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

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HIGHLIGHTS

- Increase in US or Global uncertainty may increase uncertainty in some US states.
- Unlikely that aggregate uncertainty is affected by state-specific developments.
- Estimate a Panel IV model linking state-level uncertainty and real activity.
- US-wide and Global uncertainty used as instruments for state-level uncertainty.
- On average across states, higher uncertainty reduces real activity.

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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.

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 endogeneity 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

[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.

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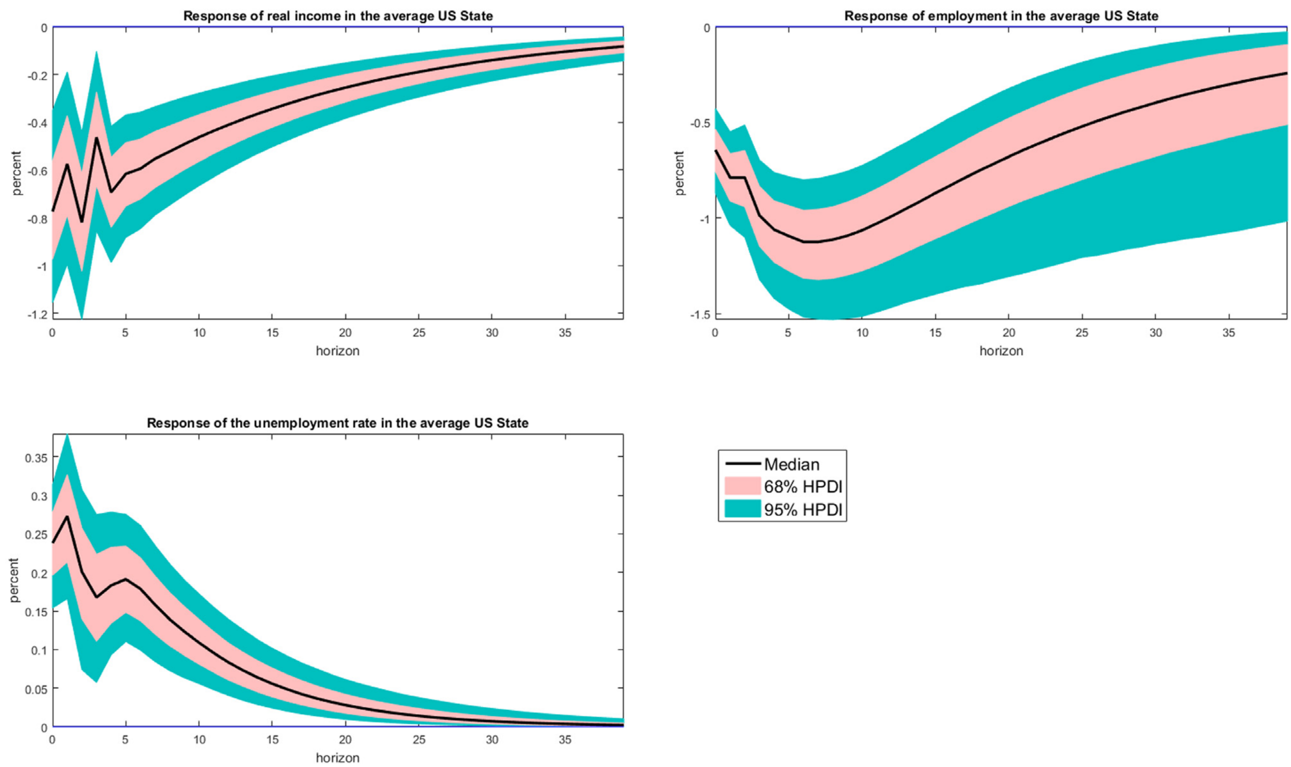

Fig. 1. Impact of a 20% increase in uncertainty.

reduces employment and real income by 0.6% and 0.8% while the unemployment rate rises by 0.25%.

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 Eq. (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 $\tilde{\beta}_i = [\beta_{i0}, \ldots, \beta_{iP}, \rho_{i1}, \ldots, \rho_{iP}]$:

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

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 $\lambda \rightarrow 0$, the coefficients become homogeneous across states while larger values of λ implies heterogeneous 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 $j = 1, 2, \ldots, J$ 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).

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.