Does uncertainty affect real activity? Evidence from state-level data.

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March 15, 2018

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Abstract

We use variation in the effect of US-wide or global uncertainty on state-level uncertainty to identify the impact of this shock on real activity. We find that increases in uncertainty do have an adverse impact on real income, employment and unemployment. Thus, uncertainty shocks can be a source of economic fluctuations.

Key words: Uncertainty shocks, Instrumental variables, US states.

JEL codes: C2,C11, E3

1 Introduction

Does an increase in uncertainty affect real activity or is it a manifestation of the effects of recessions? The recent literature has attempted to account for endogeniety when estimating the transmission of uncertainty shocks. For example, Ludvigson *et al.* (2015) use a VAR model with restricted structural disturbances to identify uncertainty shocks and report that financial uncertainty shocks affect real activity while negative shocks to output result in heightened macroeconomic uncertainty. Carriero *et al.* (2016) achieve identification via a VAR with stochastic volatility in mean and report that macroeconomic uncertainty can be considered as an exogenous disturbance, a result at odds with Ludvigson *et al.* (2015) . Angelini *et al.* (2017) use regime switches in VAR parameters for identification and find, in consonance with Carriero *et al.* (2016), that uncertainty is a source of economic fluctuations.

In this note we adopt an alternative approach to address endogeneity concerns in the uncertainty-real activity relationship. We use the geographical variation in the effect of US-wide or global macroeconomic uncertainty on US states to identify the relationship. A positive innovation in US or global uncertainty is likely to make economic conditions more uncertain in some US states. However, it is unlikely that US or global uncertainty would increase if uncertainty is higher in an individual state that is experiencing an economic downturn. This implies that in a state-level regression model linking real activity to state-level uncertainty, these aggregate uncertainty measures can be used as instruments. This identifying assumption is in the spirit of Nakamura and Steinsson (2014) who identify government spending shocks using state-level data.

As well as being simple, our approach exploits both time-series and cross-sectional variation for identification while the above-mentioned methods focus on temporal changes only.[1] Our results suggest that, in an average state, a 20% increase in uncertainty reduces employment and real income by 0.6% and 0.8% while the unemployment rate rises by 0.25%.

[1] Mumtaz *et al.* (2016) also use state-level data to estimate the effect of uncertainty shocks. However their focus is on the impact of aggregate uncertainty which is restricted to affect real income after one period.

2 Empirical model and data

2.1 Model

Our regression model for US state i is given by:

$$Y_{it} = \alpha_i + d_t + D_i \tau_{it} + \sum_{p=0}^{P} \beta_{ip} U_{it-p} + \sum_{p=1}^{P} \rho_{ip} Y_{it-p} + v_{it} \tag{1}$$

where α_i and d_t are state and time fixed effects, τ_{it} is a linear time trend, Y_{it} is a measure of real activity while U_{it} is a measure of uncertainty in state i. Both are described in section 2.2.

The contemporaneous value U_{it} appearing in equation 1 is endogenous and described by the following equation:

$$U_{it} = c_i + \delta_i Z_{it} + e_{it} \tag{2}$$

where Z_{it} denotes a set of instruments assumed to be uncorrelated with v_{it} and:

$$cov\left(e_{it}, v_{it}\right) = \Omega_i = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix} \tag{3}$$

We adopt a hierarchical prior for the regression coefficients $\tilde{\beta}_i = [\beta_{i0}, .., \beta_{iP}, \rho_{i1}, .., \rho_{iP}]$:

$$p\left(\tilde{\beta}_i | \bar{\beta}\right) \tilde{\ } N\left(\bar{\beta}, \lambda \Xi_i\right) \tag{4}$$

where $\bar{\beta}$ denotes the cross-sectional weighted mean of the coefficients and Ξ_i is a diagonal matrix with diagonal elements reflecting the scale of the individual elements of $\tilde{\beta}_i$. The degree of pooling is determined by the parameter λ: As $\lambda \to 0$, the coefficients become homogenous across states while larger values of λ implies heterogenous effects. $\bar{\beta}$ is assumed to be unknown and its posterior distribution is approximated by the estimation algorithm. This allows us to estimate the impact of uncertainty for the average state while allowing for heterogeneity.

The prior for the variance controlling the degree of pooling λ is assumed to be an inverse Gamma distribution $IG(s,v)$. We follow the suggestion in Gelman (2006) and use $v=-1$ and $s=0$ which implies a uniform prior for the standard deviation $\lambda^{1/2}$. The remaining priors are standard and described in the appendix.

The Gibbs sampling algorithm to approximate the posterior is based on the sampler for Bayesian IV regressions described in Rossi *et al.* (2005) and extended to sample from the conditional posterior of $\bar{\beta}$ and λ. See the appendix for details.

2.2 Data and specification

We construct macroeconomic uncertainty measures for each state using the methods described in Jurado *et al.* (2015). Let $X_{it,j}$ denote the jth data series for state i. Uncertainty for $X_{it,j}$ is estimated using the k-period ahead forecast error variance of a factor augmented forecasting regression with stochastic volatility in the regression residuals and the error term for the factor dynamics. The measure thus depends on uncertainty in $X_{it,j}$ and the factors. State-level uncertainty U_{it} is defined as the average of the one year ahead uncertainty measures for the $j=1,2,..,J$ series for state i. X_{it} includes the growth rate of real personal income per-capita and its components (social insurance, dividends, benefits and other income), employment growth, unemployment change and real house prices growth. The data is obtained from the Federal Reserve Bank of St Louis data base for the period 1976Q1 to 2015Q3 for 50 states and the District of Columbia[2]. The factors in the forecasting regression F_{it} for state i are extracted using data for the remaining states and a US wide panel of macroeconomic and financial data (FRED-QD database).

We estimate the model using the log of real personal income per capita, log of employment and unemployment rate respectively as the dependent variables. Note that we control for aggregate shocks by including the time effects d_t.

In the benchmark model, our instrument is the log of the one year ahead US macroeconomic uncertainty constructed by Jurado *et al.* (2015) $\left(Z_t^{JLN}\right)$. As an alternative, we also use the log of global macroeconomic uncertainty estimated in Mumtaz and Theodoridis (2017) $\left(Z_t^{W}\right)$. State-level uncertainty rises with an increase in aggregate uncertainty as the latter affects uncertainty of the predictors F_{it} used in forecasting

[2] We shown in the appendix that similar results are obtained if the analysis is limited to the post-1990 period enabling the use of more series per state.

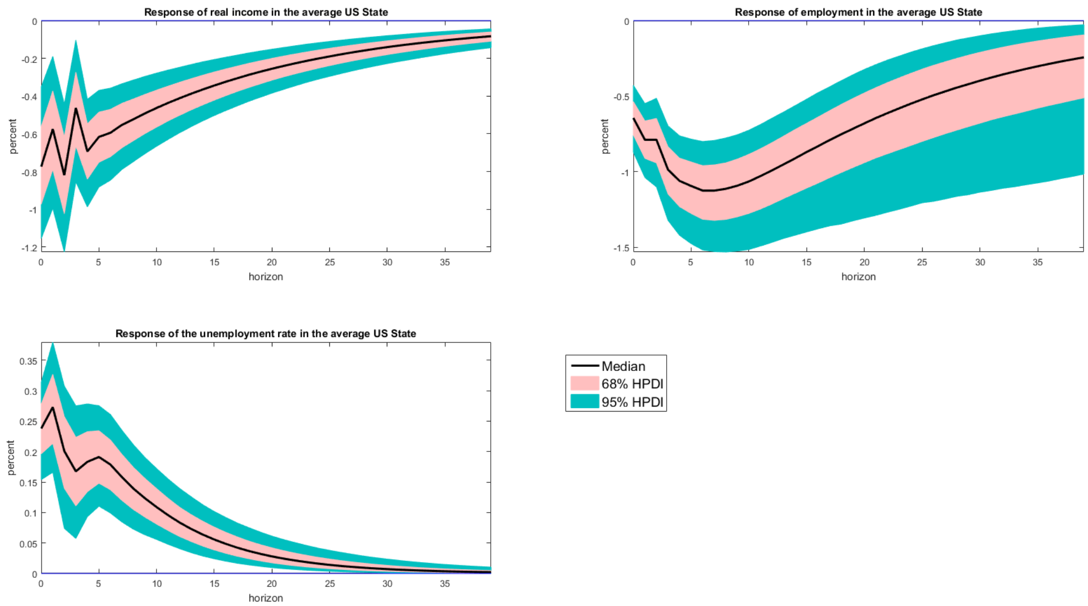

Figure 1: Impact of a 20% increase in uncertainty.

regression for $X_{it,j}$. However, this relationship is heterogenous with uncertainty in some states rising by large amounts while others are less affected. This is not surprising as states differ along many economic dimensions and this affects their sensitivity to aggregate developments. We assume that US uncertainty and global uncertainty does not increase simply because uncertainty is high in an individual state experiencing an economic downturn. This assumption, together with the heterogenous impact of Z_t^{JLN}, Z_t^{W} on U_{it} allows us to identify the impact of uncertainty.

The lag length P is set to 4. The total number of Gibbs replications is set to 50,000 with a burn-in of 25,000 with every 5th draw retained for inference. The technical appendix presents evidence in favour of convergence of the algorithm.

3 Results

Posterior estimates of δ_i for the benchmark model supports our assertion that Z_t^{JLN} is a relevant instrument. The 95% highest posterior density interval (HPDI) suggests that the hypothesis that $\delta_i = 0$ is rejected for each state and the R^2 averages around 50%. However, there is heterogeneity in the magnitude of the impact

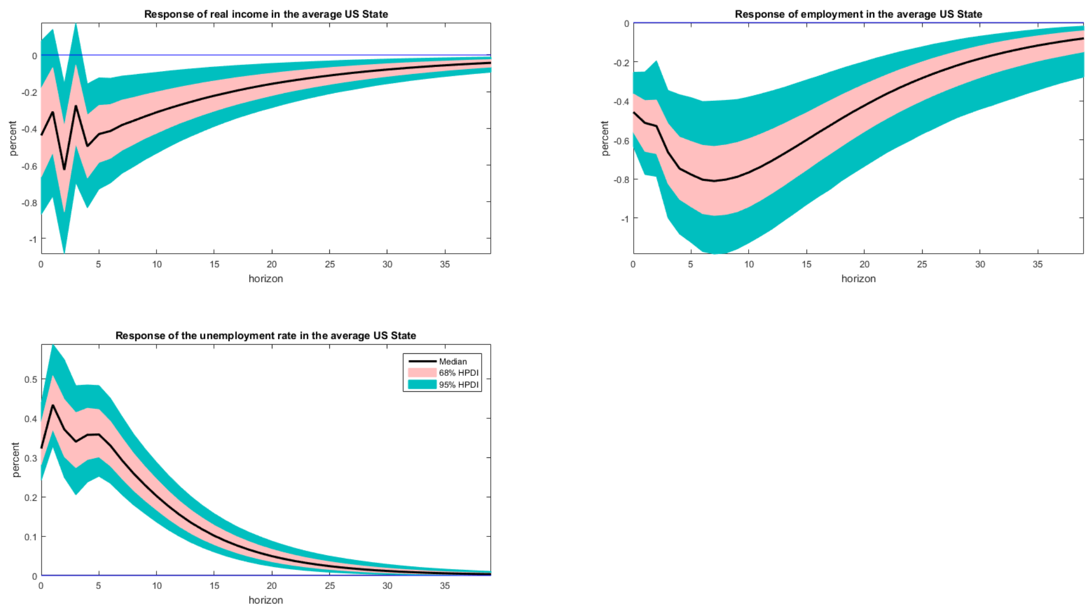

Figure 2: Impulse responses to 20% uncertainty shock using the model that uses Z_t^W as the instrument.

of Z_t^{JLN} on $\ln U_{it}$ with the posterior mean of δ_i varying between 0.05 for District of Columbia to 1.5 for Alaska.[3] We use the draws for $\bar{\beta}$ to construct the response of real activity in an average state to a 20 percent increase in uncertainty, where the size of the shock approximately equals the increase in Z_t^{JLN} over 2007-2008 (see Figure 1). In response to the shock, income and employment fall by about 0.8% and 0.6% while the unemployment rate rises by 0.25%. The total effect of the shock is long-lasting with the response dissipating only after about 40 quarters.

While our main focus is the average impulse response across states, the estimated state-specific responses indicate a large degree of heterogeneity. When we examine the correlation of the latter with state characteristics (such as industry-mix, fiscal health and measures of financial frictions – see the Section 4 of the appendix) we find that states with a larger share of agriculture, mining industries and a larger share of welfare spending display less sensitivity to uncertainty shocks. In contrast, states with a larger share of construction, financial industries and a larger tax to expenditure ratio appear to be affected more adversely this shock. These results are broadly supportive of the analysis in Mumtaz *et al.* (2016).

As a robustness check we use Z_t^W as an instrument in our alternative specification. As Z_t^W is a measure of

[3] From a classical perspective, the first stage F-statistic is larger than 10 for all states.

global uncertainty, we can be more confident that it does not respond to state-level economic developments. This comes at a cost of lower relevance – the estimated magnitude of the effect of Z_t^W on U_t is generally smaller than the estimated impact of Z_t^{JLN}. This suggests that, perhaps un surprisingly, that US wide uncertainty is more relevant for state-level uncertainty than a measure of changes in this variable at a global level.[4] The estimated response of real activity shown in Figure 2 is similar to the benchmark case– both employment and income decline persistently while unemployment rises.

4 Conclusions

We use variation in the impact of aggregate uncertainty measures on state-level uncertainty to identify the impact of uncertainty shocks on real activity. The identification exploits the argument that US-wide or global uncertainty does not increase if uncertainty is higher in an individual state that is in a recession. Our results support the finding reported in VAR based studies that uncertainty affects real activity (e.g. Bloom (2009), Jurado *et al.* (2015)) and is not simply a consequence of economic downturns.

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[4]The first stage F statistic is greater than 10 for 40 states which suggests that there is moderate evidence in favour of relevance. Thus, there is the possibility that error bands may be subject to the caveats raised in Montiel Olea *et al.* (2018) regarding inference in the presence of weak instruments.

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