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# The State Level Impact of Uncertainty Shocks

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## Abstract

This paper uses a FAVAR model with stochastic volatility to estimate the impact of uncertainty shocks on real income growth in US states. The results suggest that there is a large degree of heterogeneity in the magnitude and the persistence of the response to uncertainty shocks across states. The response is largest in Michigan, Indiana and Arkansas while the real income in New York, Alaska and New Mexico seems least sensitive to uncertainty. We relate the cross section of responses to state-level characteristics and find that the magnitude of the decline in income is largest in states with a large share of manufacturing, agriculture and construction industries, a high fiscal deficit and a more volatile housing market. In contrast, a higher share of mining industries and larger inter-governmental fiscal transfers ameliorate the impact of uncertainty.

JEL Codes: C15, C32, E32

Key Words: FAVAR, Stochastic Volatility, Uncertainty Shocks, Regional effects

## 1 Introduction

The recent financial crisis and ensuing recession have led to a renewed interest in the impact of uncertainty shocks. A number of proxies for uncertainty have been proposed in the recent literature and several papers use VAR based analyses to estimate the impact of uncertainty shocks (see for example Bloom (2009) and

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Jurado *et al.* (2013) ). In addition, a growing DSGE based literature has documented the transmission mechanism of these shocks from a theoretical point of view (see for example Fernandez-Villaverde *et al.* (2015)).

Overall, the empirical literature on this subject provides strong evidence that uncertainty shocks can have a significant adverse impact on the economy. For example, the analysis in Bloom (2009) suggests that a unit increase in uncertainty leads to a 1% decline in US industrial production and similar results are reported in related papers.

However, the estimates reported in these papers typically focus on the impact on aggregate data for the US. To our knowledge, the impact of uncertainty shocks at the level of US states has remained unexplored in the literature. This is surprising given the strong evidence that points to structural differences across US states. For example, the literature on the regional impact of monetary policy shocks (see Carlino and Defina (1998) amongst others), shows that states differ substantially in terms of the type and concentration of industry, the banking sector and the degree of credit frictions. These differences make it likely that their response to US-wide uncertainty shocks may also differ.

This paper attempts to fill this gap in the literature. We propose an extended factor augmented VAR (FAVAR) model that allows the estimation of a measure of uncertainty that encompasses volatility from the real and financial sectors of the economy and is a proxy for macroeconomic uncertainty. The proposed FAVAR model allows this measure of uncertainty to affect state-level real income while accounting for the possible impact of idiosyncratic uncertainty shocks. We find that the impact of uncertainty shocks differs markedly across states. The magnitude and persistence of the response is estimated to be the largest in Michigan, Indiana and Arizona, with income declining by about 0.3% and the impact persisting for more than three years. In contrast, the uncertainty shock has a smaller impact on states such as New York, Alaska and New Mexico. We then investigate which state-specific characteristics can explain the heterogeneous impact of uncertainty shocks. We find that income in states characterised by a larger share of manufacturing, agriculture and construction industries, a high fiscal deficit to expenditure ratio and more volatile housing market appears to be affected to a larger degree by these shocks. In contrast, a higher share of mining/oil and gas industries and larger inter-governmental fiscal transfers mitigate the impact of uncertainty.

The analysis in the paper adds to the literature on uncertainty by systematically investigating how the impact of uncertainty differs across US states. The empirical model proposed in the paper builds upon existing VAR and FAVAR models by simultaneously allowing the estimation of time-varying volatility and the impact of this volatility on a large number of state-level and aggregate variables.

The paper is organised as follows: Sections 3 and 4 introduce the empirical model and discuss the estimation method. The results from the FAVAR model are presented in Section 5. In section 6 we relate the state-level impulse responses to various characteristics of the states. Finally, section 7 concludes.

## 2 Sources of heterogeneity in the response to uncertainty shocks

Recent theoretical research on the transmission of uncertainty shocks has highlighted a number of factors that may affect the magnitude of the response to uncertainty shocks. As discussed below these factors vary in intensity and importance across US states thus making it likely that the response to uncertainty shocks is heterogeneous.

### 2.1 Financial frictions

A number of recent papers have argued that uncertainty affects the economy mainly through its impact on financial markets (see for example Christiano *et al.* (2014) and Gilchrist *et al.* (2014)). According to this view, if financial markets are subject to moral hazard, uncertainty shocks can affect investment through their impact on the external finance premium. This implies that the magnitude of the impact of these shocks may be linked to the intensity of financial frictions. Empirical evidence at the aggregate US level supporting this view has been presented recently in Alessandri and Mumtaz (2014) who show that uncertainty shocks have a larger impact during periods of financial stress.

There is some evidence to suggest that the degree of financial frictions also differs markedly across states. Simple proxies that attempt to capture the intensity of these frictions appear to vary by state. For example, figure 1 (based on an updated version of the data reported in Carlino and Defina (1998) ) shows the proportion of lending by small banks, where these are defined as those below the 90th percentile in terms of assets. As is well known from the work of Kashyap and Stein (1995), the size of banks may affect

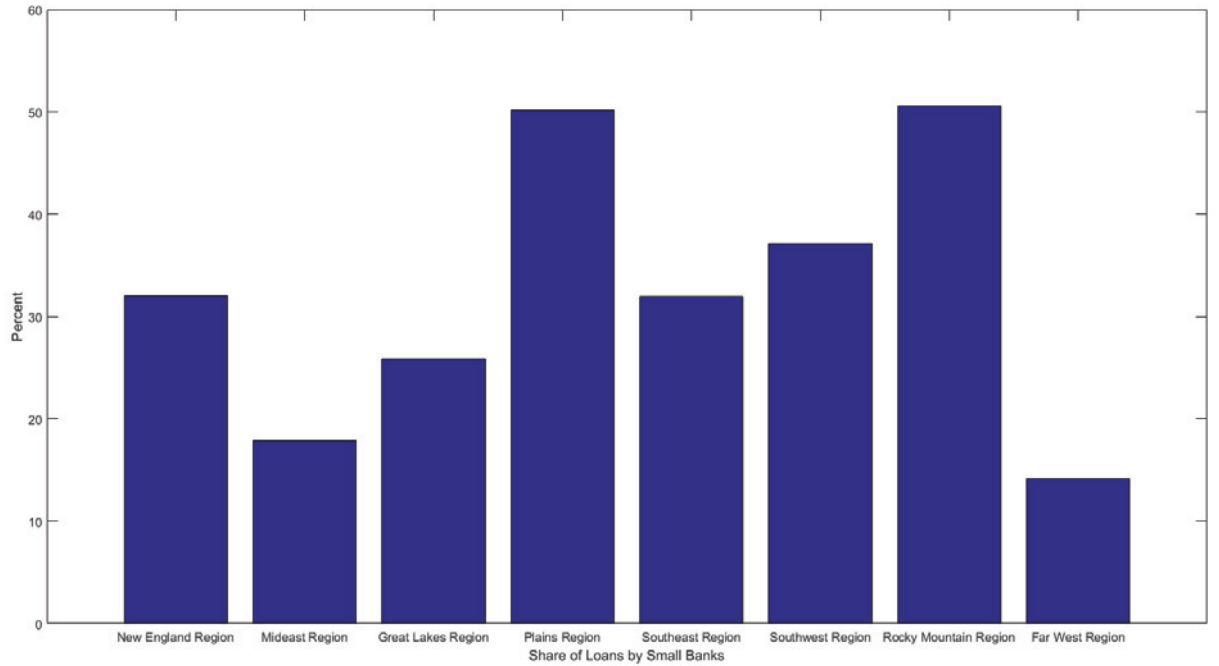


Figure 1: Share of total loans made by small banks

their ability to finance their lending with larger banks expected to have access to more sources of funding. Figure 1 shows that the proportion of lending varies substantially across US regions. This provides prima facie evidence that some states may face a higher degree of credit frictions. A similar picture is suggested by measures of the ‘broad credit channel’ which emphasises the vulnerability of small firms to information asymmetries problems. That is, the importance of small firms also varies substantially across regions with these establishments providing the largest share of employment in the Far West and Rocky Mountain region. In addition, it is likely that the structure of housing markets varies substantially across states, with these differences possibly contributing to heterogenous behaviour of agents in response to uncertainty shocks.

## 2.2 Industry composition

If uncertainty shocks have a large impact on the financial markets, they are likely to affect states with a heavier concentration of the financial and real-estate sector. Similarly, the response of commodity prices (for e.g. oil) to an uncertainty shock may affect those states which are more exposed to these price fluctuations

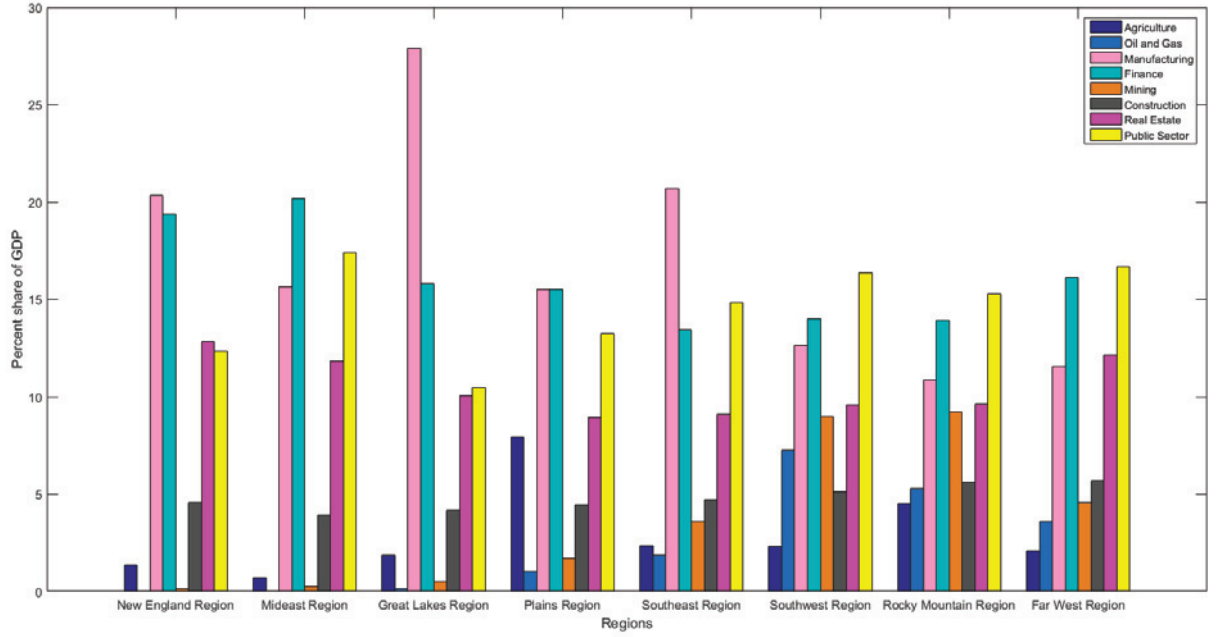


Figure 2: Share of GDP by industry. Average over the period 1963-2014

due to heavier concentration of oil and gas and mining industries. Moreover, as pointed out in Carlino and Defina (1998), the manufacturing industry might be more sensitive to changes in the short-term interest rate. If uncertainty shocks affect interest rates (perhaps via the reaction function of the Fed), then the cumulative impact of these shocks may be larger in regions where manufacturing is more dominant. In figure 2 we plot the share of GDP accounted for by key industries within US regions. It is clear from the figure that industry concentration is quite heterogeneous. For example, manufacturing accounts for a large share in the Great Lakes region, finance is important in the Mid-East, agriculture in the Plains while the mining, oil and gas and construction is concentrated in the Far/South West and the Rocky Mountain regions.

### 2.3 State-Level fiscal indicators

As discussed in Owyang and Zubairy (2013), US states also differ substantially in terms of fiscal indicators. This is clear from figure 3 which shows, for example, that the proportion of expenditure on unemployment insurance varies from about 0.3% in the Plains region to greater than 0.6% in the Mid East. The debt to total expenditure ratio is close to 80% in New England while being relatively low in the South East and

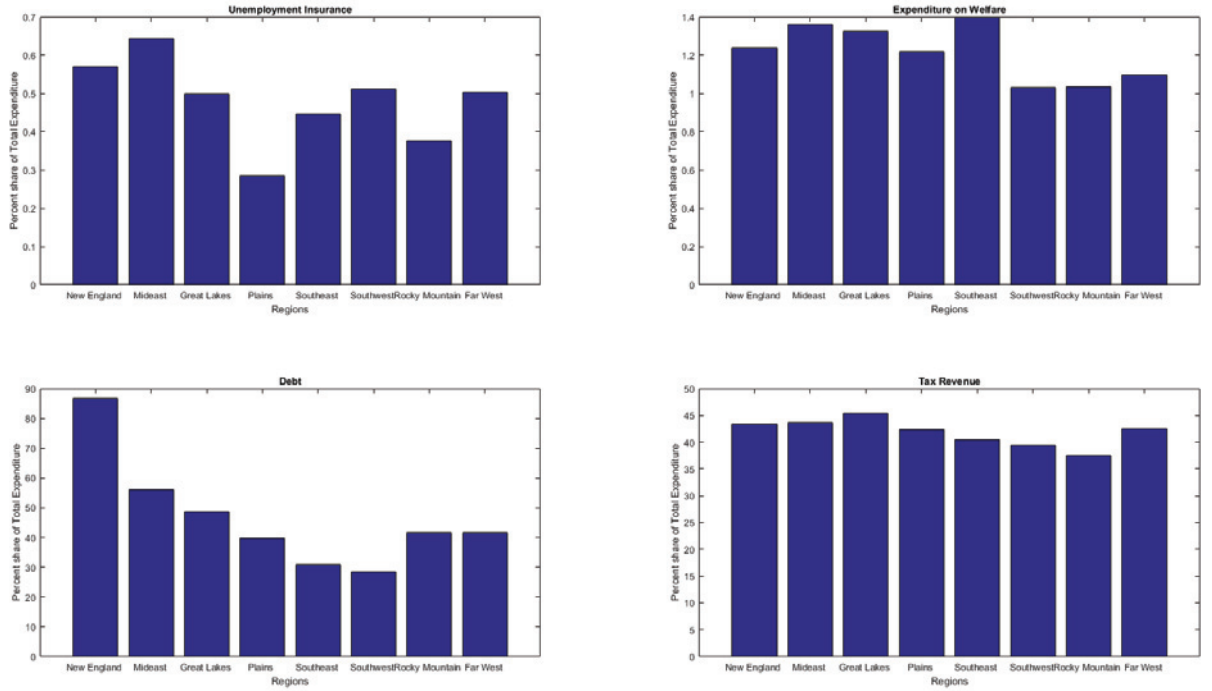


Figure 3: Fiscal indicators for US regions

South West regions. There also appears to be some variation in welfare spending and tax revenue. State-level differences in fiscal capacity may also contribute to heterogeneity in the response to uncertainty shocks. For example, the magnitude of the impact of uncertainty shocks may be affected by the level of support available for agents when faced with a drop in income or employment prospects. In addition, as noted by Carriere-Swallow and Céspedes (2013), fiscal policies may also influence the degree to which state-level credit frictions can amplify the impact of uncertainty.

## 2.4 Labour market rigidities

Heterogeneity in the degree of labour market rigidities across the US can also be an important determinant of the magnitude of the impact of uncertainty. As emphasised in recent theoretical work on uncertainty shocks (see for e.g. Leduc and Liu (2012)), labour market frictions can play an important role in determining the magnitude of the effect of uncertainty shocks on employment. If labour market are rigid, the impact of a decline in aggregate demand after an uncertainty shock may be magnified if delays in hiring and firing reduce

the job-finding rate. On the other hand, a more rigid labour market may imply that the initial negative impact of uncertainty shocks is mitigated to a degree.

In summary, there are a number of reasons to suggest that the impact of uncertainty shocks is heterogeneous across US states. In the sections below, we first estimate the response of real income in each state to this shock. We then investigate if the differences in the response across states can be explained by some of the factors discussed above.

### 3 Empirical model

In this section we propose an empirical model that can be used to extract a measure of US-wide uncertainty while simultaneously allowing the estimation of the impact of uncertainty shocks on aggregate and state-level US variables. The core of this empirical model is the following vector autoregression:

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

where  $F_t$  is a set of unobserved common factors described below that effectively summarise the state of the US economy and capture the co-movement in state-level data. As in Cogley and Sargent (2005), the covariance matrix of the residuals is defined as:

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

where  $A$  is lower triangular.

Following Carriero *et al.* (0), the volatility of the shocks  $e_t$  is given by:

$$\begin{aligned} H_t &= \lambda_t S \\ S &= \text{diag}(s_1, \dots, s_N) \end{aligned} \quad (2)$$



The overall volatility evolves as an AR(1) process:

$$\ln \lambda_t = \alpha + \beta \ln \lambda_{t-1} + Q^{1/2} \eta_t \quad (3)$$

and the diagonal elements of  $S$  are scaling factors.

The factors  $F_t$  are linked to the observed data  $X_{it}$  via the following observation equation:

$$X_{it} = B_i F_t + \sum_{k=1}^K \rho_{k,i} \ln h_{it-k} + v_{it} \quad (4)$$

As described below,  $X_{it}$  contains both aggregate US data covering real activity, inflation and the financial sector and real personal income for each state. The idiosyncratic shock is assumed to be heteroscedastic

$$v_{it} = R_t^{1/2} \varepsilon_{it} \quad (5)$$

with  $R_t = \text{diag}(h_{1t}, \dots, h_{Nt})$  and

$$\ln h_{it} = a_i + b_i \ln h_{it-1} + q_i^{1/2} n_{it} \quad (6)$$

The FAVAR model described by equations 1 to 6 has a number of distinctive features. First, the model allows for time-variation in the volatility of idiosyncratic errors  $v_{it}$  and in the volatility of shocks to the common components  $e_t$ . The time-varying volatility of  $v_{it}$  possibly captures changes in the variance of idiosyncratic shocks and accounts for variable specific features such as measurement error. On the other hand,  $\lambda_t$  is the average volatility of shocks to the common components  $F_t$ . Given that  $F_t$  summarise the macroeconomic, financial and state-level data included in  $X_{it}$ , we interpret the variance of the unpredictable component of  $F_t$  as a measure of economy-wide uncertainty and  $\eta_t$  as the uncertainty shock. As we show below, this specification produces estimates of uncertainty that are plausible from a historical perspective and compares favourably to semi-parametric measures of uncertainty recently suggested in the literature.

The volatility in mean formulation of equation 1 implies that shocks to  $\lambda_t$  have an impact on the variables included in  $X_{it}$ . We can therefore estimate the response of these variables to uncertainty shocks. Note that

this estimated response is net of the impact of idiosyncratic volatility as the observation equation 4 allows  $\ln h_{it}$  to enter as a regressor. For the state-specific variables of interest, this implies that we account for the possible impact of state level uncertainty as partly captured by  $h_{it}$ .

The common factors  $F_t$  capture the co-movement among the variables included in the panel. In particular, they account for the relationship between state-specific series and the correlation of state data with aggregate US data. While the FAVAR model does not explicitly model spill-overs across states, it accounts for cross-state relationships via  $F_t$ .<sup>1</sup> Thus, the estimated responses of state-specific variables to aggregate uncertainty shocks reflect any indirect impact of these shocks that is transmitted via cross-state channels.

The formulation presented in equations 2 and 3 is related to a number of recent empirical contributions. For example, the structure of the stochastic volatility model used above closely resembles the formulations used in time-varying VAR models (see Cogley and Sargent (2005) and Primiceri (2005)). Our model differs from these studies in that it allows a direct impact of the volatilities on the level of the endogenous variables. The model proposed above can be thought of as a multivariate extension of the stochastic volatility in mean model proposed in Koopman and Uspensky (2000) and applied in Berument *et al.* (2009), Kwiatkowski (2010) and Lemoine and Mougin (2010). In addition, our model has similarities with the stochastic volatility models with leverage studied in Asai and McAleer (2009) and the non-linear model proposed in Aruoba *et al.* (2011). Finally, the model is based on the VAR with stochastic volatility introduced in Mumtaz and Zanetti (2013), Mumtaz and Theodoridis (n.d.) and Mumtaz and Surico (2013). Models with a common volatility specification are used in Mumtaz and Theodoridis (2014) and Alessandri and Mumtaz (2014).

## 4 Estimation and model specification

The model defined in equation 1 and 4 is estimated using an MCMC algorithm. In this section we summarise the key steps of the algorithm and provide the details in the technical appendix.<sup>2</sup> The appendix also presents the details on the prior distributions which are standard.

As noted in Bernanke *et al.* (2005), the FAVAR model is subject to rotational indeterminacy of the

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<sup>1</sup>In other words, while the model is suited to estimating the impact of aggregate uncertainty shocks, a more complex structure is required if interest centers on estimating the impact of state  $i$  uncertainty shocks on the economy of state  $j$ . In the FAVAR, such shocks are ‘filtered out’ by accounting for the impact of  $h_{it}$  in the observation equation.

<sup>2</sup>The appendix presents a small Monte-Carlo experiment that shows that the algorithm displays a satisfactory performance.

factors and factor loadings. Following Bernanke *et al.* (2005), we impose a normalisation under which the first  $K \times K$  block of the factor loadings is fixed to an identity matrix.

The MCMC algorithm consists of the following steps:

1. Conditional on a draw for the stochastic volatility  $\lambda_t$ , the factors  $F_t$  the matrix  $A$ , and the variances  $S$ , equation (1) represents a VAR model with a known form of heteroscedasticity. The algorithm of Carter and Kohn (2004) is used to draw the VAR coefficients from their conditional posterior density while accounting for the time-varying variance via the Kalman filter.
2. Conditional on a draw for the stochastic volatility  $F_t, \lambda_t$  and  $S$  the non-unity and non-zero elements of  $A$  are drawn using methods for linear regressions with heteroscedasticity.
3. Given  $A$  and  $\lambda_t$ , The elements of  $S$  have an inverse Gamma posterior and these parameters can be easily simulated from this distribution.
4. Conditional on  $\lambda_t$ , the constant  $\alpha$ , autoregressive parameter  $F$  and variance  $Q$  can be drawn using standard results for linear regressions.
5. Conditional on a draw for the factors  $F_t$  and the volatilities  $h_{it}$  methods for heteroscedastic linear regressions can be used to draw the factor loadings  $B_i$  and the coefficients  $\rho_{k,i}$ .
6. Conditional on a draw for the factors  $F_t$  and the factor loadings  $B_i$ , the coefficients  $\rho_{k,i}$  and the parameters of the transition equations 6, the stochastic volatilities  $h_{it}$  can be drawn using a date by date independence Metropolis step as described in Cogley and Sargent (2005) and Jacquier *et al.* (1994) (see also Carlin *et al.* (1992)). The same algorithm is used to draw the common volatility  $\lambda_t$ .
7. Given the parameters of the observation equation 4 and the transition equation 1, the Carter and Kohn (2004) algorithm is used to draw from the conditional posterior distribution of the factors  $F_t$ .

In the benchmark specifications, we use 200,000 replications and base our inference on the last 5,000 replications. The recursive means of the retained draws (see technical appendix) show little fluctuation providing support for convergence of the algorithm.

## 4.1 Model specification

We consider models with 3 to 7 factors and select the model which minimises the Bayesian Deviance Information Criterion (DIC). Introduced in Spiegelhalter *et al.* (2002), the *DIC* is a generalisation of the Akaike information criterion – it penalises model complexity while rewarding fit to the data. As shown in the appendix, the DIC can be calculated as  $DIC = \bar{D} + p_D$  where  $\bar{D}$  measures goodness of fit and  $p_D$  approximates model complexity. A model with a lower *DIC* is preferred. Table 1 shows that the *DIC* is minimised for the model with 3 factors. Therefore, we select 3 factors in our benchmark model.

	<i>DIC</i>
3 factors	36652.03
4 factors	38096.85
5 factors	41663.51
6 factors	65216.41
7 factors	72648.66

Table 1: Model Comparison via DIC. Best fit indicated by lowest DIC

In the benchmark model, the lag length  $P$  and  $J$  is set to 4. We show in the technical appendix that the results do not change substantially for alternative specifications of the model.

## 4.2 Data

The dataset is quarterly and runs from 1950Q1 to 2014Q1. The panel contains 92 aggregate variables and the real income for each of the 51 US states. Non-stationary variables are log-differenced. Finally, the series are de-meanned. The 92 aggregate variables cover real activity, prices, short-term and long term interest rates, various corporate bond spreads and series on money and credit growth. Data on stock market variables, commodity prices and exchange rates is included. In summary, the aggregate dataset covers the key sectors of the US economy and incorporates a wide range of information. The technical appendix provides a list of the series included in the panel.

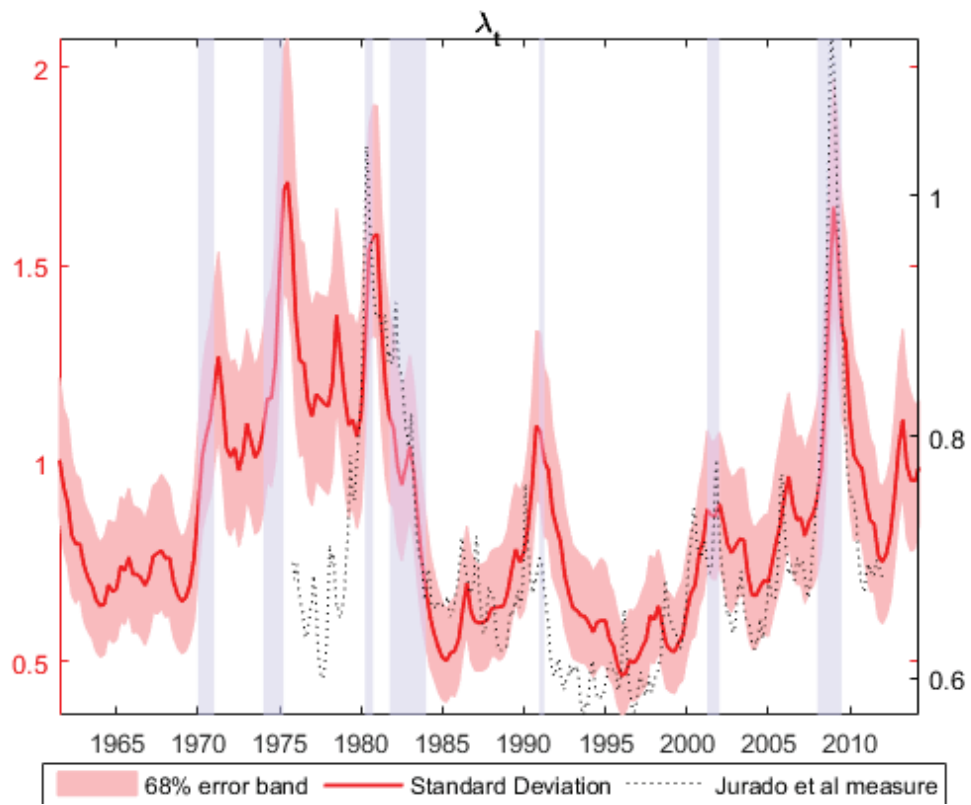


Figure 4: Estimated Volatility  $\lambda_t$ . The posterior estimates of  $\lambda_t$  are compared with the measure of uncertainty reported in Jurado *et al.* (2013). The shaded areas represent the NBER recession dates.

## 5 Empirical results

### 5.1 The Measure of Uncertainty

Figure 4 plots the posterior median and the 68% bands for  $\lambda_t$ . The figure also plots the uncertainty measure recently proposed in Jurado *et al.* (2013) for comparison. The measure of uncertainty is high during the early and the mid-1970s reaching a large peak during the early 1980s. The mid-1980s saw the onset of the great moderation and  $\lambda_t$  declined and remained low until the recession during the early 1990s and then during the early 2000s. The recent financial crisis saw a substantial increase in uncertainty with the level of  $\lambda_t$  during 2008/2009 matching the volatility seen during the 1970s and the early 1980s.

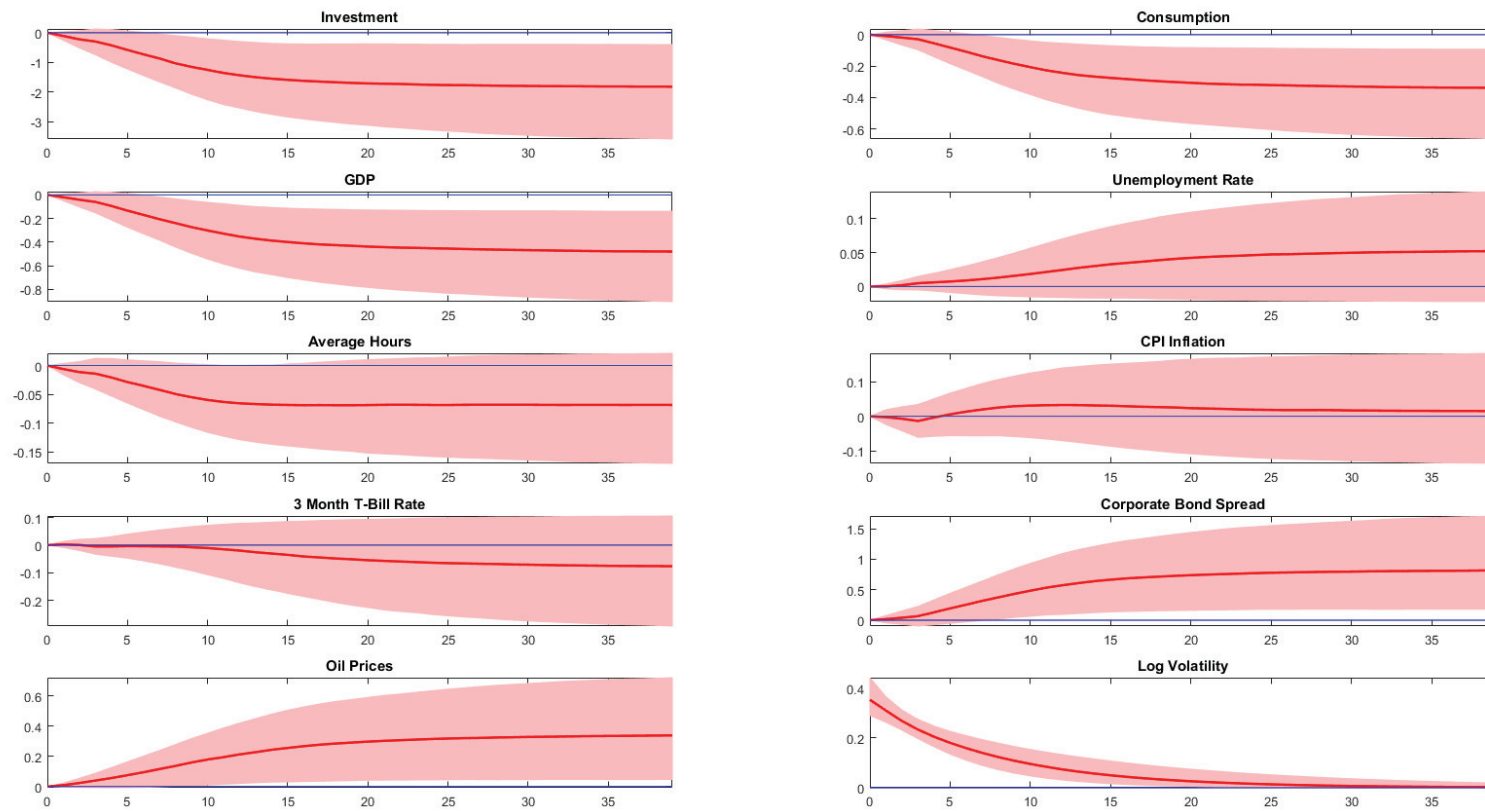


Figure 5: Response of aggregate variables to uncertainty shocks

It is interesting to note that the estimate of  $\lambda_t$  is highly correlated with the measure of uncertainty proposed in Jurado *et al.* (2013). This reflects the fact that the underlying method of capturing uncertainty has a number of similarities with the calculation in Jurado *et al.* (2013). The uncertainty measure in Jurado *et al.* (2013) is the average time-varying variance in the unpredictable component of a large set of real and financial time-series. The volatility specification in equations 2 and 3 has a similar interpretation as it attempts to capture the average volatility in the *shocks* to  $Z_t$  where the factors summarise real and financial conditions. However, as discussed above, the model used in this paper offers a distinct advantage for the purpose of estimating the impact of uncertainty shocks – it allows one to recover the responses to overall uncertainty shocks while ‘filtering out’ the effects of idiosyncratic uncertainty and measurement error captured by  $h_{it}$ . In figure 5 we consider how innovations to  $\lambda_t$  affect aggregate variables. A one standard deviation uncertainty shock results in a decline in real activity with a fall in hours, investment, consumption and GDP and an increase in the unemployment rate. These estimates are consistent with impulse responses reported in Bloom (2009) and Leduc and Liu (2012) and confirm the conventional view on the impact of uncertainty shocks on real activity. The response of inflation is imprecisely estimated but suggests that the total impact is positive at the two year horizon providing some support to the ‘pricing bias’ channel postulated in Fernandez-Villaverde *et al.* (2015)—in other words, when the economy is characterised by price and wage rigidity, inflation rises in the face of uncertainty because forward looking agents bias their pricing decision upwards in order to avoid supplying goods when demand and costs are high. The uncertainty shock is associated with a deterioration in financial conditions and the corporate bond spread increases. In addition, oil prices rise by about 0.2% in response to an increase in uncertainty.



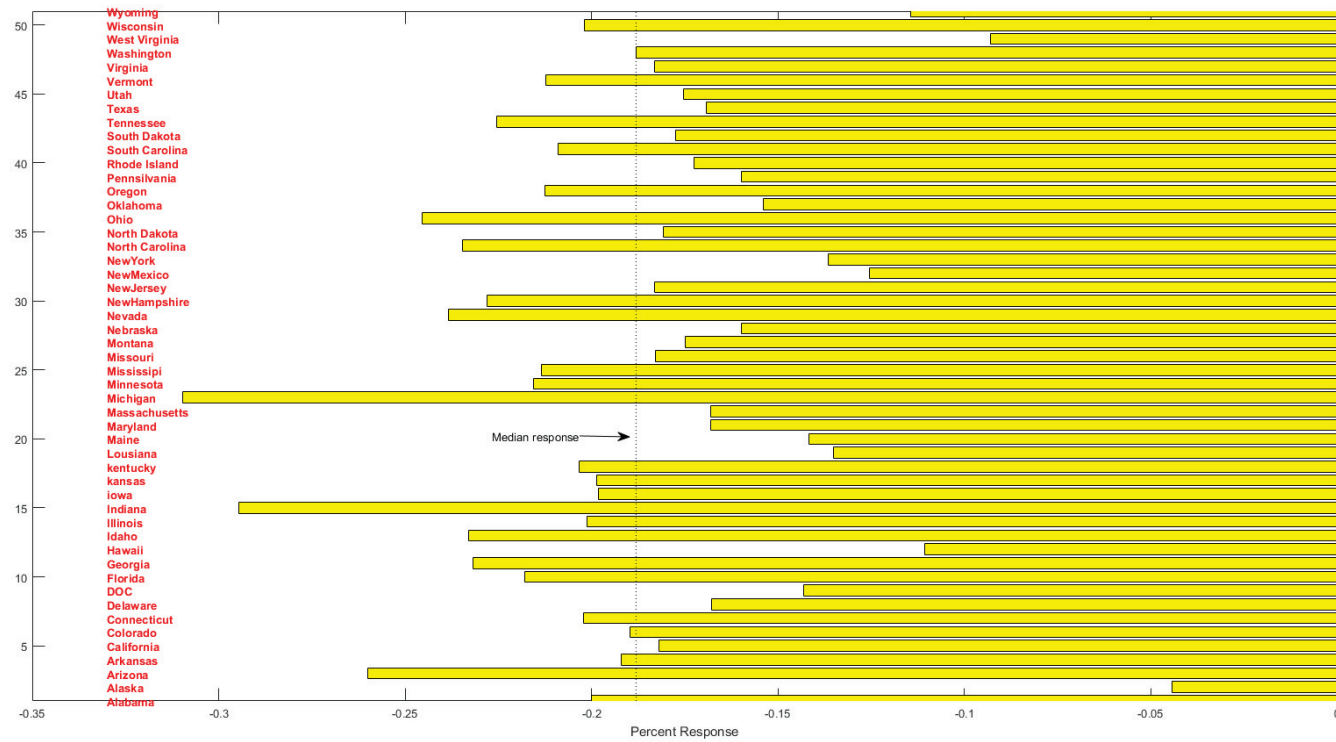


Figure 6: Cumulated response of real income growth to uncertainty shocks at the two year horizon

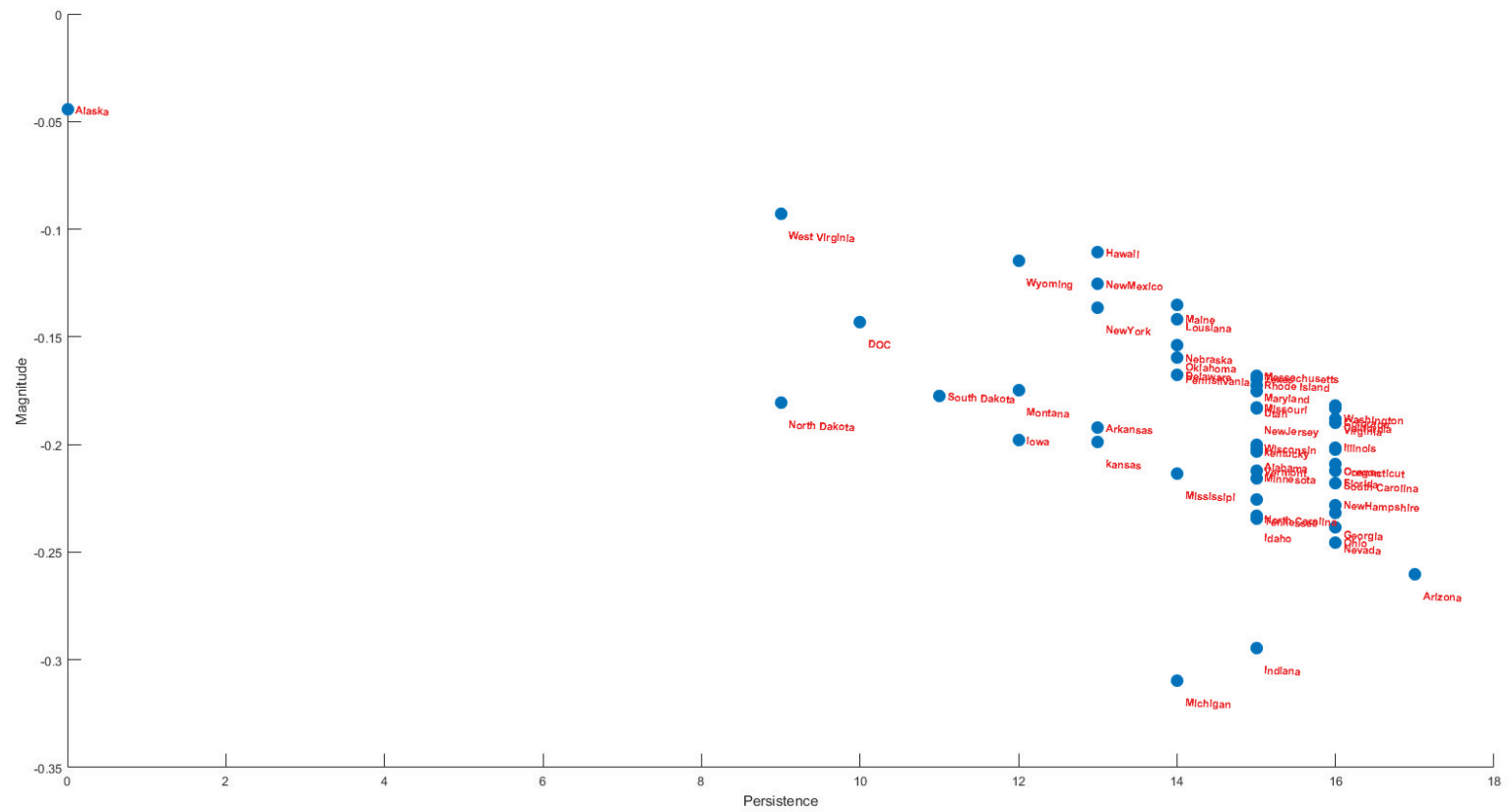


Figure 7: The relationship between magnitude and persistence of the response of real income in each state

## 5.2 State-Level response of uncertainty shocks

In this section we consider the response the real income growth to uncertainty shocks across US states and investigate the presence of heterogeneity at the state level. Figure 6 presents the median estimate of the cumulated response of state-level real income to a one standard deviation uncertainty shock at the two year horizon. Real income declines in all states in response to an increase in US wide uncertainty, with the median decline estimated at 0.18%. The magnitude of the decline is largest in Michigan, Indiana and Arkansas with income falling by about 0.26% to 0.3%. The response in the majority of the states lies within the range -0.15% and -0.25%. States with the lowest response (i.e. larger than -0.15%) include New York, Alaska and New Mexico.

Figure 7 shows that the persistence of the response to uncertainty shocks is larger in states where the impact is estimated to be of a higher magnitude. We measure the persistence by the number of quarters before the hypothesis of a zero response cannot be rejected.<sup>3</sup> In states such as Michigan, Arizona and Indiana, the effects of the uncertainty shock persist for longer than three years. In contrast, there is scant statistical evidence that the impact of the shock is persistent in states such as Alaska.

## 6 Explaining the heterogeneity of state-level responses

As discussed in section 2, cross-state differences in the response of income to uncertainty shocks can be driven by cross-state variations in financial and fiscal conditions, industry mix and the labour market. In this section we attempt to quantify these possible relationships by estimating regressions of the following form:

$$response_i^h = \alpha + D_j + \beta X_i + v_i \quad (7)$$

where  $response_i^h$  denotes the h-period cumulated response of state i's real income.  $\alpha$  is an intercept while  $D_j$  represents a set of dummies defined for the BEA regions. The regressors  $X_i$  include proxies that attempt to capture the role of the state-specific factors discussed above.

The first set of regressors that we consider account for heterogeneity in the structure of industry. We

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<sup>3</sup>The 68% posterior error bands are used to calculate the persistence. For states where the error bands include a zero response at more than one point on the horizon, the last instance is used as the persistence measure.

consider 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 regressors attempts to account for the degree of 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 with establishments employing less than 250 workers categorised as small. 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 homeownership rate and the variance of these two variables.

In order to capture the fiscal situation in each state we use a number of proxies. State-specific revenue is accounted for by including the share of inter-governmental revenue in the total. We attempt to capture variation in expenditure across states by using the proportion of expenditure on welfare and on subsidies. The budget situation is accounted for via the budget balance and debt as a share of expenditures. Finally, we explore the role played by labour market rigidities and include the degree of unionization in some of the specifications.

The source of this cross section data and the construction of the variables closely follows previous studies such as Carlino and Defina (1998) and Guisinger *et al.* (2015). Details on each variable are provided in the technical appendix to the paper. In the section below we present the results from our preferred specifications that retain the most important regressors from a statistical point of view. An extensive sensitivity analysis is presented in the technical appendix and discussed below.

## 6.1 Benchmark results

Table 2 shows the results using our preferred specifications. The first eight columns of the table refer to the baseline case which uses the impulse response of income cumulated at the two year horizon as the dependent variable. The final column of the table considers the response cumulated at the one-year horizon as the dependent variable.

The first column of the table relates the estimated responses to variables accounting for the structure of industry in each state. Here we present the result for the industry variables that displayed a robust

relationship with the uncertainty responses across a variety of specifications. This additional robustness analysis is presented in Table 1 in the on-line technical appendix. The results in the first column of Table 2 clearly show that the coefficients on the share of manufacturing and mining industries are highly significant. The negative coefficient on the share of manufacturing suggests that states with a higher concentration of manufacturing also experience a larger drop in real income in the face of uncertainty shocks. In contrast, a larger ratio of mining industries in GDP is associated with a smaller negative response. As shown in the technical appendix, very similar results are obtained when the share of mining in GDP is replaced by the share of oil and gas, a sub-category of mining in the classification of industries. As shown in figure 5 that the uncertainty shock results an increase in the price of some commodities like oil which may help to ameliorate the negative effects of uncertainty in states where a larger share of GDP is accounted for by such industries.

Columns two to five of Table 2 consider the role industry mix and fiscal indicators jointly. As before, in these columns we present results from specifications that deliver the most robust results. Table 2 in the technical appendix shows the different specifications used to arrive at these benchmark estimates.<sup>4</sup> In terms of industry mix, the role of manufacturing and mining remains robust. In column four, the coefficients on the share of agriculture and construction are also significant – the negative coefficients indicate that states where these industries are heavily concentrated are more vulnerable to uncertainty shocks. In terms of fiscal indicators, budget deficits and inter-governmental transfers display a robust relationship with the dependent variable. States with a larger budget deficit as a share of expenditure are associated with a larger negative response of real income to uncertainty shocks. On the other hand, a larger proportion of inter-governmental transfers appear to have a positive effect—a smaller negative response of real income is associated with states with a larger ratio of inter-governmental transfers to total expenditures.

Columns six and seven consider the possible role played by proxies for financial frictions such as the proportion of loans made by small banks and the share of small firms in total employment. The coefficients on these variables are estimated imprecisely. There is some weak evidence that a larger proportion of loans made by small banks is associated with a bigger drop in income due to uncertainty shocks. However as shown in Table 3 in the technical appendix, this result is not robust. Across a variety of specifications (that

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<sup>4</sup>We also consider the degree of unionisation in this table. We find that this variable has a negligible relationship with the estimated response to uncertainty shocks.

use different definitions of these variables) the main conclusion appears to be that these proxies for financial frictions are not significantly related to the response to uncertainty shocks.

Column eight of Table 2 shows that the coefficient on the home vacancy rate is significant and negative. States with a larger home vacancy rate experience a larger drop in income in the face of uncertainty shocks. This suggest that a higher vacancy rate may signal the inability or unwillingness of agents to absorb negative shocks. Similar results are obtained if the home vacancy rate is replaced by the standard deviation of this variable (see Table 4 in the technical appendix). The home ownership rate and its volatility also has a negative relationship with response to uncertainty but appears to be less significant.

In the final column of table 2 we consider if the results are robust to the horizon of the impulse response used to construct the dependent variable. This specification uses the impulse response cumulated over four quarters. The results suggest that while the magnitude of the estimated coefficients is somewhat smaller, the sign and significance are broadly similar to the benchmark case.

In summary, the benchmark estimates and the detailed robustness checks presented in the technical appendix suggest the following results: (1) States with a heavy concentration of manufacturing, agriculture and construction industries experience a larger drop in income when hit by an uncertainty shock. In contrast, states with mining as a larger proportion of GDP appear to be affected less by this shock. (2) The fiscal position of states plays an important role – a larger budget deficit is associated with a more negative response of state-level income to uncertainty shocks while the proportion of inter-governmental transfers appear to ameliorate the impact of uncertainty. (3) Income in States with a more volatile housing market declines by a larger amount in the face of uncertainty shocks.

## 7 Conclusions

This paper uses an extended factor augmented VAR (FAVAR) model to study the impact of uncertainty shocks on the real income of US states. We find that the impact of uncertainty shocks is heterogenous. The

	(1) IRF 2yr	(2) IRF 2yr	(3) IRF 2yr	(4) IRF 2yr	(5) IRF 2yr	(6) IRF 2yr	(7) IRF 2yr	(8) IRF 2yr	(9) IRF 1yr
Manufacturing	-0.352*** (0.105)	-0.340*** (0.097)	-0.433*** (0.121)	-0.542*** (0.089)	-0.221** (0.088)	-0.343*** (0.099)	-0.552*** (0.089)	-0.464*** (0.084)	-0.187*** (0.033)
Mining	0.400*** (0.146)	0.410*** (0.110)	0.505*** (0.151)	0.385*** (0.111)	0.581*** (0.123)	0.479*** (0.112)	0.416*** (0.121)	0.310*** (0.096)	0.124*** (0.045)
Agriculture			-0.225 (0.173)	-0.365*** (0.124)			-0.319** (0.131)	-0.450*** (0.135)	-0.130** (0.056)
Construction			-2.466** (1.088)	-2.822*** (0.971)			-3.022*** (0.926)	-2.082** (0.935)	-0.894** (0.376)
Financial services			0.281 (0.200)		0.459*** (0.136)				
Small banks ( $\leq 90^{th}$ pctl)						-0.041* (0.024)			
Budget deficit		-0.162** (0.065)	-0.158** (0.061)	-0.148** (0.059)	-0.166** (0.062)	-0.182*** (0.058)	-0.160** (0.063)	-0.126** (0.057)	-0.053** (0.025)
Intergov't transfers		0.225*** (0.083)	0.232*** (0.072)	0.216*** (0.077)	0.256*** (0.070)	0.201** (0.089)	0.223** (0.083)	0.176** (0.067)	0.075*** (0.026)
Small firms (< 250)							-0.148 (0.173)		
Home vacancy rate								-3.071*** (0.861)	-0.939** (0.350)
Observations	51	50	50	50	50	50	50	50	50
Adjusted $R^2$	0.460	0.545	0.634	0.627	0.590	0.558	0.624	0.679	0.640
All models include regional dummies									
* $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$									

Table 2: Cross-sectional regression results

magnitude and persistence of the response is estimated to be the largest in Michigan, Indiana and Arizona. In contrast, the uncertainty shock has a smaller impact on income in states such as New York, Alaska and New Mexico. Cross-sectional regressions relating the state-specific impulse responses to state features suggest that income declines by more in states characterised by a larger share of manufacturing, agriculture and construction industries, higher fiscal deficit to expenditure ratio and home vacancy rate. States that have a higher share of mining industries and larger inter-governmental fiscal transfers appear to be affected less by uncertainty.

These results highlight the importance of industrial structure and concentration for the transmission of uncertainty shocks. In future work, It would be interesting to explore how these features can be introduced into theoretical models used to study the impact of uncertainty. It would also be useful to explore, in detail, the interaction between uncertainty shocks and prices of commodities such as oil and the role played by commodity prices in propagating the effect of uncertainty at an international level.

## References

- Alessandri, Piergiorgio and Haroon Mumtaz, 2014, Financial Regimes and Uncertainty Shocks, *Working Papers 729*, Queen Mary University of London, School of Economics and Finance.
- Aruoba, Boragan, Luigi Bocola and Frank Schorfheide, 2011, A New Class of Nonlinear Times Series Models for the Evaluation of DSGE Models, *In progress*.
- Asai, Manabu and Michael McAleer, 2009, Multivariate stochastic volatility, leverage and news impact surfaces, *Econometrics Journal* **12**(2), 292–309.
- Bernanke, B. S., J. Boivin and P. Elias, 2005, Measuring the Effects of Monetary Policy: A Factor Augmented Vector Autoregressive (FAVAR) Approach, *Quarterly Journal of Economics* **120**, 387–422.
- Berument, Hakan, Yeliz Yalcin and Julide Yildirim, 2009, The effect of inflation uncertainty on inflation: stochastic volatility in mean model within a dynamic framework, *Economic Modelling* **26**(6), 1,201–07.
- Bloom, Nicholas, 2009, The Impact of Uncertainty Shocks, *Econometrica* **77**(3), 623–85.



- Carlin, Bradley P., Nicholas G. Polson and David S. Stoffer, 1992, A Monte Carlo Approach to Nonnormal and Nonlinear State-Space Modeling, *Journal of the American Statistical Association* **87**(418), 493–500.
- Carlino, Gerald and Robert Defina, 1998, The Differential Regional Effects Of Monetary Policy, *The Review of Economics and Statistics* **80**(4), 572–587.
- Carriere-Swallow, Yan and Luis Felipe Céspedes, 2013, The impact of uncertainty shocks in emerging economies, *Journal of International Economics* **90**(2), 316 – 325.
- Carriero, Andrea, Todd E. Clark and Massimiliano Marcellino, 0, Common Drifting Volatility in Large Bayesian VARs, *Journal of Business & Economic Statistics* **0**(ja), 00–00.
- Carter, C and P Kohn, 2004, On Gibbs sampling for state space models, *Biometrika* **81**, 541–53.
- Christiano, Lawrence J., Roberto Motto and Massimo Rostagno, 2014, Risk Shocks, *American Economic Review* **104**(1), 27–65.
- Cogley, T. and T. J. Sargent, 2005, Drifts and Volatilities: monetary policies and outcomes in the Post WWII U.S., *Review of Economic Dynamics* **8**, 262–302.
- Fernandez-Villaverde, Jesús, Pablo Guerrón-Quintana, Keith Kuester and Juan Rubio-Ramírez, 2015, Fiscal Volatility Shocks and Economic Activity, *American Economic Review* **105**(11), 3352–84.
- Gilchrist, Simon, Jae W. Sim and Egon Zakrajsek, 2014, Uncertainty, Financial Frictions, and Investment Dynamics, *Working Paper 20038*, National Bureau of Economic Research.
- Guisinger, Amy Y., Ruben Hernandez-Murillo, Michael T. Owyang and Tara M. Sinclair, 2015, A State-Level Analysis of Okun’s Law, *Working Paper 1523*, Federal Reserve Bank of Cleveland.
- Jacquier, E, N Polson and P Rossi, 1994, Bayesian analysis of stochastic volatility models, *Journal of Business and Economic Statistics* **12**, 371–418.
- Jurado, Kyle, Sydney C. Ludvigson and Serena Ng, 2013, Measuring Uncertainty, *NBER Working Papers 19456*, National Bureau of Economic Research, Inc.

- Kashyap, Anil and Jeremy Stein, 1995, The impact of monetary policy on bank balance sheets, *Carnegie-Rochester Conference Series on Public Policy* **42**(1), 151–195.
- Koopman, Siem Jan and Eugenie Hol Uspensky, 2000, The Stochastic Volatility in Mean Model, *Tinbergen Institute Discussion Paper 00-024/4*, Tinbergen Institute.
- Kwiatkowski, Lukasz, 2010, Markov Switching In-Mean Effect. Bayesian Analysis in Stochastic Volatility Framework, *Central European Journal of Economic Modelling and Econometrics* **2**(1), 59–94.
- Leduc, Sylvain and Zheng Liu, 2012, Uncertainty shocks are aggregate demand shocks, *Technical report*.
- Lemoine, M. and C. Mougin, 2010, The Growth-Volatility Relationship: new Evidence Based on Stochastic Volatility in Mean Models, *Working Paper 285*, Banque de France.
- Mumtaz, Haroon and Francesco Zanetti, 2013, The Impact of the Volatility of Monetary Policy Shocks, *Journal of Money, Credit and Banking* **45**(4), 535–558.
- Mumtaz, Haroon and Konstantinos Theodoridis, 2014, The Changing Transmission of Uncertainty shocks in the US: An Empirical Analysis, *Working Papers 735*, Queen Mary University of London, School of Economics and Finance.
- Mumtaz, Haroon and Konstantinos Theodoridis, n.d., The international transmission of volatility shocks: an empirical analysis, *Journal of European Economic Association* .
- Mumtaz, Haroon and Paolo Surico, 2013, Policy Uncertainty and Aggregate Fluctuations, *Working Papers 708*, Queen Mary University of London, School of Economics and Finance.
- Owyang, Michael T. and Sarah Zubairy, 2013, Who benefits from increased government spending? A state-level analysis, *Regional Science and Urban Economics* **43**(3), 445 – 464.
- Primiceri, G, 2005, Time varying structural vector autoregressions and monetary policy, *The Review of Economic Studies* **72**(3), 821–52.

Spiegelhalter, David J., Nicola G. Best, Bradley P. Carlin and Angelika Van Der Linde, 2002, Bayesian measures of model complexity and fit, *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **64**(4), 583–639.

# The State Level Impact of Uncertainty Shocks (Technical Appendix)

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## 1 Model

The FAVAR model is defined as

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

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

$$R_t = \text{diag}(h_{1t}, \dots, h_{Nt}) \quad (3)$$

$$\Omega_t = A^{-1} H_t A^{-1'} \quad (4)$$

$$H_t = \text{diag}(S_k \lambda_t), k = 1, 2, \dots, N \quad (5)$$

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

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

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

## 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  $F_{0 \setminus 0}$  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  $\tilde{b} = \{c, b, \delta\}$  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  $\tau = 0.1$ .

#### 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:  $P(s_i) \sim IG(S_{0,i}, V_0)$ . 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

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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  $A_0 \sim N(\hat{a}^{ols}, V(\hat{a}^{ols}))$  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.  $V(\hat{a}^{ols})$  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  $IG(Q_0, V_{Q0})$  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  $\beta$  is  $N(F_0, L_0)$  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  $IG(q_0, V_{q0})$  where  $q_0 = 0.01$  and  $V_{q0} = 5$ . The prior for  $b$  is  $N(F_0, L_0)$  where  $F_0 = 0.8$  and  $L_0 = 1$ .

## 2.2 Gibbs algorithm

The Gibbs algorithm cycles through the following steps:

1.  $G(F_t \setminus \Xi)$ : Given a draw for all other parameters (denoted by  $\Xi$ ), the algorithm of Carter and Kohn (2004) is used to sample from the conditional posterior distribution of  $F_t$ . The conditional posterior is:  $F_t \setminus X_{it}, \Xi \sim N(F_{T \setminus T}, P_{T \setminus T})$  and  $F_t \setminus F_{t+1}, X_{it}, \Xi \sim N(F_{t \setminus t+1, F_{t+1}}, P_{t \setminus t+1, B_{t+1}})$  where  $t = T-1, \dots, 1$ . As shown by Carter and Kohn (2004) the simulation proceeds as follows. First we use the Kalman filter to draw  $F_{T \setminus T}$  and  $P_{T \setminus T}$  and then proceed backwards in time using  $F_{t|t+1} = F_{t|t} + P_{t|t} f' P_{t+1|t}^{-1} (F_{t+1} - f F_{t|t} - \mu_t)$  and  $P_{t|t+1} = P_{t|t} - P_{t|t} f' P_{t+1|t}^{-1} f P_{t|t}$ . Here  $f$  denotes the autoregressive coefficients of the transition equation 2  $b$  in companion form, while  $\mu_t$  denotes the pre-determined regressors in that equation in companion form.
2.  $G(\tilde{B}_i \setminus \Xi)$ : Given a draw for the factors and the variance of the idiosyncratic component, a separate 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  $\tilde{F}_t = [F_t, \ln h_{it-1}, \ln h_{it-2}, \dots]$ . 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:  $N(B_i^*, \Lambda_B)$

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

3.  $G(h_{it} \setminus \Xi)$ : 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  $i$ :

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

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

4.  $G(\tilde{b} \setminus \Xi)$ . Given a draw of  $\lambda_t$ , the left and the right hand side variables of the VAR:  $y_t = F_t$  and  $x_t = [c, F_{t-1}, F_{t-2}, \dots, F_{t-j}, \lambda_t, \lambda_{t-1}, \dots, \lambda_{t-j}]$  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

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

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

5.  $G(A \setminus \Xi)$ . 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  $\text{VAR}(\tilde{e}_t) = H_t$ . 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  $j$ th equation of this system is given as  $v_{jt} = -\alpha v_{-jt} + \tilde{e}_{jt}$  where the subscript  $j$  denotes the  $j$ th 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  $\text{var}(\tilde{e}_{jt}^*) = 1$ . The conditional posterior for  $\alpha$  is normal with mean and variance given by  $M^*$  and  $V^*$ :

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

6.  $G(S \setminus \Xi)$ . Given a draw for the VAR parameters  $A'(v_t) = \tilde{e}_t$ . The  $j$ th 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  $\lambda_t$  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  $\lambda_t$ . 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:

$$\tilde{h}_t \setminus Z_t, \Xi \propto f(\tilde{h}_t \setminus \tilde{h}_{t-1}) \times f(\tilde{h}_{t+1} \setminus \tilde{h}_t) \times f(Z_t \setminus \tilde{h}_t, \Xi) \quad (9)$$

where  $\Xi$  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  $\lambda_t$  and  $\lambda_{t+1}$  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  $f(\tilde{h}_t \setminus \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi) \propto f(\tilde{h}_t \setminus \tilde{h}_{t-1}) \times f(\tilde{h}_{t+1} \setminus \tilde{h}_t)$  and show that this is given as

$$f(\tilde{h}_t \setminus \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi) \sim N(B_{2t} b_{2t}, B_{2t}) \quad (10)$$

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  $\tilde{h}_t \setminus Z_t, \Xi$  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  $f(Z_t \setminus \tilde{h}_t, \Xi)$  at the old and the new draw. To implement the algorithm we begin with an initial estimate of  $\tilde{h} = \ln \tilde{\lambda}_t$ . 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  $\frac{f(Z_t \setminus \tilde{h}_t^{new}, \Xi)}{f(Z_t \setminus \tilde{h}_t^{old}, \Xi)}$  where  $f(Z_t \setminus \tilde{h}_t, \Xi)$  is the likelihood of the VAR for observation  $t$  and defined as  $|\Omega_t|^{-0.5} \exp(-0.5 \tilde{e}_t' \Omega_t^{-1} \tilde{e}_t)$  where  $\tilde{e}_t = F_t - \left( c + \sum_{j=1}^P \beta_j F_{t-j} + \sum_{j=1}^J \gamma_j \ln \lambda_{t-j} \right)$  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 volatilities.<sup>1</sup>

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

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

where the elements of the mean vector  $\mu$  are defined as  $\frac{\alpha}{1-\beta}$ . Conditional on a draw for  $\tilde{h}_t$  and  $\mu$  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  $\beta$  is  $N(\theta^*, L^*)$  where

$$\begin{aligned} \theta^* &= \left( L_0^{-1} + \frac{1}{Q} \tilde{h}_{t-1}^* \tilde{h}_{t-1}^{*'} \right)^{-1} \left( L_0^{-1} F_0 + \frac{1}{Q} \tilde{h}_{t-1}^* \tilde{h}_t^* \right) \\ L^* &= \left( L_0^{-1} + \frac{1}{Q} \tilde{h}_{t-1}^* \tilde{h}_{t-1}^{*'} \right)^{-1} \end{aligned}$$

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

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

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

8.  $G(a_i, b_i, q_i \setminus \Xi)$ . 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  $i = 1, 2, \dots, 100$ .

The dynamics of the factors are defined as

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

The variance process is defined as

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

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<sup>1</sup>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).

We generate 500 observations for  $X_{it}$  and drop the first 100 observations to reduce the influence of 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.

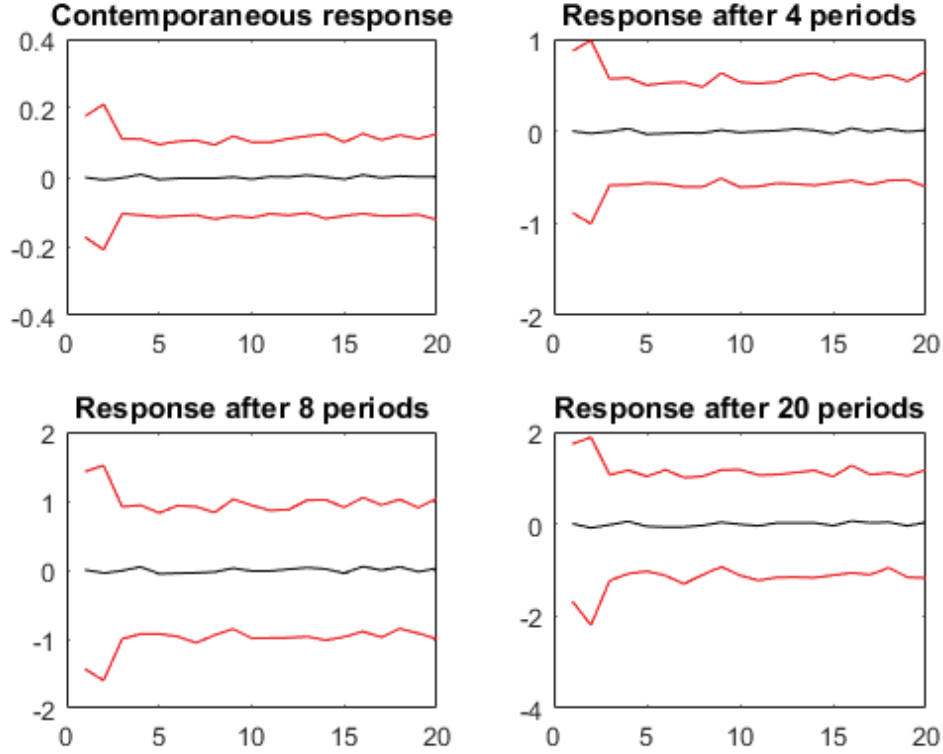


Figure 1: Monte-Carlo experiment

### 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.<sup>2</sup> 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.

<sup>2</sup>The long run response is proxied by the cumulated response at the 40 quarter horizon



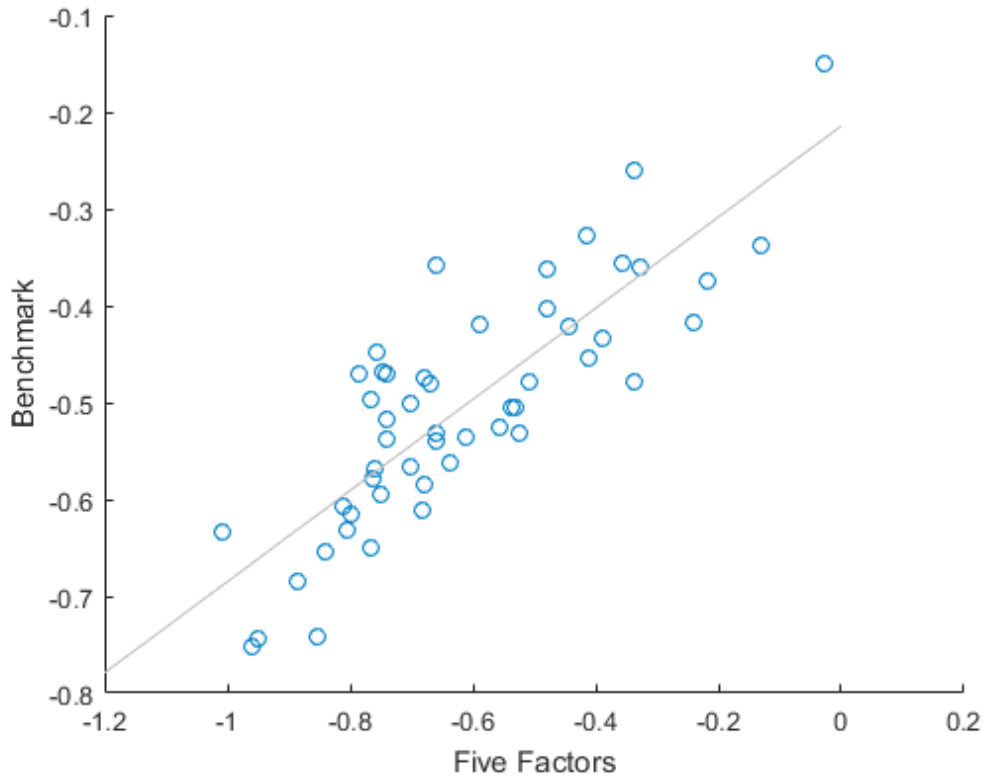


Figure 2: using five factors

### 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.

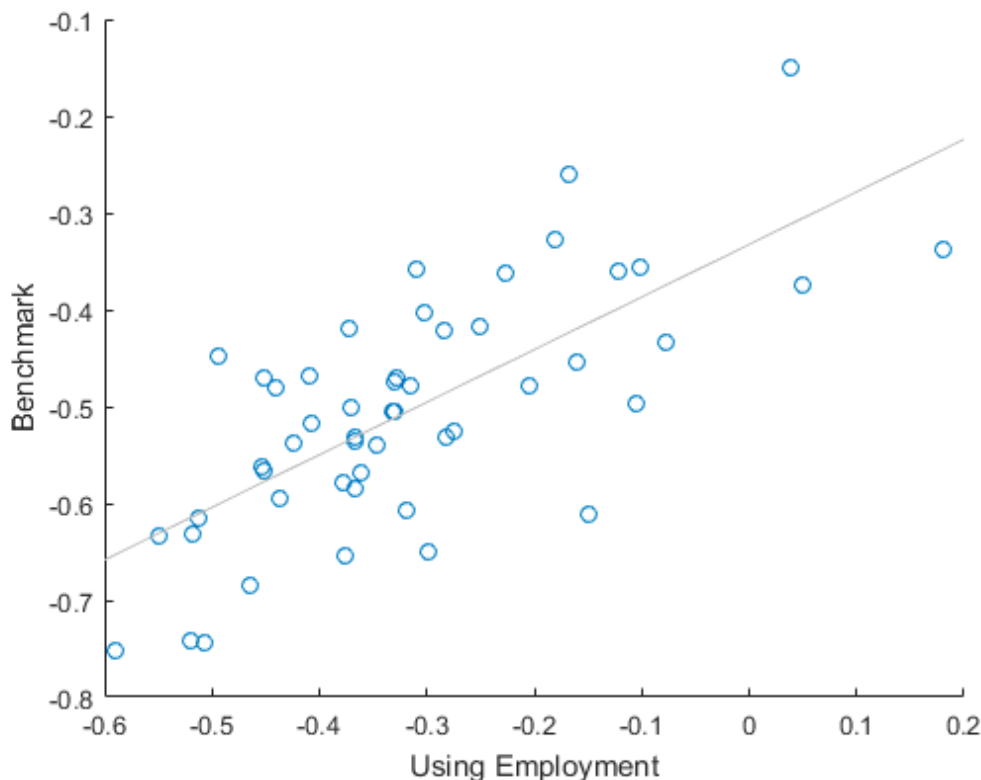


Figure 3: using Employment

### 3.3 Robustness of the cross section results

Table (1) documents further evidence on the industry mix effects on the state response to uncertainty shocks, after controlling for our baseline mix of public finance and housing market effects. Column 1 is the baseline specification. Columns 2 and 3 show that the financial services industry is important by itself, but not after controlling for the prevalence of agriculture and construction in a state. Column 4 and 5 documents the same pattern using the real estate sector, a subsector of the financial industry, with the same conclusion. Columns 6 through 10 are the same as columns 1 through 5, except using the oil industry instead of mining as a whole. These columns show both sectors play largely similar roles in shaping state responses to uncertainty shocks. Column 11 shows that the size of the public sector in a state has no significant effect on its response to uncertainty shocks.

Table (2) 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 expenditures on social security play a role in dampening the adverse effects of uncertainty shocks, but not after controlling for the effects of state government deficits and federal transfers. Columns 4, 5 and 6 show that debt, expenditures on welfare programs and an indicator for the extent of labor market protection (rate of union membership) have no significant effects on state-level uncertainty shock responses.

Table (3) explores the roles of proxies for financial frictions used in the literature on explaining state-level heterogeneity along various dimensions. It shows that none are significant, after controlling for our baseline mix of industry, public finance and housing market effects. Column 1 is again the baseline specification. We next investigate where the prevalence of small banks plays an important role. Column 2 includes as a regressor the fraction of loans extended by small banks where small is defined as at or below the 90th percentile of the national asset distribution of financial institutions. Column 3 includes the same measure where small banks are at or below the 70th percentile. Both have negative, but not significant effects. Next we explore the role of small firms. Column 4 includes as a regressor the share of employment accounted for by small establishments, where small is defined as establishments with less than 250 employees. Column 5 defines establishments as small if they have less than 10 employees. Neither measure has a significant effect on the response to uncertainty shocks. Finally column 6

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Manufacturing	-0.464*** (0.084)	-0.196** (0.082)	-0.404*** (0.121)	-0.249** (0.098)	-0.558*** (0.117)	-0.467*** (0.080)	-0.232*** (0.082)	-0.454*** (0.141)	-0.278*** (0.097)	-0.588*** (0.131)	-0.433*** (0.097)
Mining	0.310*** (0.096)	0.498*** (0.128)	0.387** (0.153)	0.406*** (0.137)	0.166 (0.156)						0.328*** (0.101)
Oil						0.337*** (0.123)	0.497*** (0.164)	0.355 (0.226)	0.415** (0.169)	0.129 (0.231)	
Agriculture	-0.450*** (0.135)		-0.360* (0.189)		-0.662** (0.270)	-0.471*** (0.155)		-0.453* (0.256)		-0.737** (0.314)	-0.426*** (0.138)
Construction	-2.082** (0.935)		-1.918* (1.012)		-1.997** (0.922)	-2.028** (0.859)		-1.991* (1.009)		-1.949** (0.861)	-2.134** (0.932)
Financial services		0.390** (0.154)	0.169 (0.240)				0.270 (0.211)	0.035 (0.313)			
Real estate				0.236 (0.249)	-0.436 (0.373)				0.109 (0.293)	-0.572 (0.437)	
Public sector											0.168 (0.152)
Budget deficit	-0.126** (0.057)	-0.153** (0.063)	-0.134** (0.059)	-0.142** (0.066)	-0.121** (0.056)	-0.097** (0.047)	-0.111** (0.051)	-0.097* (0.048)	-0.112** (0.054)	-0.108** (0.050)	-0.115** (0.055)
Intergov't transfers	0.176** (0.067)	0.201*** (0.062)	0.187*** (0.066)	0.185*** (0.061)	0.151** (0.066)	0.181** (0.072)	0.198*** (0.065)	0.184** (0.069)	0.182*** (0.063)	0.146** (0.068)	0.149* (0.077)
Home vacancy rate	-3.071*** (0.861)	-2.974*** (0.879)	-2.864*** (0.915)	-3.156*** (0.908)	-3.701*** (1.214)	-3.170*** (0.852)	-3.141*** (0.892)	-3.133*** (0.977)	-3.283*** (0.920)	-3.942*** (1.250)	-2.961*** (0.866)
Observations	50	50	50	50	50	50	50	50	50	50	50
Adjusted $R^2$	0.679	0.644	0.676	0.610	0.680	0.664	0.608	0.656	0.588	0.676	0.676

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

	(1)	(2)	(3)	(4)	(5)	(6)
Budget deficit	-0.126** (0.057)		-0.102 (0.087)			-0.134** (0.065)
Intergov't transfers	0.176** (0.067)		0.155** (0.073)			0.197*** (0.067)
Social security		0.349** (0.163)	0.109 (0.248)			
Assistance/subsidies				0.365 (0.791)		
Gov't debt					-0.000 (0.020)	
Union membership						0.001 (0.001)
Manufacturing	-0.464*** (0.084)	-0.495*** (0.090)	-0.480*** (0.085)	-0.480*** (0.090)	-0.470*** (0.092)	-0.446*** (0.095)
Mining	0.310*** (0.096)	0.340*** (0.096)	0.332*** (0.098)	0.300** (0.133)	0.294** (0.141)	0.341*** (0.111)
Agriculture	-0.450*** (0.135)	-0.304** (0.145)	-0.388** (0.159)	-0.460*** (0.139)	-0.461*** (0.139)	-0.339** (0.166)
Construction	-2.082** (0.935)	-1.912** (0.877)	-1.907** (0.935)	-2.037** (0.920)	-1.958** (0.895)	-1.919** (0.859)
Home vacancy rate	-3.071*** (0.861)	-3.121*** (0.907)	-2.818*** (0.937)	-3.711*** (0.974)	-3.740*** (1.052)	-2.560*** (0.877)
Observations	50	50	50	50	50	50
Adjusted $R^2$	0.679	0.657	0.677	0.623	0.622	0.684

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

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Table 2: Fiscal Indicators

is the specification used in Carlino and Defina (1998), which does not include our baseline controls, but only the manufacturing share, small banks and small firms measures. Again, neither the bank nor the firm measure are significant.

Table (5) shows that our results are robust to considering the uncertainty shock response at different horizons. 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.

## **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)	(6)
Small banks ( $\leq 90^{th}$ pctile)		-0.018 (0.029)				-0.018 (0.022)
Small banks ( $\leq 70^{th}$ pctile)			-0.026 (0.053)			
Small firms ( $< 250$ )				-0.278 (0.166)		0.249 (0.227)
Small firms ( $< 10$ )					-0.076 (0.252)	
Manufacturing	-0.464*** (0.084)	-0.455*** (0.089)	-0.462*** (0.086)	-0.471*** (0.082)	-0.465*** (0.085)	-0.477*** (0.106)
Mining	0.310*** (0.096)	0.349*** (0.124)	0.345** (0.130)	0.357*** (0.102)	0.320*** (0.098)	
Agriculture	-0.450*** (0.135)	-0.382** (0.179)	-0.389** (0.184)	-0.375*** (0.135)	-0.426** (0.161)	
Construction	-2.082** (0.935)	-2.014** (0.960)	-2.146** (0.886)	-2.347*** (0.829)	-2.042** (0.972)	
Budget deficit	-0.126** (0.057)	-0.139** (0.060)	-0.135** (0.060)	-0.145** (0.061)	-0.128** (0.058)	
Intergov't transfers	0.176** (0.067)	0.163** (0.073)	0.163** (0.075)	0.182** (0.074)	0.179** (0.070)	
Home vacancy rate	-3.071*** (0.861)	-3.034*** (0.858)	-2.977*** (0.859)	-3.540*** (0.945)	-3.145*** (0.914)	
Observations	50	50	50	50	50	51
Adjusted $R^2$	0.679	0.674	0.673	0.693	0.671	0.312

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

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Table 3: Financial Frictions

	(1)	(2)	(3)	(4)
Home vacancy rate	-3.071*** (0.861)			
Home vacancy rate (sd)		-0.131*** (0.034)		
Home ownership rate			-0.038 (0.172)	
Home ownership rate (sd)				-0.027** (0.011)
Manufacturing	-0.464*** (0.084)	-0.528*** (0.083)	-0.521*** (0.139)	-0.543*** (0.086)
Mining	0.310*** (0.096)	0.225** (0.091)	0.400*** (0.134)	0.371*** (0.095)
Agriculture	-0.450*** (0.135)	-0.360** (0.137)	-0.341* (0.186)	-0.373*** (0.126)
Construction	-2.082** (0.935)	-1.606 (1.042)	-2.705** (1.311)	-2.039** (0.915)
Budget deficit	-0.126** (0.057)	-0.136*** (0.048)	-0.153** (0.065)	-0.163*** (0.057)
Intergov't transfers	0.176** (0.067)	0.112* (0.060)	0.218*** (0.077)	0.182** (0.078)
Observations	50	50	50	50
Adjusted $R^2$	0.679	0.706	0.618	0.671

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

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Table 4: Housing Market

	(1) IRF 2yr	(2) stateirf_1	(3) stateirf_12	(4) IRF 4yr
Manufacturing	-0.464*** (0.084)	-0.045*** (0.009)	-0.670*** (0.127)	-0.751*** (0.152)
Mining	0.310*** (0.096)	0.022** (0.010)	0.492*** (0.151)	0.602*** (0.187)
Agriculture	-0.450*** (0.135)	-0.054*** (0.016)	-0.514** (0.203)	-0.442* (0.248)
Construction	-2.082** (0.935)	-0.135 (0.083)	-3.264** (1.502)	-4.072** (1.909)
Budget deficit	-0.126** (0.057)	-0.015** (0.006)	-0.183** (0.086)	-0.206* (0.104)
Intergov't transfers	0.176** (0.067)	0.010 (0.007)	0.275*** (0.099)	0.339*** (0.114)
Home vacancy rate	-3.071*** (0.861)	-0.118 (0.087)	-4.562*** (1.364)	-5.563*** (1.693)
Observations	50	50	50	50
Adjusted $R^2$	0.679	0.561	0.671	0.657
All models include regional dummies				
* $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$				

Table 5: Using IRFs at different horizons



Table 6: 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 6: 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 6: 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 6: 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)

## 5 Recursive means of retained draws

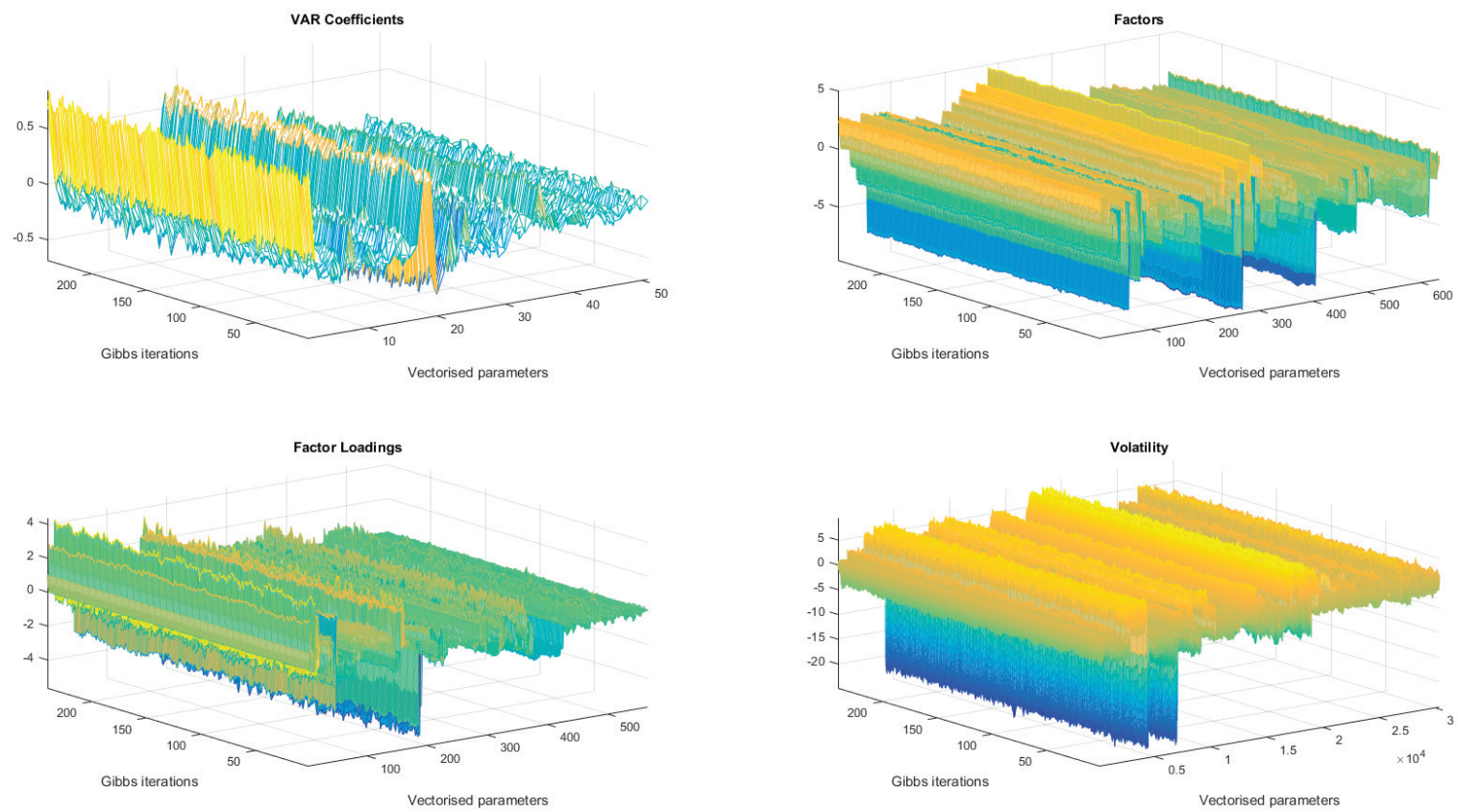


Figure 1: Recursive means calculated every 20 draws

## References

- Banbura, Marta, Domenico Giannone and Lucrezia Reichlin, 2010, Large Bayesian vector auto regressions, *Journal of Applied Econometrics* **25**(1), 71–92.
- Barry T. Hirsch, David A. Macpherson, Wayne G. Vroman, 2001, Estimates of union density by State, *Monthly Labor Review* **124**(7), 51–55.
- Carlin, Bradley P., Nicholas G. Polson and David S. Stoffer, 1992, A Monte Carlo Approach to Nonnormal and Nonlinear State-Space Modeling, *Journal of the American Statistical Association* **87**(418), 493–500.
- Carlino, Gerald and Robert Defina, 1998, The Differential Regional Effects Of Monetary Policy, *The Review of Economics and Statistics* **80**(4), 572–587.
- Carter, C and P Kohn, 2004, On Gibbs sampling for state space models, *Biometrika* **81**, 541–53.
- Jacquier, E, N Polson and P Rossi, 1994, Bayesian analysis of stochastic volatility models, *Journal of Business and Economic Statistics* **12**, 371–418.

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