inefficiency Factors. For the VAR coefficients, constants, variances and contemporaneous coefficients, the figure reports the average for each state in the two regimes.

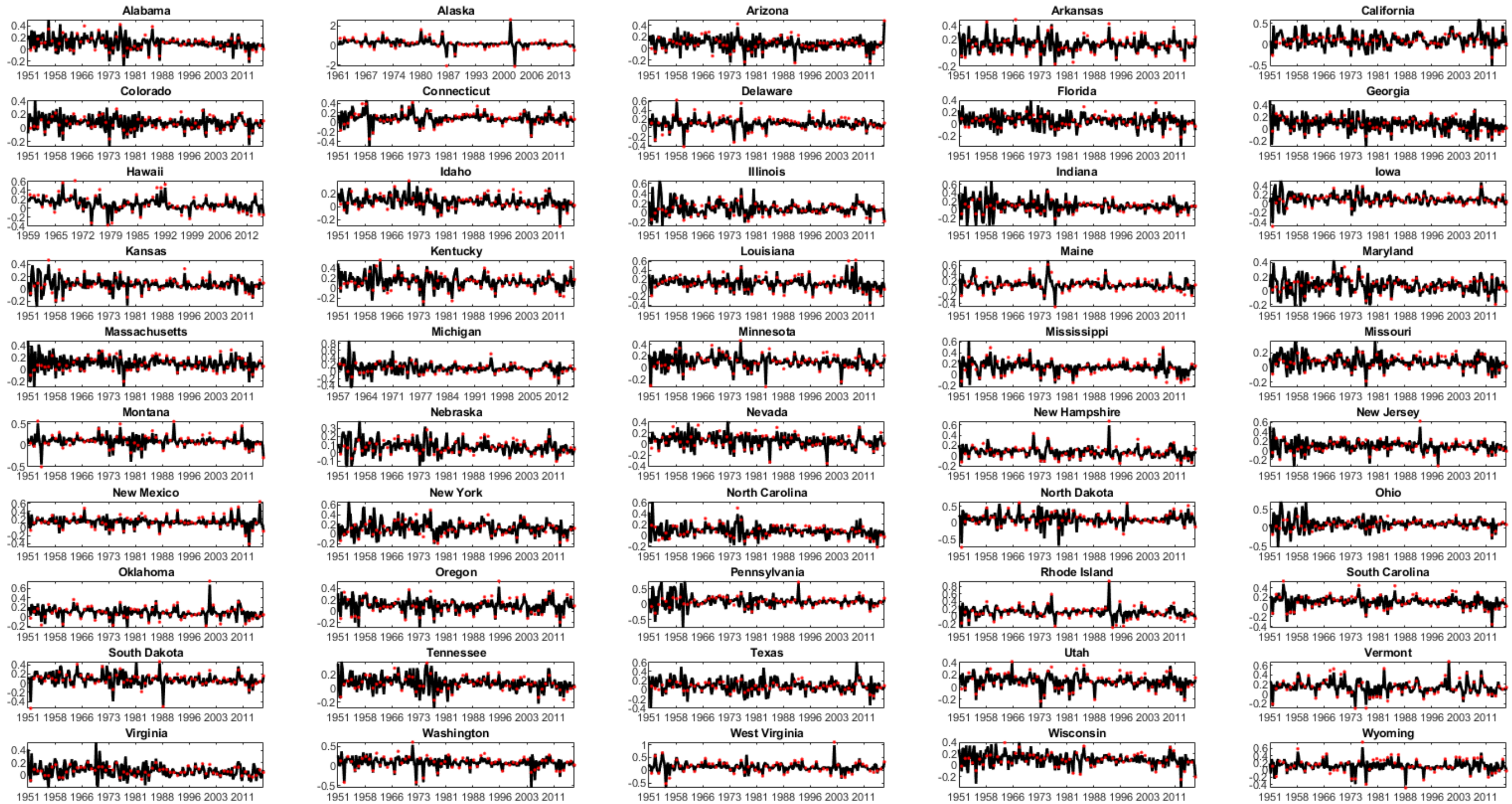

Figure 2: The black line is the median estimate of G_{it} while the red dots are the annual observations.

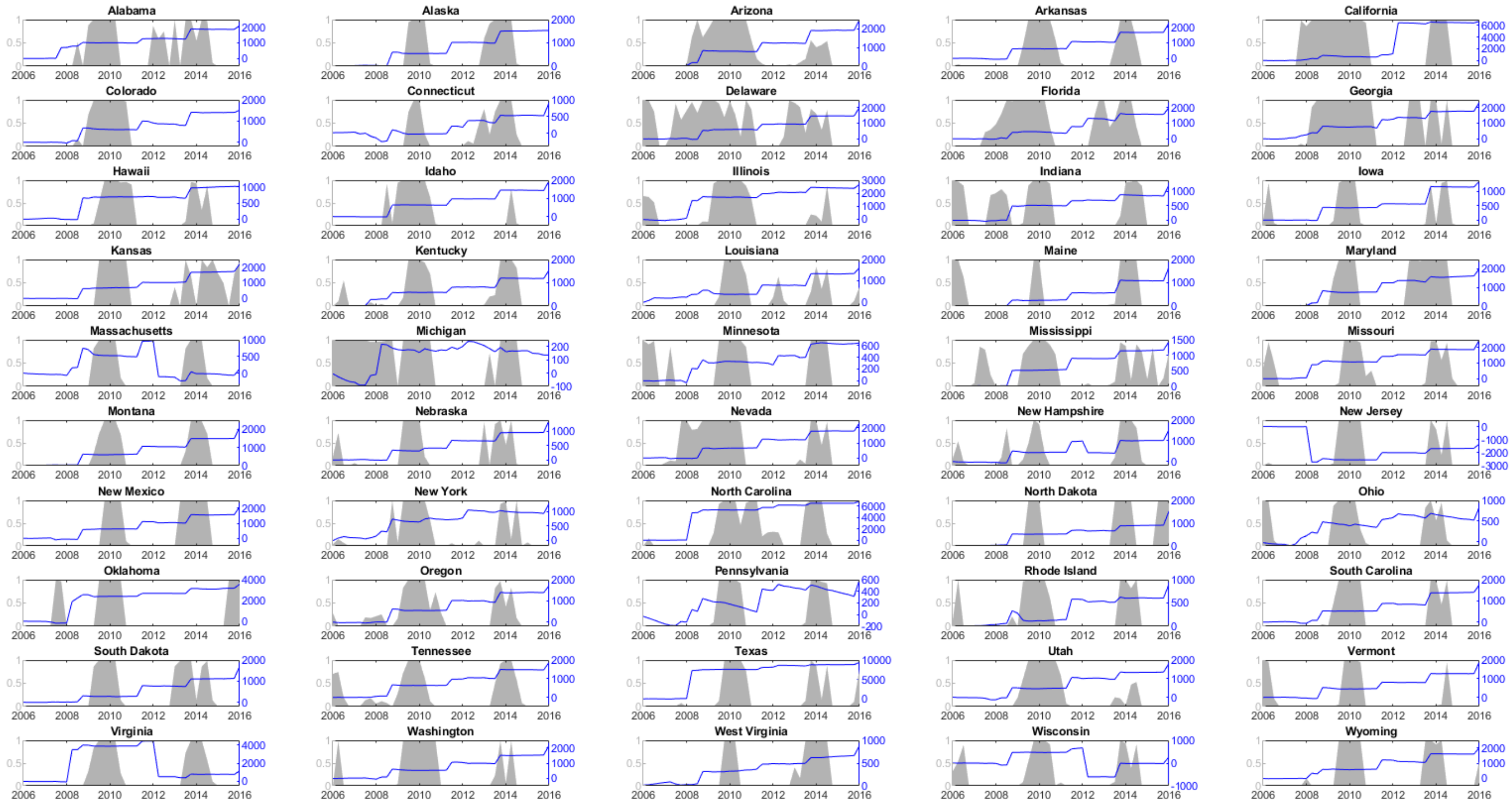

Figure 3: Cumulated log score and the probability of regime 1

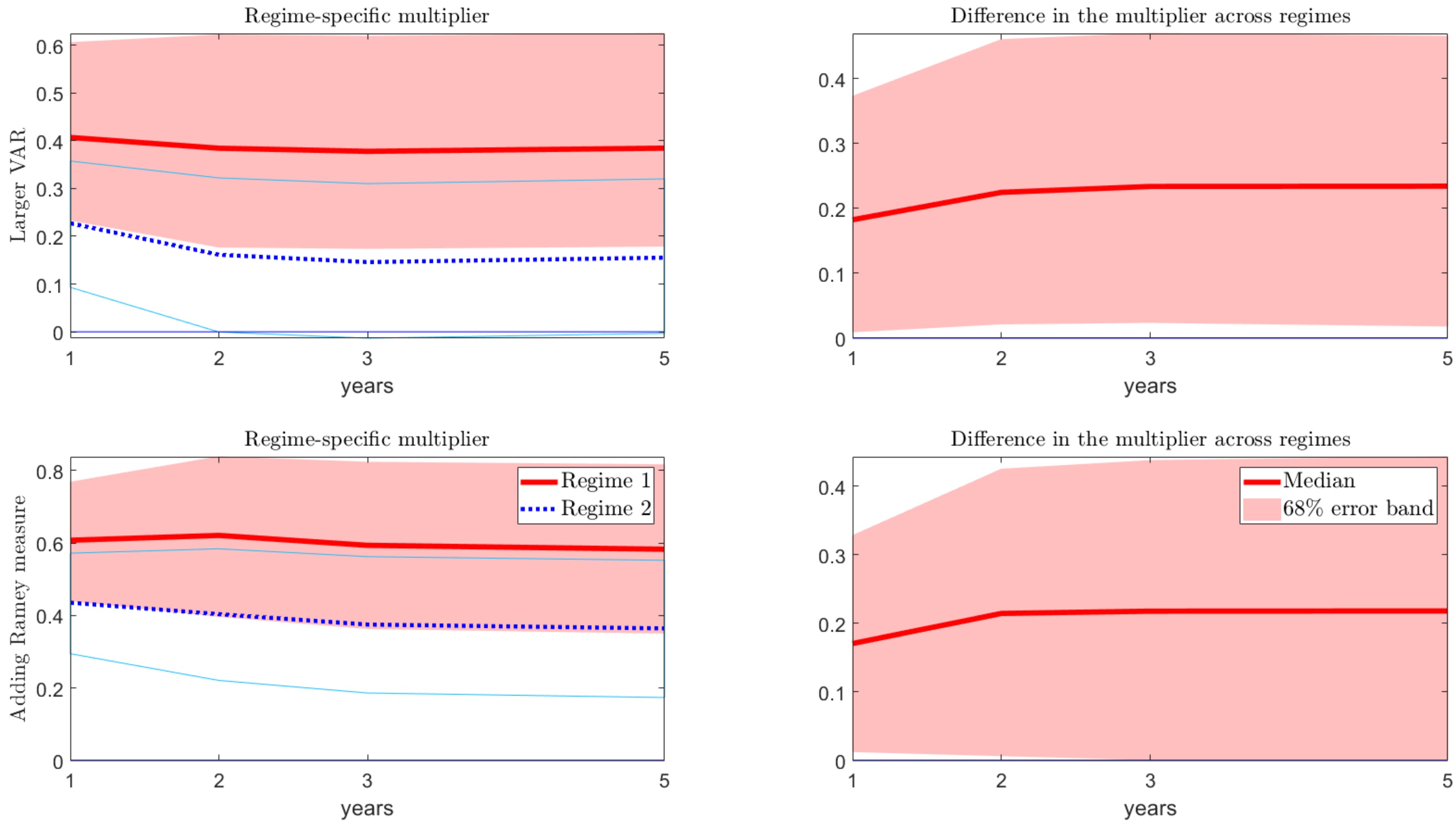

Figure 4: Robustness analysis

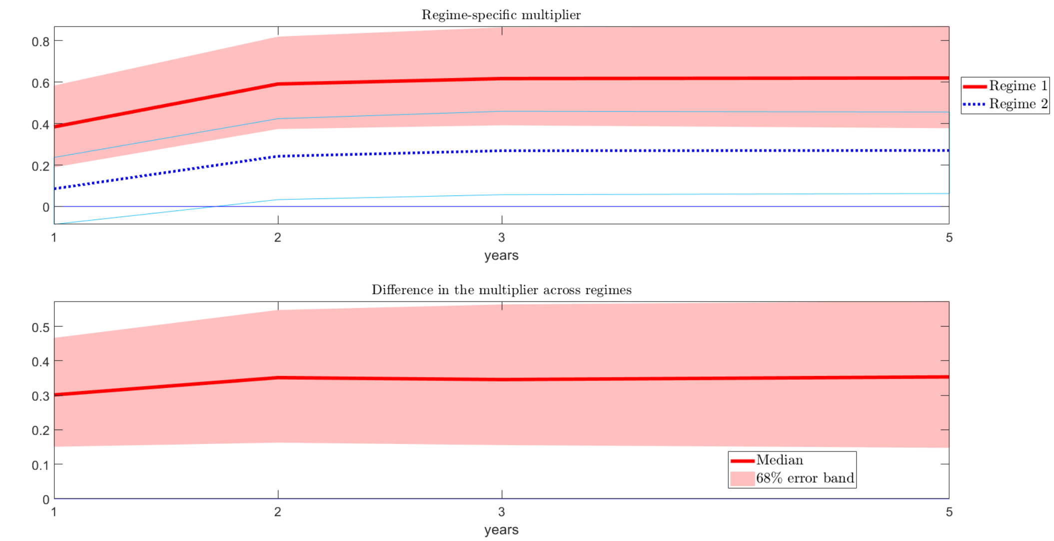

Figure 5: Multipliers estimated using a fixed effects version of the benchmark model. The model includes state-specific and time-dummies.

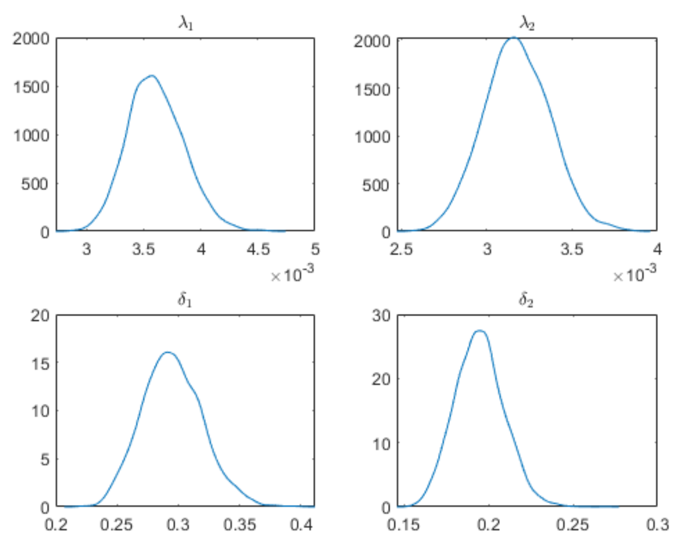

Figure 6: Parameters controlling coefficient heterogeneity in the benchmark model.

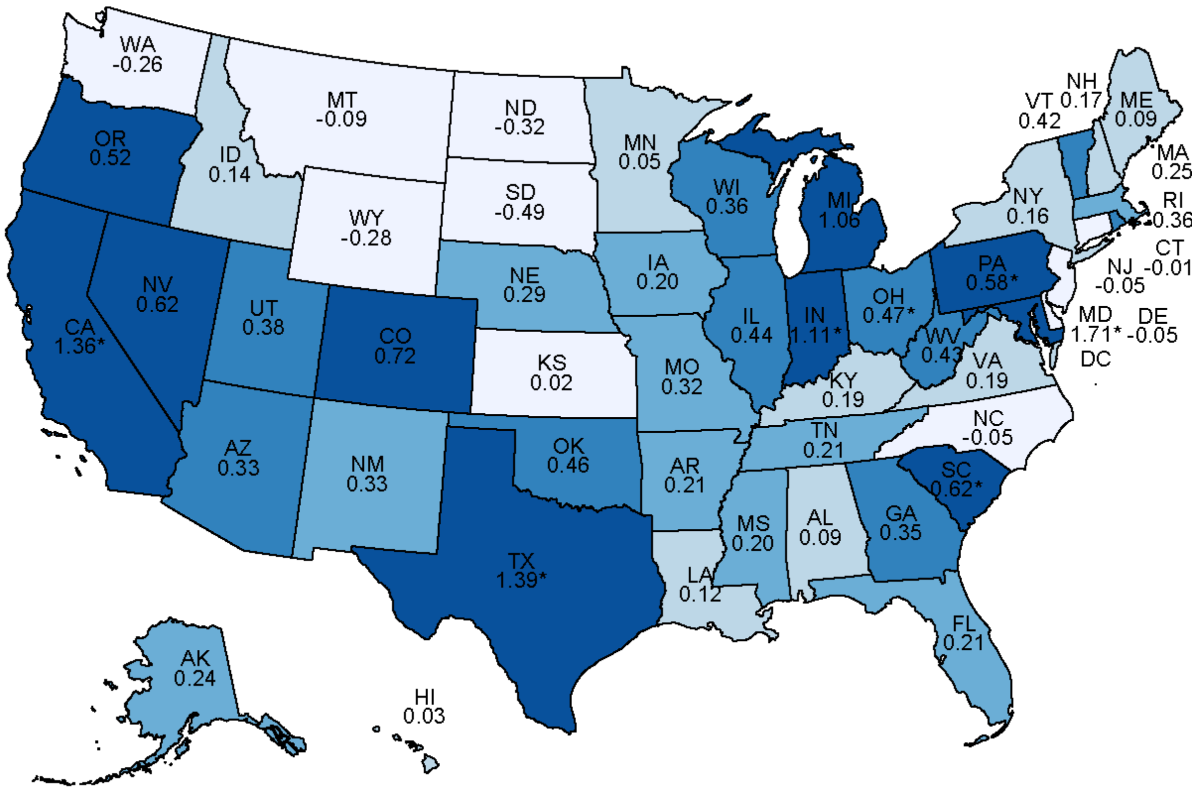

Figure 7: Difference in the multiplier between regime 1 and regime 2. Positive number indicates higher multiplier during downturns (regime 1).

Figure 2 presents the posterior median estimates of G_{it}. Figure 3 shows the cumulated log score along with the probability of regime 1. The top panel of 4 shows the income multiplier from the model that includes the state-specific unemployment rate and house prices. The bottom panel is benchmark model where the Ramey (2011) measure of defense news is added as an extra exogenous variable. Figure 5 presents results from a version of the benchmark model with homogenous slopes and error covariances. In this restricted model, we are able to include both cross-section and time fixed effects/dummies (where the latter replace the exogenous variables). The main purpose of estimating this version of the model is to check if the addition of time-effects alters our conclusions regarding the non-linearity of the multiplier. We stress that this model with homogenous coefficients is not supported by the data as we find a large degree of heterogeneity with the variances. Figure 5 shows the estimated multipliers using this model. The figure shows that the conclusions regarding non-linearity are not altered. The level of the multipliers is estimated to be slightly smaller than the benchmark at short horizons. However, this possibly reflects a bias from imposing homogeneity (see Pesaran and Smith (1995)). As shown in figure 6, the posterior distributions of λ_R and δ_R in the benchmark model shown in the main text are centered away from zero, suggesting the presence of parameter heterogeneity.

Figure 7 displays state-specific multipliers using a heat map. In particular, the figure shows the median difference in the multiplier (at the 20 quarter horizon) between recessions and expansions, with positive numbers indicating that the estimates in recessions are larger. In all but 7 states, the median estimate of the multiplier in recessions is larger. States such as Maryland, Texas, California and Michigan top this list with the effect of spending shocks estimated to be more than 1 unit larger. When the posterior distribution of the multipliers is considered, the null hypothesis that this difference equals zero can be rejected for 7 of these states. For some states, the impact of spending shocks appears to be larger in expansions. Examples include Washington, Wyoming, South and North Dakota.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Home Vacancy Rate	141.320**	11.919	7.476	0.702**	129.507**	107.791***	124.507***	147.250***
	(55.636)	(21.346)	(21.394)	(0.276)	(62.392)	(34.815)	(43.006)	(50.123)
Mining	−10.535**	−1.819	−0.758	−0.654**	−7.006	−9.213*	−9.959**	−13.290**
	(4.608)	(2.799)	(2.227)	(0.286)	(7.110)	(4.743)	(4.566)	(5.585)
Agriculture	−26.400***	−11.646	−6.154	−0.773***	−13.633	−21.859***	−24.534***	−32.786***
	(8.672)	(7.771)	(7.181)	(0.254)	(8.219)	(7.458)	(8.134)	(11.632)
Manufacturing	−9.607**	1.355	1.558	−0.709**	−9.930*	−7.675**	−8.650**	−10.991**
	(4.122)	(3.133)	(1.911)	(0.304)	(5.415)	(3.360)	(3.606)	(4.315)
Small Banks	3.248**	1.425**	0.944*	0.751**	3.272*	2.995**	3.107**	2.198*
	(1.268)	(0.686)	(0.550)	(0.293)	(1.906)	(1.376)	(1.293)	(1.253)
Tax revenue	−9.092*	0.201	0.889	−0.519*	−12.618	−9.728	−9.386*	−11.260**
	(5.247)	(2.150)	(1.767)	(0.300)	(8.325)	(5.806)	(5.390)	(5.169)
Small firms	−16.959	−1.589	3.954	−0.409	−33.248*	−21.039*	−18.930	−4.766
	(11.543)	(6.386)	(6.386)	(0.279)	(18.590)	(11.750)	(11.252)	(14.546)
obs	50	50	50	50	50	50	50	50
R^2	0.40	0.13	-0.01	0.40	0.14	0.31	0.37	0.39

Table 1: Regression results. Dependent variable: Percentage difference in government spending multiplier in recession relative to expansion." * p<0.1, ** p<0.05, ***P<0.001. Robust Standard errors in parenthesis. Regional dummies included

Table 1 presents some robustness analysis for the cross-section regression. Column 1 presents the baseline results. Column 2 shows the regression when the dependent variable is multiplier in busts. Column 3 shows the regression when the dependent variable is multiplier in booms. Column 4 is the benchmark model where the independent variables are standardized.

Column 5 to 7 show the regression where the dependent variable is calculated at horizons of 4, 8 and 12 quarters, respectively. In column 8, weighted least squares is used for estimation of the benchmark regression. The weights are the inverse of the posterior variance of the multiplier estimated using the panel threshold model.

3 Data for cross-section regressions

The first set of covariates that we consider account for differences in the structure of industry. We include the share of the proportion of nominal state-level GDP accounted for by manufacturing, finance, real estate, agriculture, construction, mining, oil and gas, and the government.

The next set of variables attempts to account for financial frictions. Following Carlino and Defina (1998), we include the percentage of each state's loans that are made by small banks. To proxy for the broad credit channel the proportion of small firms in terms of employment are included.

In order to account for cross-state differences in the housing market we use the homeowner vacancy rate in the benchmark specification, but also consider the rental vacancy rate and the homeownership rate.

To capture the fiscal situation in each state we use a number of proxies: Taxes and net intergovernment transfers (each as a share of total government revenue), as well as expenditures on welfare and unemployment insurance (each as a share of total government expenditures). The budget situation is accounted for via the budget balance and debt as a share of expenditures.

We explore the role played by labour market rigidities. To proxy this, we include the degree of unionization in some of the specifications. In addition, we construct a dummy variable that takes the value of 1 for states where 'right to work' laws are in existence. These laws represent an attempt to provide the right to work to employees without the implicit or explicit requirement to join a union. We also consider the degree of business creation as an additional proxy in some of the specifications discussed below.

Details of data sources and construction are below. See also Mumtaz *et al.* (2018).

- Small establishment employment share: Employment at the 6-digit NAICS industry level, by state and establishment size, annual 1986 to 2013. Source: Census Bureau, County Business Patterns. Small establishments are defined as those with less than 10 employees. We aggregate to the state level, and average over time.
- Industry shares of GDP: State-level GDP by industry, annual 1963 to 2013, average over time. Source: BEA. Industry classification is NAICS since 1997, SIC prior to that.
- Share of loans extended by small banks: Bank balance sheet data on all FDIC-insured financial institutions excluding bank holding companies, quarterly 2001Q1 to 2015Q3. Source: Call Reports from the FFIEC. Small banks are defined as at or below the 90th percentile of the national distribution of bank size by assets. The small bank loans share is the time-average of the fraction of total loans on small bank balance sheets in each state. The panel contains 449,777 observations, the cross-section contains on average 150 institutions per state.
- State government finance variables: State government sources of revenues and expenditures, annual 1992 to 2013, average over time. Source: Census Bureau. Net intergovernment transfers are the sum of transfers to/from federal and local governments.
- Housing sector variables: Homeowner and rental vacancy rate, and homeownership rate, quarterly 2005Q1-2015Q4. Source: Census Bureau.
- Union membership as a share of nonagricultural employment by state, average of 1964, 1984 and 2000. Source: Barry T. Hirsch (2001)
- Business creation: Net entry rate of firms, 1977-2014 average. Source: Census Bureau.
- Right to work: Dummy for whether a state has right to work legislation as of 2016. Source: http://www.nrtw.org/right-to-work-states/.

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