The State-Level Impact of Uncertainty Shocks (On-line Technical Appendix. Not for Publication)

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September 4, 2017

1 Model

The FAVAR model is defined as

$$X_{it} = B_i F_t + \sum_{k=1}^{K} \rho_{k,i} \ln h_{it-k} + v_{it} \tag{1}$$

$$F_t = c + \sum_{j=1}^{P} \beta_j F_{t-j} + \sum_{j=1}^{J} \gamma_j \ln \lambda_{t-j} + \Omega_t^{1/2} e_t \tag{2}$$

$$R_t = diag(h_{1t}, ..h_{Nt}) \tag{3}$$

$$\Omega_t = A^{-1} H_t A^{-1'} \tag{4}$$

$$H_t = diag(S_k \lambda_t), k = 1, 2, ..N \tag{5}$$

$$\ln \lambda_t = \alpha + \beta \ln \lambda_{t-1} + Q^{1/2} \eta_t \tag{6}$$

$$\ln h_{it} = a_i + b_i \ln h_{it-1} + q_i^{1/2} n_{it} \tag{7}$$

$$\varepsilon_{it}, e_t, \eta_t, n_{it} \tilde{} N(0,1) \tag{8}$$

2 Estimation

2.1 Priors

2.1.1 Factor loadings

The prior on $\tilde{B}_i = [B_i; \rho_i]$ is normal and is assumed to be $N(B_{i,0}, V_B)$ where $B_{i,0}$ is set equal to the loadings obtained using a principal component estimate of F_t. The variance V_B is assumed to be equal to 1. The initial estimate of the factors F_t^{PC} provides the initial value of the factors $F_{0\backslash 0}$ with the initial variance set equal to the identity matrix.

2.1.2 VAR Coefficients

Following Banbura *et al.* (2010) we introduce a natural conjugate prior for the VAR parameters $\tilde{b} = \{c, b, \gamma\}$ via dummy observations. In our application, the prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. As is standard for US data, we set the overall prior tightness $\tau = 0.1$.

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2.1.3 Elements of S, A and the parameters of the common volatility transition equation

The elements of S have an inverse Gamma prior: $P(s_i)\tilde{}IG(S_{0,i}, V_0)$. The degrees of freedom V_0 are set equal to 1. The prior scale parameters are set by estimating the following regression: $\bar{\lambda}_{it} = S_{0,i}\bar{\lambda}_t + \varepsilon_t$ where $\bar{\lambda}_t$ is the first principal component of the stochastic volatilities $\bar{\lambda}_{it}$ obtained using a univariate stochastic volatility model for the residuals of each equation of the VAR in equation 2 estimated via OLS using the principal components F_t^{PC}.

The prior for the off-diagonal elements A is $A_0 \sim N\left(\hat{a}^{ols}, V\left(\hat{a}^{ols}\right)\right)$ where $\hat{a}^{ols}$ are the off-diagonal elements of the inverse of the Cholesky decomposition of $\hat{v}^{ols}$, with each row scaled by the corresponding element on the diagonal. These OLS estimates are obtained using the initial VAR model described above. $V\left(\hat{a}^{ols}\right)$ is assumed to be diagonal with the elements set equal to 10 times the absolute value of the corresponding element of $\hat{a}^{ols}$.

We set a normal prior for the unconditional mean $\mu = \frac{\alpha}{1-\beta}$. This prior is $N(\mu_0, Z_0)$ where $\mu_0 = 0$ and $Z_0 = 10$.The prior for Q is $IG\left(Q_0, V_{Q0}\right)$ where Q_0 is the average of the variances of the transition equations of the initial univariate stochastic volatility estimates and $V_{Q0} = 5$. The prior for β is $N\left(F_0, L_0\right)$ where $F_0 = 0.8$ and $L_0 = 1$.

2.1.4 Parameters of the idiosyncratic shock volatility transition equation

We set a normal prior for the unconditional mean $\tilde{\mu} = \frac{a}{1-b}$. This prior is $N(\mu_0, Z_0)$ where $\mu_0 = 0$ and $Z_0 = 10$.The prior for q_i is $IG\left(q_0, V_{q0}\right)$ where $q_0 = 0.01$ and $V_{q0} = 5$. The prior for b is $N\left(F_0, L_0\right)$ where $F_0 = 0.8$ and $L_0 = 1$.

2.2 Gibbs algorithm

The Gibbs algorithm cycles through the following steps:

1. $G\left(F_t \backslash \Xi\right)$: Given a draw for all other parameters (denoted by Ξ), the algorithm of Carter and Kohn (2004) is used to sample from the conditional posterior distribution of F_t. The conditional posterior is: $F_t \backslash X_{it}, \Xi \sim N\left(F_{T\backslash T}, P_{T\backslash T}\right)$ and $F_t \backslash F_{t+1}, X_{it}, \Xi \sim N\left(F_{t\backslash t+1, F_{t+1}}, P_{t\backslash t+1, B_{t+1}}\right)$ where $t = T-1, ..1$. As shown by Carter and Kohn (2004) the simulation proceeds as follows: First, we use the Kalman filter to draw $F_{T\backslash T}$ and $P_{T\backslash T}$ and then proceed backwards in time using $F_{t|t+1} = F_{t|t} + P_{t|t}f'P_{t+1|t}^{-1}\left(F_{t+1} - fF_{t\backslash t} - \mu_t\right)$ and $P_{t|t+1} = P_{t|t} - P_{t|t}f'P_{t+1|t}^{-1}fP_{t|t}$. Here f denotes the autoregressive coefficients of the transition equation 2 b in companion form, while μ_t denotes the pre-determined regressors in that equation in companion form.

2. $G\left(\tilde{B}_i \backslash \Xi\right)$: Given a draw for the factors and the variance of the idiosyncratic component, a seperate heteroscedastic linear regression model applies to each X_{it} and the standard formulae for linear regressions apply. In particular, the model for each i is

$$X_{it} = \tilde{B}_i \tilde{F}_t + h_{it}^{1/2}\varepsilon_{it}$$

   where $\tilde{F}_t = [F_t, \ln h_{it-1}, \ln h_{it-2}, ...]$. The model can be transformed to remove heteroscedasticity by creating $X_{it}^* = \frac{X_{it}}{\sqrt{h_{it}}}, \tilde{F}_t^* = \frac{\tilde{F}_t}{\sqrt{h_{it}}}$ The conditional posterior is $N\left(B_i^*, \Lambda_B\right)$ where

$$\begin{aligned} B_i^* &= \left(V_B^{-1} + \tilde{F}_t^{*\prime}\tilde{F}_t^*\right)^{-1}\left(V_B^{-1}B_{i,0} + \tilde{F}_t^{*\prime}X_{it}^*\right) \\ \Lambda_B &= \left(V_B^{-1} + \tilde{F}_t^{*\prime}\tilde{F}_t^*\right)^{-1} \end{aligned}$$

3. $G\left(h_{it} \backslash \Xi\right)$: Given a draw for the factors, the parameters of the transition equation 7 and the factor loadings $\tilde{B}_i$, a univariate stochastic volatility in mean model applies for each i:

$$\begin{aligned} X_{it} &= B_i F_t + \sum_{k=1}^{K}\rho_{i,l}\ln h_{it-l} + h_{it}^{1/2}\varepsilon_{it} \\ \ln h_{it} &= a_i + b_i \ln h_{it-1} + q_i^{1/2} n_{it} \end{aligned}$$

   The algorithm of Jacquier *et al.* (1994) (described below) is used to draw h_{it}.

4. $G(\tilde{b}\backslash\Xi)$.Given a draw of λ_t, the left and the right hand side variables of the VAR: $y_t = F_t$ and $x_t = [c, F_{t-1}, F_{t-2}, ..F_{t-j}, \lambda_t, \lambda_{t-1}, ..\lambda_{t-j}]$ can be transformed to remove the heteroscedasticity in the following manner

$$\tilde{y}_t = \frac{y_t}{\lambda_t^{1/2}}, \tilde{x}_t = \frac{x_t}{\lambda_t^{1/2}}$$

Then the conditional posterior distribution for the VAR coefficients is standard and given by

$$N(\tilde{b}^*, \bar{\Omega} \otimes (X^{*\prime}X^*)^{-1})$$

where $\tilde{b}^* = (X^{*\prime}X^*)^{-1}(X^{*\prime}Y^*), \bar{\Omega} = A^{-1}diag(S)A^{-1\prime}$ and Y^* and X^* denote the transformed data appended with the dummy observations.

5. $G(A\backslash\Xi)$. Given a draw for the VAR parameters the model can be written as $A'(v_t) = \tilde{e}_t$ where $v_t = F_t - \left(c + \sum_{j=1}^{P} \beta_j F_{t-j} + \sum_{j=1}^{J} \gamma_j \ln \lambda_{t-j}\right)$ and $VAR(\tilde{e}_t) = H_t$. This is a system of linear equations with a known form of heteroscedasticity. The conditional distributions for a linear regression apply to each equation of this system after a simple GLS transformation to make the errors homoscedastic. The jth equation of this system is given as $v_{jt} = -\alpha v_{-jt} + \tilde{e}_{jt}$ where the subscript j denotes the jth column while $-j$ denotes columns 1 to $j-1$. Note that the variance of $\tilde{e}_{jt}$ is time-varying and given by $\lambda_t S_j$. A GLS transformation involves dividing both sides of the equation by $\sqrt{\lambda_t S_j}$ to produce $v_{jt}^* = -\alpha v_{-jt}^* + \tilde{e}_{jt}^*$ where * denotes the transformed variables and $var\left(\tilde{e}_{jt}^*\right) = 1$. The conditional posterior for α is normal with mean and variance given by M^* and V^* :

$$\begin{aligned} M^* &= \left(V\left(\hat{a}^{ols}\right)^{-1} + v_{-jt}^{*\prime}v_{-jt}^*\right)^{-1}\left(V\left(\hat{a}^{ols}\right)^{-1}\hat{a}^{ols} + v_{-jt}^{*\prime}v_{jt}^*\right) \\ V^* &= \left(V\left(\hat{a}^{ols}\right)^{-1} + v_{-jt}^{*\prime}v_{-jt}^*\right)^{-1} \end{aligned}$$

6. $G(S\backslash\Xi)$. Given a draw for the VAR parameters $A'(v_t) = \tilde{e}_t$. The jth equation of this system is given by $v_{jt} = -\alpha v_{-jt} + \tilde{e}_{jt}$ where the variance of e_{jt} is time-varying and given by $\lambda_t S_j$. Given a draw for λ_t this equation can be re-written as $\bar{v}_{jt} = -\alpha\bar{v}_{-jt} + \bar{e}_{jt}$ where $\bar{v}_{jt} = \frac{v_{jt}}{\lambda_t^{1/2}}$ and the variance of $\bar{e}_{jt}$ is S_j. The conditional posterior is for this variance is inverse Gamma with scale parameter $\bar{e}_{jt}'\bar{e}_{jt} + S_{0,j}$ and degrees of freedom $V_0 + T$.

7. Elements of λ_t. Conditional on the VAR coefficients, and the parameters of the volatility transition equation, the model has a multivariate non-linear state-space representation. Carlin *et al.* (1992) show that the conditional distribution of the state variables in a general state-space model can be written as the product of three terms:

$$\tilde{h}_t\backslash Z_t, \Xi \propto f\left(\tilde{h}_t\backslash\tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1}\backslash\tilde{h}_t\right) \times f\left(Z_t\backslash\tilde{h}_t, \Xi\right) \tag{9}$$

where Ξ denotes all other parameters, Z_t denotes the endogenous variables in equation 2 and $\tilde{h}_t = \ln \lambda_t$. In the context of stochastic volatility models, Jacquier *et al.* (1994) show that this density is a product of log normal densities for λ_t and λ_{t+1} and a normal density for Z_t.Carlin *et al.* (1992) derive the general form of the mean and variance of the underlying normal density for $f\left(\tilde{h}_t\backslash\tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \propto f\left(\tilde{h}_t\backslash\tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1}\backslash\tilde{h}_t\right)$ and show that this is given as

$$f\left(\tilde{h}_t\backslash\tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \sim N\left(B_{2t}b_{2t}, B_{2t}\right) \tag{10}$$

where $B_{2t}^{-1} = Q^{-1} + F'Q^{-1}F$ and $b_{2t} = \tilde{h}_{t-1}F'Q^{-1} + \tilde{h}_{t+1}Q^{-1}F$. Note that due to the non-linearity of the observation equation of the model an analytical expression for the complete conditional $\tilde{h}_t\backslash Z_t, \Xi$ is unavailable and a metropolis step is required. Following Jacquier *et al.* (1994) we draw from 9 using a date-by-date independence metropolis step using the density in 10 as the candidate generating density. This choice implies that the acceptance probability is given by the ratio of the conditional likelihood $f\left(Z_t\backslash\tilde{h}_t, \Xi\right)$ at the old and the new draw. To implement the algorithm we begin with an initial estimate of $\tilde{h} = \ln \bar{\lambda}_t$ We set the matrix $\tilde{h}^{old}$ equal to the initial volatility estimate. Then at each date the following two steps are implemented:

   (a) Draw a candidate for the volatility $\tilde{h}_t^{new}$ using the density 9 where $b_{2t} = \tilde{h}_{t-1}^{new}F'Q^{-1} + \tilde{h}_{t+1}^{old}Q^{-1}F$ and $B_{2t}^{-1} = Q^{-1} + F'Q^{-1}F$

(b) Update $\tilde{h}_t^{old} = \tilde{h}_t^{new}$ with acceptance probability $\frac{f\left(Z_t \backslash \tilde{h}_t^{new}, \Xi\right)}{f\left(Z_t \backslash \tilde{h}_t^{old}, \Xi\right)}$ where $f\left(Z_t \backslash \tilde{h}_t, \Xi\right)$ is the likelihood of the VAR for observation t and defined as $|\Omega_t|^{-0.5} - 0.5 \exp\left(\tilde{e}_t \Omega_t^{-1} \tilde{e}_t'\right)$ where $\tilde{e}_t = F_t - \left(c + \sum_{j=1}^{P} \beta_j F_{t-j} + \sum_{j=1}^{J} \gamma_j \ln \lambda_{t-j} + \Omega_t^{1/2} e_t\right)$ and $\Omega_t = A^{-1}\left(\exp(\tilde{h}_t) S\right) A^{-1'}$

Repeating these steps for the entire time series delivers a draw of the stochastic volatilties.[1]

7. $G(\alpha, \beta, Q \backslash \Xi)$.We re-write the transition equation in deviations from the mean

$$\tilde{h}_t - \mu = \beta\left(\tilde{h}_{t-1} - \mu\right) + \eta_t \tag{11}$$

where the elements of the mean vector μ are defined as $\frac{\alpha}{1-\beta}$. Conditional on a draw for $\tilde{h}_t$ and μ the transition equation 11 is a simply a linear regression and the standard normal and inverse Gamma conditional posteriors apply. Consider $\tilde{h}_t^* = \beta \tilde{h}_{t-1}^* + \eta_t, VAR(\eta_t) = Q$ and $\tilde{h}_t^* = \tilde{h}_t - \mu, \tilde{h}_{t-1}^* = \tilde{h}_{t-1} - \mu$. The conditional posterior of β is $N(\theta^*, L^*)$ where

$$\begin{aligned}
\theta^* &= \left(L_0^{-1} + \frac{1}{Q} \tilde{h}_{t-1}^{*\prime} \tilde{h}_{t-1}^*\right)^{-1} \left(L_0^{-1} F_0 + \frac{1}{Q} \tilde{h}_{t-1}^{*\prime} \tilde{h}_t^*\right) \\
L^* &= \left(L_0^{-1} + \frac{1}{Q} \tilde{h}_{t-1}^{*\prime} \tilde{h}_{t-1}^*\right)^{-1}
\end{aligned}$$

The conditional posterior of Q is inverse Gamma with scale parameter $\eta_t' \eta_t + Q_0$ and degrees of freedom $T + V_{Q0}$.

Given a draw for β, equation 11 can be expressed as $\bar{\Delta} \tilde{h}_t = C\mu + \eta_t$ where $\bar{\Delta} \tilde{h}_t = \tilde{h}_t - \beta \tilde{h}_{t-1}$ and $C = 1 - \beta$. The conditional posterior of μ is $N(\mu^*, Z^*)$ where

$$\begin{aligned}
\mu^* &= \left(Z_0^{-1} + \frac{1}{Q} C'C\right)^{-1} \left(Z_0^{-1} \mu_0 + \frac{1}{Q} C' \bar{\Delta} \tilde{h}_t\right) \\
Z^* &= \left(Z_0^{-1} + \frac{1}{Q} C'C\right)^{-1}
\end{aligned}$$

Note that α can be recovered as $\mu(1 - \beta)$

8. $G(a_i, b_i, q_i \backslash \Xi)$. Given a draw for h_{it}, the conditional posterior distributions for the parameters of the transition equations 7 are as described in step 7.

2.3 A Monte-Carlo experiment

In order to examine the performance of this algorithm, we consider a small Monte-Carlo experiment

2.3.1 Data Generating Process

We generate data from the following FAVAR model with 2 factors:

$$X_{it} = B_i F_t + R^{1/2} \varepsilon_{it}$$

where $R = 0.1$, the factor loadings B_i are drawn from $N(0, 0.1)$ and $i = 1, 2, ...100$.

The dynamics of the factors are defined as

$$\begin{pmatrix} F_{1t} \\ F_{2t} \end{pmatrix} = \begin{pmatrix} 0.7 & 0.1 \\ -0.1 & 0.5 \end{pmatrix} \begin{pmatrix} F_{1t-1} \\ F_{2t-1} \end{pmatrix} + \begin{pmatrix} -0.5 \\ 0.5 \end{pmatrix} \ln \lambda_t + \begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix}, var \begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix} = \Omega_t$$

[1] In order to take endpoints into account, the algorithm is modified slightly for the initial condition and the last observation. Details of these changes can be found in Jacquier *et al.* (1994).

The variance process is defined as

$$\begin{aligned}
\Omega_t &= A^{-1}\left(S\lambda_t\right)A^{-1'} \\
A &= \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix} \\
S &= \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix} \\
\ln\lambda_t &= -0.1 + 0.75\ln\lambda_{t-1} + (0.5)^{\frac{1}{2}}\, v_t
\end{aligned}$$

We generate 500 observations for X_{it} and drop the first 100 observations to reduce the influenceof initial conditions. The experiment is repeated 500 times. At each iteration, the FAVAR model is estimated using the MCMC algorithm described above using 5000 iterations with a burn-in of 4000 observations. The retained draws are used to calculate the impulse response of X_{it} to a 1 standard deviation shock to $\ln\lambda_t$ for a horizon of 20 periods. In the figures below we report the difference between the cumulated response at various horizons estimated via the MCMC algorithm and the response using the true parameter values for each of the N X_{it}. The figure below shows that, on average, the difference in the estimated responses and the true responses is zero across the panel and across the different horizons considered. This provides evidence that the MCMC algorithm performs well.

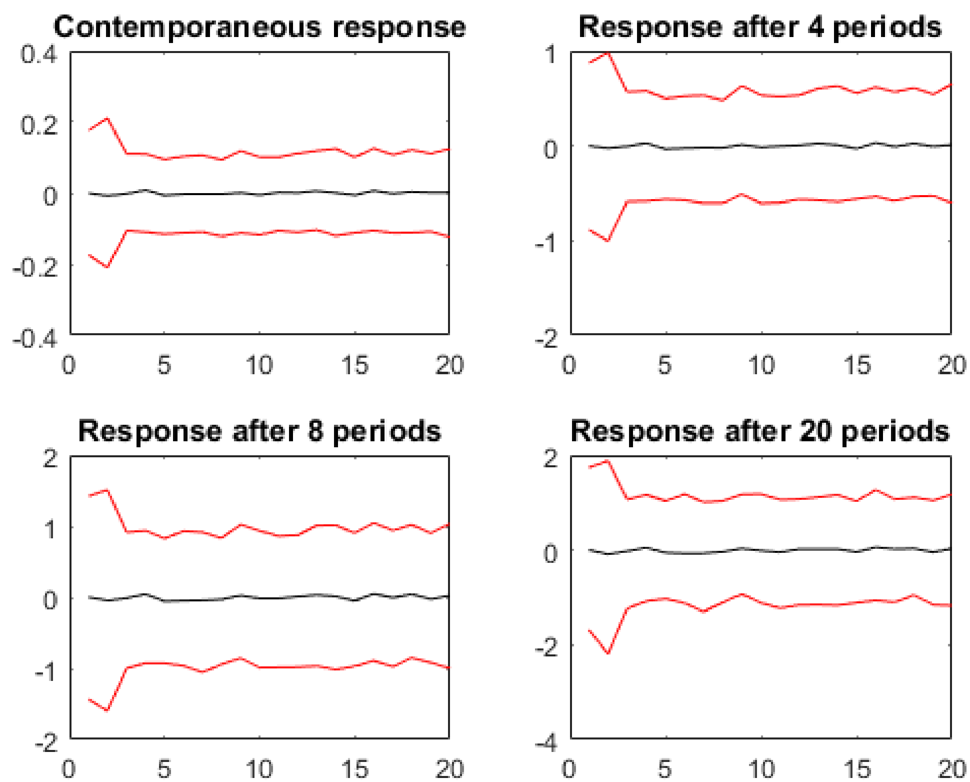

Figure 1: Monte-Carlo experiment

3 Sensitivity Analysis

3.1 Number of factors

We re-estimate the model and set the number of factors to 5. Figure 2 shows the correlation between the long run cumulated response of state-level income obtained from the five-factor model and the benchmark model.[2] The scatter plot in the figure shows that the pattern of state-level responses in this model is very similar to the benchmark case– in fact the cross-sectional correlation between the two sets of responses at this horizon is 0.8.

[2] The long run response is proxied by the cumulated response at the 40 quarter horizon

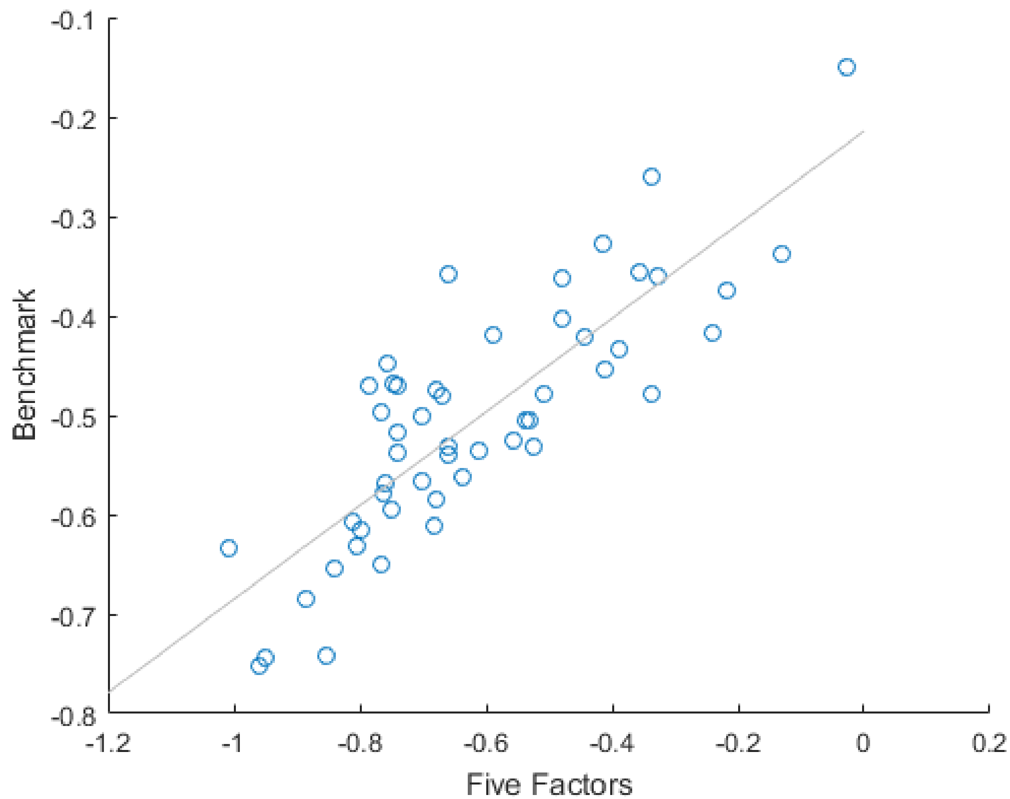

Figure 2: using five factors

3.2 Using Employment

We re-estimate the benchmark model replacing state-level real income with the growth of non-farm employment in each state. Figure 3 plots the long run cumulated responses of state-level real income from the benchmark model against the long run cumulated response of state-level employment. The figure shows that there is a high correlation (of about 70%) between the benchmark estimates and the employment responses.

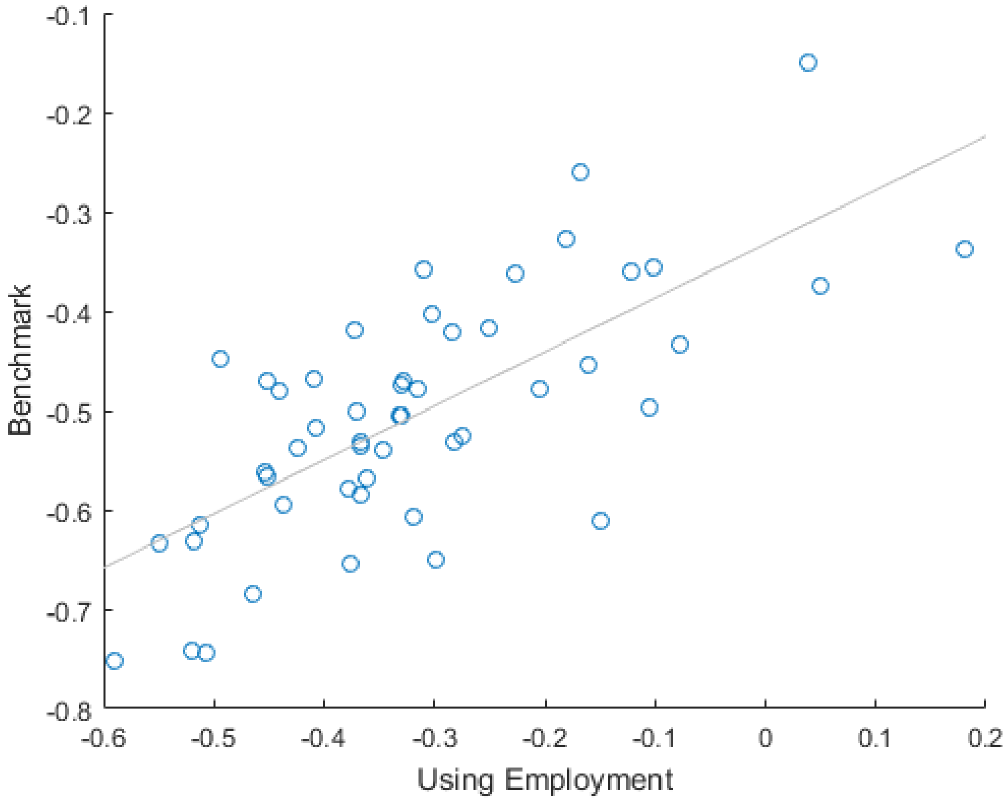

Figure 3: using Employment

3.3 Using a simple FAVAR model

We consider an alternative (and simpler) FAVAR model:

$$
\begin{aligned}
X_{it} &= B_i \tilde{F}_t + v_{it} \\
Z_t &= c + \sum_{j=1}^{P} \beta_j Z_{t-j} + e_t \\
var\,(e_t) &= \Omega = A_0 A_0'
\end{aligned}
\tag{12}
$$

where $\tilde{F}_t$ represents a set of common factors (X_{it} is the panel of data) and $Z_t = [\, \tilde{F}_t, \ln \varpi_t]$ with ϖ_t the uncertainty measure taken from Jurado *et al.* (2015). This is a standard FAVAR where $\ln \varpi_t$ is considered an observed factor. One can then calculate the response of state-level income included in X_{it} to shocks to the equation for $\ln \varpi_t$ in the VAR model $Z_t = c + \sum_{j=1}^{P} \beta_j Z_{t-j} + e_t$. We assume that A_0 is the Cholesky decomposition of Ω with the ordering $[\, \tilde{F}_t, \ln \varpi_t]$ that is consistent with our benchmark model. We use three factors as in the benchmark model, setting the lag length to 4.

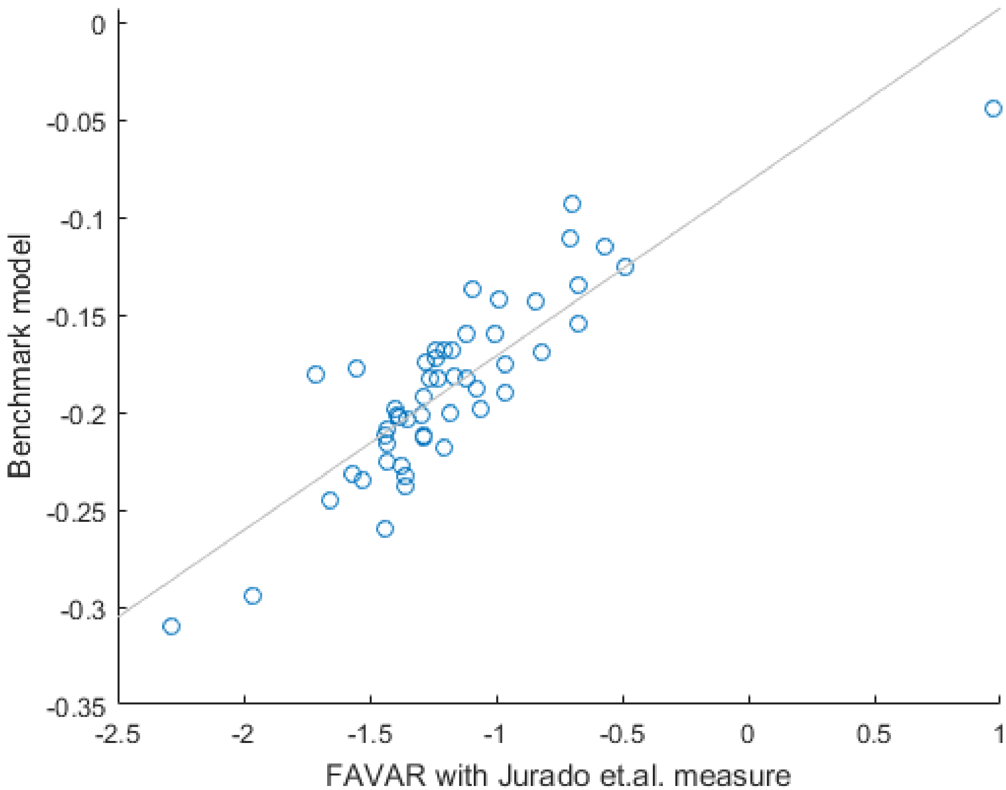

Figure 4: using a simple FAVAR

In Figure 4 we compare the cumulated response of the state-level income to a one standard deviation uncertainty shock (at the 2 year horizon) obtained from this FAVAR (using the Jurado *et al.* (2015) measure of uncertainty) with the same response obtained from the benchmark model in the paper. The x-axis shows the 51 state-level responses from the FAVAR model (using the Jurado *et al.* (2015) measure of uncertainty) while y-axis shows the 51 state-level responses from the benchmark model. It is clear from the scatter plot that the FAVAR delivers a pattern of responses very similar to the Benchmark model with a correlation coefficient of 0.86 between the two cross-sections. This is re-assuring as it provides further support for the results in the paper. Notice, however, that while the cross-state pattern delivered by the models is similar, there is a large difference in the scale of the responses. The simple FAVAR delivers responses with a larger magnitude for all states.[3] Recall that a key difference between this FAVAR and our proposed model is the fact that the observation equation of this model $X_{it} = B_i \tilde{F}_t + v_{it}$ does not account for the impact of idiosyncratic/State-specific uncertainty shocks which are proxied by the term $\sum_{k=1}^{K} \rho_{k,i} \ln h_{it-k}$ in the observation equation of the proposed model. This omission may explain why the simpler model indicates that aggregate uncertainty shocks have quite large effects on state-level income, a result that may simply reflect a statistical bias.

3.4 Robustness of the cross section results

Table (1) documents further evidence on the industry mix effects on the state response to uncertainty shocks, after controling for our baseline effects. Column 1 is the baseline specification. Column 2 shows that oil and mining have very similar effects. Columns 3 through 5 show that agriculture, financial services and housing sectors are not important once we have controlled for our baseline mix. Column 6 shows that construction is only significant once we control for the effects of budget deficts and intergovernment transfers.

Table (2) explores the roles of regressors used in the literature on explaining state-level heterogeneity. Column 1 is again the baseline specification. We next investigate where the prevalence of small banks plays an important role. Columns 2 and 3 include as regressors the fraction of loans extended by small banks where small is defined as at

[3] This result does not depend on the scale of the shock. That is, if the shock is scaled to be exactly the same in the two models, the same results are obtained.

	(1)	(2)	(3)	(4)	(5)	(6)
Manufacturing	-0.379***	-0.381***	-0.404***	-0.382***	-0.386***	-0.260***
	(0.080)	(0.075)	(0.083)	(0.095)	(0.091)	(0.080)
Mining	0.475***		0.441***	0.470***	0.461***	0.426***
	(0.099)		(0.113)	(0.117)	(0.120)	(0.126)
Oil		0.493***				
		(0.099)				
Home vacancy rate	-2.742***	-2.834***	-2.928***	-2.750***	-2.769***	-3.833***
	(0.866)	(0.820)	(0.918)	(0.882)	(0.902)	(0.881)
Right to work	-0.028***	-0.025**	-0.024*	-0.029**	-0.030**	-0.027***
	(0.009)	(0.010)	(0.013)	(0.012)	(0.012)	(0.009)
Small firms (< 250)	-0.443***	-0.374**	-0.395**	-0.448***	-0.444***	-0.254*
	(0.136)	(0.139)	(0.179)	(0.161)	(0.141)	(0.142)
Budget deficit	-0.132**	-0.090**	-0.127*	-0.131**	-0.131**	
	(0.063)	(0.044)	(0.063)	(0.064)	(0.063)	
Intergov't transfers	0.193**	0.198**	0.193**	0.193**	0.190**	
	(0.073)	(0.076)	(0.074)	(0.072)	(0.071)	
Construction	-2.421***	-2.193***	-2.459***	-2.438***	-2.394***	-1.178
	(0.701)	(0.657)	(0.710)	(0.743)	(0.710)	(0.730)
Agriculture			-0.147			
			(0.215)			
Financial services				-0.015		
				(0.199)		
Real estate					-0.063	
					(0.268)	
Observations	50	50	50	50	50	51
Adjusted R^2	0.719	0.675	0.716	0.712	0.712	0.630

All models include regional dummies. Dependent variable: IRF at 2 year horizon

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 1: Industry Mix

or below the 90th and 70th, respectively, percentile of the national asset distribution of financial institutions. Both have negative, but not significant effects. Column 4 includes as a regressor the share of employment accounted for by small establishments, where small is defined as establishments with less than 10 employees rather than 250 as in the baseline. The effect is significant but less so that for the baseline measure. Finally column 6 is the specification used in Carlino, which does not include our baseline controls, but only the manufacturing share, small banks and small firms measures. Neither the bank nor the firm measure are significant.

Table (3) further investigates the role of various aspects of state government finances in driving the uncertainty shock responses. Comparing to the baseline specification in column 1, columns 2 and 3 show that the size of the public sector in state GDP matters conditionally on budget deficits and intergovernmental transfers. It ameliorates the state response to an uncertainty shock. Column 3 through 6 show that expenditures on unemployment insurance, welfare programs and government debt have no significant effects on state-level uncertainty shock responses.

Table (4) shows in column 2 that an alternative measure of labor market flexibility, union membership, mirrors the effect of right to work legislation but is not significant. Column 3 and 4 show that business creation as measured by the net entry rate of establishments is not significant once controlling for the share of construction in GDP - the two measures are highly correlated across states.

Table (5) shows that alternative measures of housing market conditions have comparable effects as our baseline measure of home vacancy rate. Specifically, home ownership rates, rental vacancy rates or their volatility are significant and negative - they exacerbate the state IRF to uncertainty shocks - with the only exception being the home ownership rate which turns out to be insignificant.

Table (6) shows that our results are robust to considering the uncertainty shock response at different horizons from 1 quarter to 4 years. At very short horizons of 1 quarter, the confidence intervals around the responses are wider and some effects insignificant although qualitatively comparable to the longer horizons. For all but the very shortest horizon, the results are both qualitatively and quantitatively robust.

Table (7) compares the benchmark regression estimates (first column) with those obtained when the two year cumulated IRFs from the simple FAVAR are used (second column). It is clear that the sign of the coefficients is the same across specifications. The magnitude of the coefficients differs as the magnitude of the responses obtained from the simple FAVAR is larger.

4 Data

4.1 Data for FAVAR

The FAVAR model includes 91 Macroeconomic and Financial time-series and real personal income for 51 states. The data for total personal income for each state is obtained from FRED. These series are divided by CPI and then transformed by taking the log difference and multiplying by 100. The table below lists the 91 Macroeconomic and Financial time-series. In terms of the data sources GFD refers to Global Financial Database, FRED is the Federal Reserve Bank of St Louis database. D denotes the log difference transformation (times 100), while N denotes no transformation.

	(1)	(2)	(3)	(4)	(5)
Manufacturing	-0.379***	-0.379***	-0.385***	-0.379***	-0.477***
	(0.080)	(0.082)	(0.082)	(0.091)	(0.106)
Mining	0.475***	0.488***	0.490***	0.447***	
	(0.099)	(0.099)	(0.099)	(0.104)	
Home vacancy rate	-2.742***	-2.734***	-2.709***	-2.483**	
	(0.866)	(0.874)	(0.878)	(0.920)	
Right to work	-0.028***	-0.027***	-0.027***	-0.025**	
	(0.009)	(0.010)	(0.009)	(0.010)	
Small firms (< 250)	-0.443***	-0.410**	-0.416***		0.249
	(0.136)	(0.160)	(0.152)		(0.227)
Budget deficit	-0.132**	-0.138**	-0.137**	-0.118*	
	(0.063)	(0.061)	(0.061)	(0.062)	
Intergov't transfers	0.193**	0.184**	0.183**	0.200***	
	(0.073)	(0.077)	(0.077)	(0.068)	
Construction	-2.421***	-2.367***	-2.472***	-1.768**	
	(0.701)	(0.733)	(0.699)	(0.857)	
Small banks ($\leq 90^{th}$ pctile)		-0.011			-0.018
		(0.022)			(0.022)
Small banks ($\leq 70^{th}$ pctile)			-0.021		
			(0.037)		
Small firms (< 10)				-0.404*	
				(0.208)	
Observations	50	50	50	50	51
Adjusted R^2	0.719	0.714	0.714	0.682	0.312

All models include regional dummies. Dependent variable: IRF at 2 year horizon

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2: Financial Frictions

	(1)	(2)	(3)	(4)	(5)	(6)
Manufacturing	-0.379***	-0.313***	-0.201*	-0.388***	-0.387***	-0.379***
	(0.080)	(0.078)	(0.100)	(0.084)	(0.092)	(0.079)
Mining	0.475***	0.520***	0.434***	0.468***	0.480***	0.468***
	(0.099)	(0.088)	(0.119)	(0.100)	(0.098)	(0.104)
Home vacancy rate	-2.742***	-2.608***	-3.883***	-2.571***	-2.731***	-2.975***
	(0.866)	(0.866)	(0.874)	(0.894)	(0.899)	(0.959)
Right to work	-0.028***	-0.031***	-0.027***	-0.030***	-0.029***	-0.031***
	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)	(0.011)
Small firms (< 250)	-0.443***	-0.504***	-0.233*	-0.463***	-0.445***	-0.452***
	(0.136)	(0.108)	(0.136)	(0.134)	(0.135)	(0.137)
Budget deficit	-0.132**	-0.101*		-0.135**	-0.130*	-0.129*
	(0.063)	(0.054)		(0.066)	(0.067)	(0.066)
Intergov't transfers	0.193**	0.134*		0.187**	0.192**	0.201**
	(0.073)	(0.077)		(0.073)	(0.076)	(0.081)
Construction	-2.421***	-2.685***	-0.859	-2.517***	-2.510***	-2.339***
	(0.701)	(0.630)	(0.863)	(0.669)	(0.771)	(0.717)
Public sector		0.405***	0.123			
		(0.134)	(0.148)			
Unemployment insurance				-1.150		
				(1.087)		
Assistance/subsidies					0.358	
					(1.141)	
Gov't debt						-0.016
						(0.027)
Observations	50	50	51	50	50	50
Adjusted R^2	0.719	0.744	0.628	0.716	0.713	0.714

All models include regional dummies. Dependent variable: IRF at 2 year horizon

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Government Finance

	(1)	(2)	(3)	(4)
Manufacturing	-0.379***	-0.417***	-0.379***	-0.317***
	(0.080)	(0.100)	(0.083)	(0.085)
Mining	0.475***	0.433***	0.454***	0.391***
	(0.099)	(0.104)	(0.087)	(0.086)
Home vacancy rate	-2.742***	-2.641***	-2.619***	-2.769***
	(0.866)	(0.967)	(0.876)	(0.890)
Right to work	-0.028***		-0.029***	-0.029***
	(0.009)		(0.009)	(0.009)
Small firms ($<$ 250)	-0.443***	-0.298*	-0.452***	-0.424***
	(0.136)	(0.164)	(0.139)	(0.145)
Budget deficit	-0.132**	-0.173**	-0.119*	-0.090
	(0.063)	(0.076)	(0.064)	(0.072)
Intergov't transfers	0.193**	0.206***	0.180**	0.156**
	(0.073)	(0.073)	(0.081)	(0.077)
Construction	-2.421***	-1.955**	-1.943*	
	(0.701)	(0.784)	(0.979)	
Union membership		0.001		
		(0.001)		
Net estab. entry rate			-0.800	-2.286**
			(1.309)	(1.014)
Observations	50	50	50	50
Adjusted R^2	0.719	0.684	0.715	0.701

All models include regional dummies. Dependent variable: IRF at 2 year horizon

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Labour Market

	(1)	(2)	(3)	(4)	(5)	(6)
Manufacturing	-0.379***	-0.430***	-0.457***	-0.453***	-0.396***	-0.416***
	(0.080)	(0.080)	(0.107)	(0.080)	(0.075)	(0.078)
Mining	0.475***	0.365***	0.511***	0.507***	0.523***	0.552***
	(0.099)	(0.104)	(0.104)	(0.099)	(0.098)	(0.103)
Home vacancy rate	-2.742***					
	(0.866)					
Right to work	-0.028***	-0.030***	-0.034***	-0.027***	-0.019**	-0.021*
	(0.009)	(0.008)	(0.011)	(0.010)	(0.009)	(0.011)
Small firms (< 250)	-0.443***	-0.318**	-0.362**	-0.356***	-0.458***	-0.421***
	(0.136)	(0.132)	(0.162)	(0.123)	(0.146)	(0.151)
Budget deficit	-0.132**	-0.125**	-0.127*	-0.156**	-0.167**	-0.176**
	(0.063)	(0.055)	(0.066)	(0.063)	(0.067)	(0.071)
Intergov't transfers	0.193**	0.130*	0.226***	0.201**	0.237***	0.265***
	(0.073)	(0.065)	(0.077)	(0.080)	(0.068)	(0.074)
Construction	-2.421***	-1.842**	-3.137***	-2.404***	-2.653***	-2.861***
	(0.701)	(0.870)	(0.926)	(0.722)	(0.672)	(0.659)
Home vacancy rate (sd)		-0.121***				
		(0.030)				
Home ownership rate			0.044			
			(0.135)			
Home ownership rate (sd)				-0.021**		
				(0.010)		
Rental vacancy rate					-1.123***	
					(0.351)	
Rental vacancy rate (sd)						-0.012**
						(0.005)
Observations	50	50	50	50	50	50
Adjusted R^2	0.719	0.749	0.674	0.704	0.727	0.705

All models include regional dummies. Dependent variable: IRF at 2 year horizon

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: Housing Market

	(1) IRF 1qt	(2) IRF 3yr	(3) IRF 4yr
Manufacturing	-0.035***	-0.574***	-0.667***
	(0.010)	(0.117)	(0.136)
Mining	0.038***	0.703***	0.818***
	(0.011)	(0.154)	(0.191)
Home vacancy rate	-0.064	-4.373***	-5.568***
	(0.105)	(1.333)	(1.626)
Right to work	-0.003**	-0.036**	-0.038**
	(0.001)	(0.013)	(0.016)
Small firms ($<$ 250)	-0.035***	-0.641***	-0.727***
	(0.013)	(0.208)	(0.261)
Budget deficit	-0.016**	-0.191**	-0.209*
	(0.008)	(0.093)	(0.111)
Intergov't transfers	0.011	0.301***	0.371***
	(0.007)	(0.108)	(0.126)
Construction	-0.149*	-3.835***	-4.826***
	(0.077)	(1.138)	(1.458)
Observations	50	50	50
Adjusted R^2	0.545	0.715	0.704

All models include regional dummies

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: Using IRFs at different horizons

	(1) IRF 2yr	(2) IRF 2yr sensitivity
Manufacturing	-0.379***	-1.481
	(0.080)	(0.913)
Mining	0.475***	4.993***
	(0.099)	(1.245)
Home vacancy rate	-2.742***	-14.171
	(0.866)	(9.135)
Right to work	-0.028***	-0.251**
	(0.009)	(0.105)
Small firms (< 250)	-0.443***	-4.091**
	(0.136)	(1.729)
Budget deficit	-0.132**	-1.468*
	(0.063)	(0.765)
Intergov't transfers	0.193**	0.797
	(0.073)	(0.618)
Construction	-2.421***	-3.073
	(0.701)	(7.004)
Observations	50	50
Adjusted R^2	0.719	0.660

All models include regional dummies

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: Comparison using IRFs from the simple FAVAR

Table 8: Data for the factor model.

Variable	Description	Source	Transformation
1	Industrial Production	FRED	D
2	Industrial Production: Business Equipment	FRED	D
3	Industrial Production: Consumer Goods	FRED	D
4	Industrial Production: Durable Consumer Goods	FRED	D
5	Industrial Production: Durable Materials	FRED	D
6	Industrial Production: Final Products (Market Group)	FRED	D
7	Industrial Production: Final Products and Nonindustrial Supplies	FRED	D
8	Industrial Production: Manufacturing	FRED	D
9	Industrial Production: Materials	FRED	D
10	Industrial Production: Nondurable Consumer Goods	FRED	D
11	Dow Jones Industrial Index	GFD	D
12	GDP Deflator	FRED	N
13	ISM Manufacturing: New Orders Index	FRED	N
14	ISM Manufacturing: Inventories Index	FRED	N
15	ISM Manufacturing: Supplier Deliveries Index	FRED	N
16	ISM Manufacturing: PMI Composite Index	FRED	N
17	ISM Manufacturing: Employment Index	FRED	N
18	ISM Manufacturing: Production Index	FRED	N
19	ISM Manufacturing: Prices Index	FRED	N
20	Employment	FRED	D
21	All Employees: Construction	FRED	D
22	All Employees: Financial Activities	FRED	D
23	All Employees: Goods-Producing Industries	FRED	D
24	All Employees: Government	FRED	D
25	All Employees: Trade, Transportation and Utilities	FRED	D
26	All Employees: Retail Trade	FRED	D
27	All Employees: Wholesale Trade	FRED	D
28	All Employees: Durable goods	FRED	D
29	All Employees: Manufacturing	FRED	D
30	All Employees: Nondurable goods	FRED	D
31	All Employees: Service-Providing Industries	FRED	D

Table 8: Data for the factor model.

32	All Employees: Total Nonfarm Payrolls	FRED	D
33	Real personal income excluding current transfer receipts	FRED	D
34	Business Conditions Index	GFD	N
35	Imports	Fred	D
36	Exports	Fred	D
37	Real Government Spending	Fred	D
38	Real Tax revenues	Fred	D
39	Business Investment	Fred	D
40	Real Consumption Expenditure	Fred	D
41	Real GDP	Fred	D
42	Unemployment Rate	Fred	N
43	Number of Civilians Unemployed for 15 Weeks and Over	Fred	D
44	Number of Civilians Unemployed for 15 to 26 Weeks	Fred	D
45	Number of Civilians Unemployed for 27 Weeks and Over	Fred	D
46	Number of Civilians Unemployed for 5 to 14 Weeks	Fred	D
47	Number of Civilians Unemployed for Less Than 5 Weeks	Fred	D
48	Average (Mean) Duration of Unemployment	Fred	D
49	Average Weekly Hours	Fred	D
50	Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	Fred	D
51	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing	Fred	D
52	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction	Fred	D
53	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	Fred	D
54	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	Fred	D
55	Civilian Labour Force	Fred	D
56	Civilian Participation Rate	Fred	D
57	Unit Labour Cost	Fred	D

Table 8: Data for the factor model.

58	Nonfarm Business Sector: Real Compensation Per Hour	Fred	D
59	M2 Money	Fred	D
60	Total Consumer Credit Owned and Securitized, Outstanding	Fred	D
61	Commercial and Industrial Loans, All Commercial Banks	Fred	D
62	Real Estate Loans, All Commercial Banks	Fred	D
63	Producer Price Index for All Commodities	Fred	D
64	Producer Price Index by Commodity Metals and metal products: Primary nonferrous metals	Fred	D
65	Producer Price Index by Commodity for Crude Materials for Further Processing	Fred	D
66	Producer Price Index by Commodity for Finished Consumer Goods	Fred	D
67	Producer Price Index by Commodity for Finished Goods	Fred	D
68	Producer Price Index by Commodity Intermediate Materials: Supplies and Components	Fred	D
69	Consumer Price Index	Fred	D
70	Consumer Price Index for All Urban Consumers: Apparel	Fred	D
71	Consumer Price Index for All Urban Consumers: Medical Care	Fred	D
72	Consumer Price Index for All Urban Consumers: All items less shelter	Fred	D
73	Personal Consumption Expenditures: Chain-type Price Index	Fred	D
74	3 Month Treasury Bill Rate	Fred	N
75	10 year Govt Bond Yield minus 3mth T-bill rate	GFD	N
76	6mth T-Bill rate minus 3mth T-bill rate	GFD	N
77	1 year Govt Bond Yield minus 3mth T-bill rate	GFD	N
78	5 year Govt Bond Yield minus 3mth T-bill rate	GFD	N
79	Commodity Price Index	GFD	D
80	West Texas Intermediate Oil Price	GFD	D

Table 8: Data for the factor model.

81	BAA Corporate Spread	GFD	N
82	AAA Corporate Bond Spread	GFD	N
83	S&P500 Total Return Index	GFD	D
84	NYSE Stock Market Capitalization	GFD	D
85	S&P500 P/E Ratio	GFD	N
86	Pound dollar Exchange Rate	GFD	D
87	US and Canadian Dollar exchange rate	GFD	D
88	US dollar and German Mark exchange rate	GFD	D
89	Us Dollar and Japanese Yen Exchange Rate	GFD	D
90	Nasdaq Composite	GFD	D
91	NYSE Composite	GFD	D

4.2 Data for Cross-section Analysis

- 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 250 employees. We aggregate to the state level, and average over time.
- Industry shares of GDP (oil, agriculture, finance, manufacturing): 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 debt, deficit and intergovernmental transfers: State government sources of revenues and expenditures, annual 1992 to 2013, average over time. Source: Census Bureau. Intergovernment transfers are the sum of transfers to/from federal and local governments.
- Homeownership rate: Home ownership rates, quarterly 2005Q1-2015Q4, standard deviation over time. Source: Census Bureau.
- Union membership as a share of nonagricultural employment by state, average of 1984 and 2000. Source: Barry T. Hirsch (2001)
- Business creation: Net entry rate of establishments, 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/.

5 Recursive means of retained draws

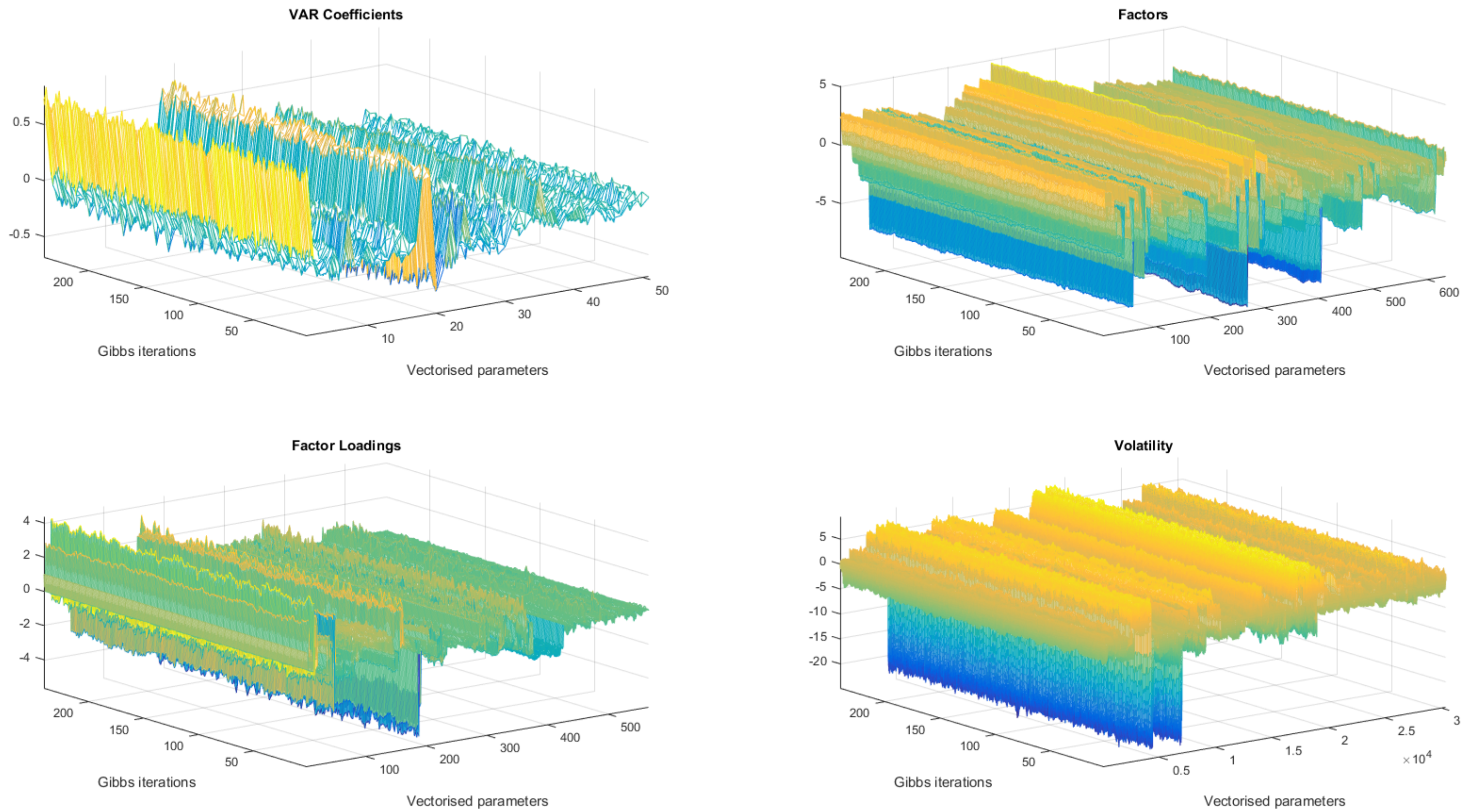

Figure 1: Recursive means calculated every 20 draws

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