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The macroeconomic effects of international uncertainty

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Abstract

This paper proposes a large-scale Bayesian vector autoregression with factor stochastic volatility to investigate the macroeconomic consequences of international uncertainty shocks in G7 countries. The curse of dimensionality is addressed by means of a global-local shrinkage prior that mimics certain features of the well-known Minnesota prior, yet provides additional flexibility in terms of achieving shrinkage. The factor structure enables us to identify an international uncertainty shock by assuming that it is the joint volatility process that determines the dynamics of the variance-covariance matrix of the common factors. To allow for first and second moment shocks we, moreover, assume that the uncertainty factor enters the VAR equation as an additional regressor. Our findings suggest that the estimated uncertainty measure is strongly connected to global equity price volatility, closely tracking other prominent measures commonly adopted to assess uncertainty. The dynamic responses of a set of macroeconomic and financial variables show that an international uncertainty shock exerts large effects on all economies and variables under consideration.

Keywords: Factor stochastic volatility, vector autoregressive models, global propagation of shocks, global uncertainty

JEL Codes: C30, E52, F41, E32.

Non-technical summary

In this paper we measure global uncertainty and assess its consequences on the global economy.

The deepening of financial integration over the last 30 years has led to a situation where individual countries appear to be particularly exposed to common uncertainty shocks. Such global shocks can severely impact quantities monitored by policy makers in central banks and governmental institutions. The recent financial crisis is a good example of the impact of global uncertainty on the real and financial sectors of the global economy.

In this paper we propose a large-scale Bayesian vector autoregression with factor stochastic volatility to investigate the macroeconomic consequences of international uncertainty shocks on the G7 countries. Compared to existing approaches, our modeling framework enables the simultaneous estimation of the autoregressive parameters and of the uncertainty index, implying that uncertainty is a latent quantity and depends on systematic failures of economic agents to form correct expectations about future macroeconomic developments. We adopt novel shrinkage priors that push unnecessary coefficients towards zero while still providing enough flexibility to allow for non-zero regression coefficients. We also allow global uncertainty to affect the economy via two different channels: directly, via regression coefficients, and indirectly through the impact on the error variances of the estimated model.

We compare our measure of uncertainty with other (US based) measures commonly adopted to measure economic uncertainty. Our estimates are strongly correlated with the VIX, the VXO, the national financial conditions index and the financial stress index. This suggests that US-based uncertainty shapes global uncertainty.

To assess the quantitative implications of a global uncertainty shock we perform impulse response analysis and investigate how the G7 economies react. Our findings are largely consistent with the existing literature on the impact of uncertainty on the US economy. We find that output, prices, short-term interest rates, and exports drop on impact after an uncertainty shock. Total credit reacts only modestly on impact, displaying a more pronounced decline after around four quarters. Most exchange rates depreciate relative to the US dollar, reproducing the common empirical finding that investors shift assets in US-dollar denominated assets in times of elevated uncertainty. These movements are largely consistent with the actual pattern of macroeconomic time series experienced during the height of the recent financial crisis in 2008.

1 Introduction

In this paper we measure global financial uncertainty and assess its consequences on the global economy. The deepening of financial integration over the last 30 years has led to a situation where individual countries appear to be particularly exposed to common financial shocks. Such global shocks can severely impact quantities monitored by policy makers in central banks and governmental institutions. Central banks, that closely track prices, employment and output, need to react to uncertainty shocks to smooth business cycle movements and reduce uncertainty (Bekaert et al. (2013)).

The recent financial crisis is a good example of the impact of uncertainty on the real and financial sectors of the global economy. Originated in the US housing market, the crisis quickly spread internationally, eventually leading to a severe global decline in real activity, asset prices and trade. The shut-down of money market funds and the sharp decline in equity prices across the globe that followed the bankruptcy of Lehman Brothers in September 2008 made it increasingly difficult for financial institutions to issue short-term debt, crucially needed to fund day-to-day operations. In addition, the marked increase in economic uncertainty as measured by the CBOE volatility index (VIX) led economic agents to postpone spending and investment activities, further intensifying the fall in real activity. Within a stylized theoretical framework, Bloom (2009) shows that companies invest and hire labor only if the current state of the economy is sufficiently good and the economic outlook is certain enough, thus providing a theoretical context to understand macroeconomic developments in the recent crisis.

As opposed to e.g. monetary policy shocks, which are typically modeled as an unpredictable innovation to the policy rate, the measurement of uncertainty is not straightforward. The literature provides valuable starting points in the form of measurable proxies of uncertainty. For instance, Bloom (2009) measures uncertainty through the implied volatility of equity price returns. In a simple vector autoregression (VAR) framework, Bloom (2009) reports a pronounced short-run decline of industrial production following an uncertainty shock. However, the presence of a volatility effect leads to an overshooting of real activity after a few months. Several other studies that measure uncertainty and its impact on the real economy (Grier et al., 2004; Benigno et al., 2012; Bachmann et al., 2013; Colombo, 2013; Fernandez-Villaverde et al., 2011; Caldara et al., 2016) rely on similar types of proxies based on stock market volatility or information on the cross-sectional dispersion of corporate profits.[1]

While the simultaneous estimation of uncertainty and its effects has advantages over the use of exogenous and possibly noisy uncertainty proxies, there are still comparatively few studies that simultaneously estimate uncertainty and its macroeconomic consequences (see, Jurado et al., 2015; Shin and Zhong, 2016; Mumtaz and Theodoridis, 2016; Mumtaz et al., 2016; Carriero et al., 2016). In a closely related paper, Jurado et al. (2015) construct a measure of uncertainty using a framework based on a dynamic factor model and show that the behavior of their measure of uncertainty departs from others which are commonly used in the literature. In a second step, this measure is used in an otherwise standard VAR to assess the dynamic effects of an unexpected movement in macroeconomic uncertainty on real activity and nominal indicators. As opposed to the findings of Bloom (2009), the VAR analysis in Jurado et al. (2015) suggests that declines in output tend to be more persistent, producing no "volatility overshoot" in the medium run. Similarly, in a recent contribution Mumtaz and Theodoridis (2016) use a factor-augmented VAR model with time-varying parameters to simultaneously estimate the latent uncertainty factor and the corresponding dynamic response of macroeconomic variables.

Most of the studies quoted above measure uncertainty or consider the likely impact of uncertainty on the real economy exclusively for a single country. A recent

[1]For a discussion on the shortcomings on using proxies of uncertainty, see Carriero et al. (2015b).

strand of the literature has emerged which investigates whether uncertainty shocks have international effects in an integrated economic model of the world economy (Chudik and Fratzscher, 2011; Gourio et al., 2013). Gourio et al. (2013), for instance, apply a simple two-country real business cycle model to data for the G7 economies. Their findings suggest that high interest rate countries tend to display lower volatility of interest rates and equity returns, whereas higher volatility is observed in low interest rate economies. The conclusion is that private agents in low interest rate countries seem to discount future economic developments less and that uncertainty about future events matters more in such economies. Carrière-Swallow and Céspedes (2013) propose a set of open-economy VAR models for a large panel of emerging economies and show that in developed economies, although uncertainty shocks produce strong declines in output initially, they lead to an overshooting of real activity in the medium run, a result which is consistent with the findings of Bloom (2009). On the other hand, emerging economies do not display a similar pattern and exhibit persistent declines in real activity over the forecast horizon.

Expanding on the existing literature, we focus on the *joint* measurement of international uncertainty and its consequences on the *global* economy. The deepening of financial integration over the last 30 years has led to a situation where individual countries appear to be particularly exposed to common shocks. This gives rise to a global uncertainty component that impacts countries differently, depending on the resilience of their domestic financial markets. Measuring global uncertainty alongside its impact on a set of selected countries requires non-standard econometric models. One key contribution of the present paper is to propose a model that combines existing techniques in an original way. We select a small number of factors and identify global uncertainty as a scalar factor that drives the variance of the common factors. Moreover, we consider the impact of uncertainty via two different channels, namely by including the uncertainty factor directly in the conditional mean equation and through its effect on the error variances. In addition, we avoid the over-shrinkage typical of large VAR models by using a more sophisticated prior that has the advantage of allowing for relevant non-zero regression coefficients in the presence of strong lag or variable-specific shrinkage. While computationally intensive, we see these technical solutions are necessary and useful in correctly identifying uncertainty in a parsimonious yet meaningful way.

From an empirical perspective, our model yields several insights. First, our measure of global uncertainty displays a similar pattern to other (mostly US based) measures adopted, showing sharp increases during the 1987 stock market crash, the period marking the unwind of long-term capital management, the terrorist attacks on 9/11 and the recent financial crisis. These periods are typically closely related to situations where economic uncertainty has been high. Second, a simple variance decomposition suggests that the explanatory power of the global uncertainty factor increases markedly during periods of economic stress, suggesting that in those moments country-specific variables tend to be more tightly linked to the global uncertainty cycle. Third, a global increase in uncertainty leads to a sharp decline in real activity, prices, exports, interest rates, credit, and equity prices. Almost all exchange rates tend to depreciate with respect to the US dollar after an uncertainty shock. These results replicate well the actual developments of the aforementioned variables during the financial crisis of 2008/2009. Fourth, regional differences in responses to global uncertainty reveal the existence of a more economically integrated area where differences appear to be smaller, and comprising the euro area countries: Germany, Italy, and France.

The remainder of the paper is structured as follows. Section 2 introduces the econometric framework adopted in our analysis, the prior specification and provides a brief overview on the estimation method employed. Section 3 describes the data set used and discusses the identification of the factor model and several specification choices. Section 4 presents the main empirical results. Finally, the last section summarizes our key findings and concludes the paper.

2 Econometric framework

2.1 The vector autoregressive model with factor stochastic volatility

We are interested in modeling the dynamic responses of a vector of time series that incorporates information on output, inflation, exchange rates, short- and long-term interest rates, equity prices, credit and exports across the G-7 countries. This M-dimensional vector $\boldsymbol{y}_t$ is assumed to follow a VAR(p) process,[2]

$$\boldsymbol{y}_t = \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{\gamma}v_t + \boldsymbol{\varepsilon}_t, \tag{2.1}$$

where $\boldsymbol{A}_j$ $(j = 1, \dots, p)$ are $M \times M$ dimensional matrices of regression coefficients and $\boldsymbol{\gamma}$ is a M-dimensional vector of regression coefficients associated with the uncertainty factor v_t, described below. Following Stock and Watson (2005), we assume that the VAR errors follow a Gaussian distribution with zero mean and variance-covariance matrix $\boldsymbol{\Omega}_t$,

$$\boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Omega}_t). \tag{2.2}$$

We assume that $\boldsymbol{\Omega}_t$ can be decomposed as follows (Geweke and Zhou, 1996; Pitt and Shephard, 1999; Aguilar and West, 2000),

$$\boldsymbol{\Omega}_t = \boldsymbol{L}\boldsymbol{V}_t\boldsymbol{L}' + \boldsymbol{\Sigma}_t = \sum_{j=1}^{q} \boldsymbol{L}_{\bullet j}\boldsymbol{L}'_{\bullet j}\exp(v_t) + \boldsymbol{\Sigma}_t, \tag{2.3}$$

with $\boldsymbol{L}$ being a $M \times q$ matrix of factor loadings and its jth column given by $\boldsymbol{L}_{\bullet j}$, $\boldsymbol{V}_t = \exp(v_t) \times \boldsymbol{I}_m$ and $\boldsymbol{\Sigma}_t = \text{diag}(\exp(s_{1t}), \dots, \exp(s_{Mt}))$ are diagonal variance-covariance

[2] For simplicity, we abstract from deterministic terms in the model. The empirical application includes a constant term.

matrices of dimensions $q \times q$ and $m \times m$, respectively. Note that the specification in Eq. (2.3) reduces the number of free parameters in the variance-covariance matrix significantly (in the $q \ll m$ case), effectively providing a parsimonious representation of the one-step-ahead prediction error variance of the VAR. Moreover, it assumes that the joint dynamics of $\boldsymbol{\Omega}_t$ effectively depend on the scalar uncertainty factor v_t, with the factor variances being proportional to v_t.

The scalar process v_t is assumed to follow an AR(1) process,

$$v_t = \mu_v + \rho_v(v_{t-1} - \mu_v) + \vartheta_v u_t. \tag{2.4}$$

Here, μ_v denotes the unconditional mean of the corresponding log volatility, ρ_v is the autoregressive parameter with support in the interval (-1, 1) and $u_t \sim \mathcal{N}(0, 1)$ is a standard normally distributed white noise error, while ϑ_v^2 denotes the innovation variance of the the log volatility process.

Similarly to Eq. (2.4), we assume that the logarithm of s_{jt}^2 evolves according to an AR(1) process,

$$s_{jt} = \mu_{sj} + \rho_{sj}(s_{jt-1} - \mu_{sj}) + \vartheta_{sj} e_{jt}, \tag{2.5}$$

with the parameters of Eq. (2.5) being defined analogously to Eq. (2.4).

The representation in Eq. (2.3) is equivalent to the following q-factor dynamic model in $\boldsymbol{\varepsilon}_t$ (see Geweke and Zhou, 1996; Aguilar and West, 2000),

$$\boldsymbol{\varepsilon}_t | \boldsymbol{L}, \boldsymbol{f}_t, \boldsymbol{\Sigma}_t \sim \mathcal{N}(\boldsymbol{L}\boldsymbol{f}_t, \boldsymbol{\Sigma}_t), \quad \boldsymbol{f}_t | \boldsymbol{V}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{V}_t) \tag{2.6}$$

which implies that the vector of m reduced-form shocks is driven by a small number of q zero-mean factors $\boldsymbol{f}_t$ which feature a time-varying variance-covariance matrix $\boldsymbol{V}_t$.[3]

[3]In contrast to factor-augmented VAR models (Bernanke et al., 2005), we do not aim to summarize the information in $\boldsymbol{y}_t$ by means of dynamic factors that effectively model the conditional mean

One important feature of our approach is that common uncertainty is assumed to arise from the common shocks in $\boldsymbol{f}_t$. Thus, if the uncertainty v_t surrounding the common component in the reduced-from shocks increases, we treat this as an increase in international uncertainty. It is noteworthy that we disentangle international uncertainty from idiosyncratic movements in uncertainty captured by the elements in $\boldsymbol{\Sigma}_t$. Compared to the existing literature our approach assumes that the common shocks are driven by a scalar hyperparameter, in the spirit of Carriero et al. (2015a). The additional layer of hierarchy allows for disentangling the global uncertainty component from variable and/or country-specific uncertainty by assuming that the idiosyncratic noise components all feature their own SV processes.

2.2 An illustrating example

As stressed in the previous section, we assume that uncertainty is measured through the latent volatility process v_t that determines the variability of the latent factors in $\boldsymbol{f}_t$. This, in turn, determines the impact of uncertainty on the elements in $\boldsymbol{y}_t$, both directly by considering the vector of regression coefficients in $\boldsymbol{\gamma}$ and indirectly through its impact on the error variances.

To provide some intuition on how v_t shapes the variance-covariance matrix $\boldsymbol{\Omega}_t$, we consider the single factor model $q = 1$. For $q = 1$, Eq. (2.3) reduces to

$$\boldsymbol{\Omega}_t = \boldsymbol{\Lambda}_{\bullet 1}\boldsymbol{\Lambda}'_{\bullet 1} \exp(v_t) + \boldsymbol{\Sigma}_t. \tag{2.7}$$

The logarithm of the main diagonal elements of Eq. (2.7) is given by

$$\omega_{ii,t} = \tilde{\lambda}_i v_t + s_{1t}, \tag{2.8}$$

of Eq. (2.1), but provide a parsimonious way of representing the variance-covariance matrix of the innovation variances. This can be seen by integrating out the latent factors in Eq. (2.1) and comparing the result with the hierarchical representation obtained by substituting Eq. (2.6) into Eq. (2.1).

whereby $\omega_{ii,t} := \ln[\boldsymbol{\Omega}_t]_{ii}$ is the logarithm of the i,i-th element of $\boldsymbol{\Omega}_t$ and $\tilde{\lambda}_i := \ln(\lambda_i^2)$. Equation (2.8) illustrates that the factor structure implies that the (log) shock variances feature a factor structure with v_t as the common factor. Thus, changes in v_t directly induce movements in the error variances, scaling them upwards or downwards.

Since Eq. (2.6) is not identified from an econometric point of view, we identify the factors and associated loadings by specifying the upper $q \times q$ block of $\boldsymbol{L}$ to be a lower triangular matrix with $[\boldsymbol{L}]_{11} = 1$. This identifies the scale of v_t.

2.3 Prior setup and posterior inference

We estimate the model proposed in the previous subsection using Bayesian methods. This makes it necessary to specify a set of prior distributions on each parameter of the model. Since, conditional on the loadings and factors, our model consists of a relatively standard VAR model, a typical variant of the well-known Minnesota prior (Litterman, 1986; Sims and Zha, 1998) can be used. However, we depart from this literature and adopt the shrinkage prior proposed in Huber and Feldkircher (2016). This prior setup possesses convenient properties for modeling large dimensional systems, avoiding issues common to traditional shrinkage priors in the Minnesota tradition like the tendency to overshrink significant signals.

We impose a Gaussian prior on the autoregressive coefficients, stored in a $K \times M$ matrix $\boldsymbol{A} = (\boldsymbol{A}_1, \dots, \boldsymbol{A}_p)'$, with $K = pM$,

$$\text{vec}(\boldsymbol{A}) \sim \mathcal{N}_K(\text{vec}(\boldsymbol{\Phi}), \boldsymbol{\Psi}). \tag{2.9}$$

The matrix of prior expected values, $\boldsymbol{\Phi}$, is of dimension $K \times M$ and $\boldsymbol{\Psi}$ is a $MK \times MK$ diagonal prior variance matrix.

For the prior expected value we mimic features of the Minnesota prior (Litterman, 1986; Kadiyala and Karlsson, 1997; Sims and Zha, 1998). This implies that we specify the prior mean $\mathbf{\Phi}$ such that

$$\phi_{j,ik} = \mathbb{E}([\boldsymbol{A}_j]_{ik}) = \begin{cases} 1, & \text{for } i = k; j = 1 \\ 0, & \text{for } i \neq j; j > 1 \end{cases} . \tag{2.10}$$

The expectation operator is denoted by $\mathbb{E}(\bullet)$ and $[\bullet]_{ij}$ selects the (i,j)th element of a given matrix. Equation (2.10) implies that the coefficient associated with the first own lag of a given variable is a priori given by unity. This reflects the prior view that the variables in the model follow a highly persistent process that can be represented by a random walk specification.

This mean specification implies that the prior on each coefficient is given by the following continuous shrinkage prior that depends on a set of local shrinkage parameters $\tau_{j,ik}$ $(j = 1, \ldots, p; \ i = 1, \ldots, M; \ k = 1, \ldots, M)$ and a lag-specific shrinkage parameter λ_j^2,

$$[\boldsymbol{A}_j]_{ik} | \tau_{j,ik}^2, \lambda_j^2 \sim \mathcal{N}(\phi_{j,ik}, 2/\lambda_j^2 \, \tau_{j,ik}^2), \tag{2.11}$$

$$\tau_{j,ik}^2 \sim \mathcal{G}(\kappa_j, \kappa_j), \tag{2.12}$$

where $\mathcal{G}$ denotes the Gamma density and κ_j is a hyperparameter chosen by the researcher. The lag-specific shrinkage parameter λ_j^2 pushes all coefficients in $\boldsymbol{A}_j$ towards zero. Another feature of the Minnesota prior is that higher lag orders are assumed to be less important for predicting $\boldsymbol{y}_t$. We thus also mimic this feature in a stochastic fashion, following Bhattacharya et al. (2011), and assume a multiplicative Gamma process prior,[4]

$$\lambda_j^2 = \prod_{n=1}^{j} \omega_n, \quad \text{for } j = 1, \dots, p, \tag{2.13}$$

$$\omega_n \sim \mathcal{G}(c_n, d_n). \tag{2.14}$$

This specification assumes that if the components ω_n exceed unity, coefficient matrices associated with higher lag orders become increasingly sparse. The lag-specific scaling parameter λ_j^2 controls the overall degree of shrinkage while $\kappa_j \in \mathbb{R}^+$ controls the thickness of the tails of the marginal prior, obtained after integrating out the local scalings. This implies that small values of κ_j place increasing mass on values near the prior mean, which equals zero for all coefficients except for the diagonal elements of A_1, but at the same time the excess kurtosis of the marginal prior increases. This property is crucial since it allows for non-zero regression coefficients in the presence of strong lag-specific shrinkage. In what follows we specify a prior on κ_j, $\kappa_j = \kappa/j^2$ and thus deterministically assume that coefficients related to higher lag orders are a priori more likely to be zero while at the same time the tail behaviour of the prior restricts the degree of overshrinkage that is often seen in typical Minnesota-prior based VAR models.

On $\boldsymbol{\gamma}$, we use a Gausisan prior on each of the M elements in $\boldsymbol{\gamma}$, $\gamma_j \sim \mathcal{N}(0, \varrho)$ with $\varrho = 10$. Likewise, we impose normally distributed priors on each element l_{ij} of $\boldsymbol{L}$,

$$l_{ij} \sim \mathcal{N}(0, v) \tag{2.15}$$

where we set $v = 10$ to render this prior effectively non-informative given the scale of the variables used in the empirical application.

[4] For a recent application of a similar prior within the general framework of state space models, see Korobilis et al. (2014).

For all log-volatility equations, following Kastner and Frühwirth-Schnatter (2014), we impose a normally distributed prior on μ_v and $\mu_{\sigma j}$ with zero mean and variance 10^2, which proves to be relatively uninformative given the scale of the data in the application. In addition, we impose a Beta prior on $\frac{\rho_v+1}{2} \sim \mathcal{B}(25, 5)$ and $\frac{\rho_{\sigma j}+1}{2} \sim \mathcal{B}(25, 5)$, placing significant prior mass on high persistence regions of the corresponding parameter. Using a (relatively non-standard) Gamma prior on $\vartheta^2_{\sigma j} \sim G(1/2, 1/(2B_\vartheta))$ and $\vartheta^2_v \sim G(1/2, 1/(2B_\vartheta))$, with $B_\vartheta = 1$, translates into a normally distributed prior on the signed standard deviation with mean zero and variance given by B_ϑ.

2.4 Full conditional posterior simulation

We draw from the posterior distributions of the parameters of interest in the model outlined above using a Markov chain Monte Carlo (MCMC) algorithm. Conditional on the latent factors and their corresponding loadings, Eq. (2.1) can be rewritten as

$$\hat{\boldsymbol{y}}_t = \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \boldsymbol{\gamma} v_t + \boldsymbol{\eta}_t \tag{2.16}$$

with $\hat{\boldsymbol{y}}_t = \boldsymbol{y}_t - \boldsymbol{L}\boldsymbol{f}_t$ and $\boldsymbol{\eta}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_t)$. Since the covariance matrix of $\boldsymbol{\eta}_t$ is diagonal, inference on the parameters of Eq. (2.16) can be carried out on an equation-by-equation basis. This implies that the computational burden is reduced considerably because the involved matrix operations are fairly low dimensional as compared to the estimation of a full VAR model.

Our MCMC design is composed by the following steps:

1. The individual scaling parameters are simulated from a Generalized Inverted Gaussian (GIG) distribution,

$$\tau^2_{j,ik} | \bullet \sim \mathcal{GIG}([\boldsymbol{A}_j]^2_{ik}, \kappa_j - 1/2, \kappa_j \lambda_j^2), \tag{2.17}$$

   The $\bullet$ indicates conditioning on the remaining parameters of the model.

2. We simulate the lag-specific shrinkage parameters from the Gamma distributed conditional posterior distribution.

$$\lambda_j^2|\bullet \sim \begin{cases} \mathcal{G}(c_1 + \kappa_1 M^2, d_1 + \kappa_1/2 \sum_{i=1}^{M} \tau_{1,i1}^2) & \text{if } j = 1, \\ \mathcal{G}(c_j + \kappa_j M^2, d_j + \kappa_j/2\ \lambda_{j-1} \sum_{i=1}^{M} \sum_{k=1}^{M} \tau_{j,ik}^2) & \text{if } j > 1. \end{cases} \tag{2.18}$$

3. Conditional on $\boldsymbol{L}$, $\boldsymbol{f}^T = (\boldsymbol{f}_1, \dots, \boldsymbol{f}_T)'$ and $\boldsymbol{\Psi}$ as well as the full history of log volatilities v_t and s_{jt}, the VAR coefficients can be sampled equation by equation from a multivariate Gaussian posterior distribution that takes a standard form (see Zellner, 1973; Karlsson, 2012, for example). Note that we normalize each equation in Eq. (2.16) by dividing by $\exp(s_{jt}/2)$.

4. Conditional on the VAR coefficients and the factors, sampling the loadings reduces to a setting with M unrelated regression models with the VAR errors as endogenous variables. Again, we render each equation conditionally homoscedastic by dividing through by $\exp(s_{jt}/2)$.

5. Conditional on the loadings and the VAR coefficients, the latent factors can be sampled from independent normal distributions for each $t = 1, \dots, T$ by exploiting basic properties of the multivariate normal distribution (see Aguilar and West, 2000, for more details)

6. We sample the full history of log volatilities s_{jt} using the algorithm proposed in Kastner and Frühwirth-Schnatter (2014).[5]

7. Finally, due to the inclusion of v_t in the conditional mean equation, the model can not be cast in the linear Gaussian state space framework. This implies that we are unable to exploit Kalman filter - based techniques and thus resort to

[5]An R package (stochvol) exists to perform this step (Kastner, 2015).

the single-step Metropolis Hastings (MH) algorithm outlined in Jacquier et al. (1994).

3 Data and model specification

Our dataset has quarterly frequency and spans the period from 1979Q4 to 2013Q4. For each of the G7 countries, we include data on real GDP, inflation, short-term interest rates, total credit, equity prices, exchange rates and exports. Thus, we include macroeconomic quantities that represent both the demand and supply side of the economy. The inclusion of equity prices, credit and interest rates serves to approximate the financial side. The data are obtained from the International Monetary Fund's International Financial Statistics, national sources and the BIS.[6] All variables except interest rates and inflation enter the model in log levels.

Given the quarterly frequency of our data, we include $p = 2$ lags[7] in the model. We set $c_j = 1.5$ and $d_j = 1$ for all j. This choice centers the prior on values slightly above unity but stays relatively uninformative.

For κ, we adopt a rather low value ($\kappa = 0.6$). This specific value is based on the findings in Huber and Feldkircher (2016), who integrate out κ in a Bayesian fashion and find that the posterior of κ is centered around 0.6 for smaller sized systems under a similar lag-wise shrinkage specification. Setting ω close to zero implies that we place significant prior mass of the off-diagonal elements in A_1 on zero and strongly center the main diagonal elements around unity while maintaining heavy tails of the underlying marginal prior. For $A_j (j > 1)$ we assume that $\omega_j^* = 0.1/l^2$ and thus place even more mass on zero. The relationship between the lag-specific shrinkage parameter λ_j^2 and ω_j, however, implies that we still do not rule out non-zero regression coefficients associated with higher lag orders.

[6] A detailed description of the dataset can be found in Feldkircher and Huber (2016).
[7] All findings presented below stay qualitatively similar if we use $p = 5$.

The results presented are based on 30,000 MCMC draws after discarding the first 15,000 draws as burn-in. Running the chain several times from different initial conditions and comparing the corresponding posterior draws gives clear indications of convergence.

Following Mumtaz and Theodoridis (2016), we select the appropriate number of latent factors by choosing the number of factors that minimizes the deviance information criterion (DIC) (Spiegelhalter et al., 2002). We evaluate the DIC over a grid of possible values for $q \in \{1, \ldots, 14\}$ and select the number of factors q^* that yields the lowest DIC. In our case, $q^* = 12$, a choice that is consistent with preliminary findings based on traditional criteria used to select the number of factors.

4 Global uncertainty and its international transmission

In this section we present our main findings concerning the quantitative assessment of global uncertainty. In the next subsection we briefly summarize the key properties of our estimated global uncertainty measure and how it relates to traditional measures adopted in the literature. We then proceed to the findings of our impulse response exercise, where we investigate the macroeconomic impact of a global uncertainty shock.

4.1 An informal assessment of global financial uncertainty

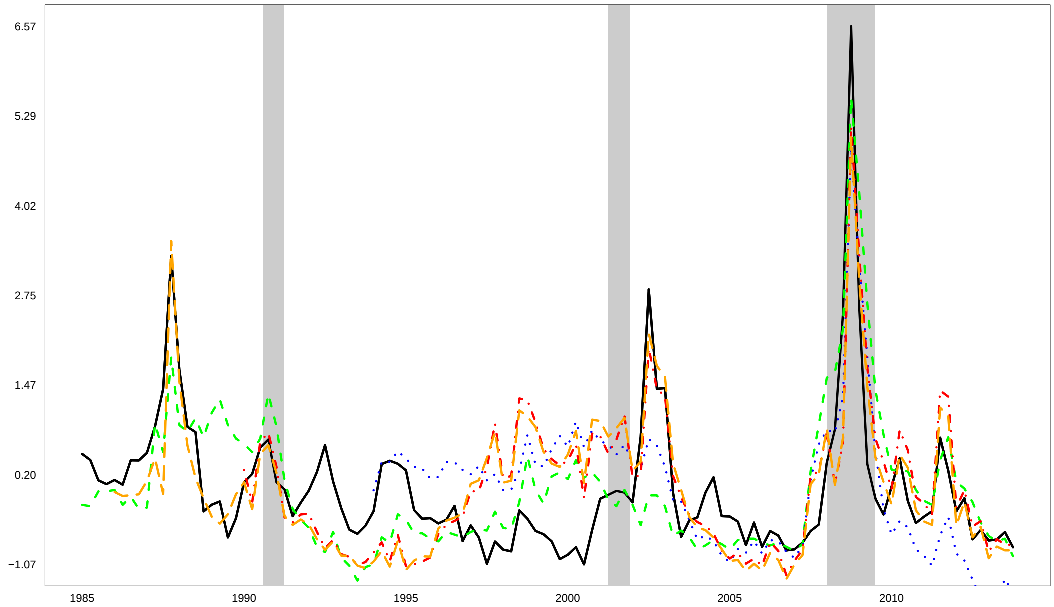
Figure 1 displays the mean of the posterior distribution of the proposed uncertainty measure alongside four commonly used measures of economic and financial uncertainty: the national financial conditions index (NFCI), the financial stress index (FSI), the volatility index (VIX) and the CBOE S&P 100 volatility index (VXO).

Our measure of international uncertainty closely tracks all four indexes used for the US. All measures display a sharp increase in uncertainty during the 1987 stock market crash, the East Asian currency crisis, the sovereign default of Russia as well as the mild recession following the 9/11 terrorist attacks. Finally, and most notably, the recent financial crisis is also well captured. As in Jurado et al. (2015), our estimates imply a smaller number of episodes of high uncertainty than those indicated by external proxies. The strong correlation of the international factor with selected US-based uncertainty measures highlights the relevant role played by the US stock market, whose volatility strongly impacts global financial uncertainty. In particular, the sharp increase in volatility during the global financial crisis reflects the fact that our uncertainty measure is more closely linked to financial uncertainty than to uncertainty stemming from business cycle movements (for a recent application that explicitly discriminates between real and financial uncertainty see Ludvigson et al., 2015).

4.2 The dynamic effects of global uncertainty shocks and economic fragility

In this section, we consider the dynamic international effects of uncertainty shocks. We normalize the size of the uncertainty shock to yield a 10% *average* decline in equity prices across all countries considered. This normalization is chosen for two reasons. First, it is implemented on equity prices because financial markets are not only a relevant cause of global shocks and uncertainty, but they also summarize past and future information of economic agents. The *common* normalization, in turn, provides impulse responses that measure the relative impact of the common uncertainty on different countries. The reaction of international equity markets is shown in Fig. 2. The range of values between the 16th and 84th percentile is depicted in light blue while the range of values between the 25th and 75th percentile is given by the dark blue area.

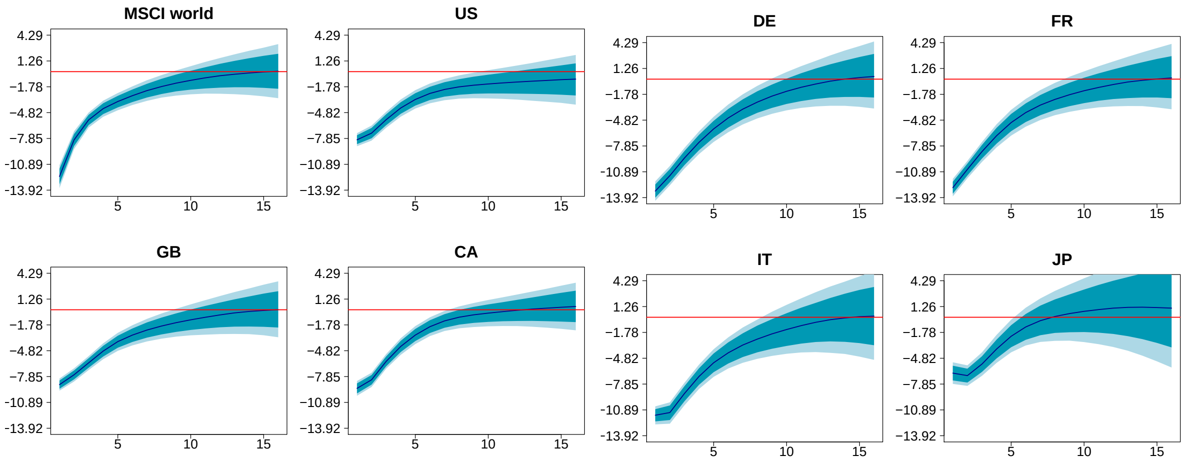
Rising uncertainty about future earnings and portfolio reshuffling of investors towards safer funds (e.g. commodities or bonds considered safe) should entail a negative effect of uncertainty on financial markets. The effects on equity prices confirm



Notes: The figure presents the posterior mean of the uncertainty measure (in solid black), the national financial conditions index (NFCI) for the US (in dashed green), the financial stress index (FSI, in dotted blue), the volatility index (VIX, in dot-dashed red) and the S&P 100 volatility index (VXO, in dashed orange). All quantities shown are standardized by substracting the mean and dividing by the corresponding standard deviation.

Fig. 1: Posterior median of the volatility of the latent factor alongside the NFCI, the FSI and the VIX

this conjecture and appear persistent and homogeneous across countries. Since we impose an average restriction on the uncertainty shock, the impact magnitudes reveal the extent to which the reaction of the different economies considered differ from that of a typical economy, measuring relative fragility. The qualitative effect is relatively similar across most countries, but the countries belonging to the Euro area are similarly (and more) affected than the average G7 economy. This result is not surprising given the high degree of economic integration and the common policies in the euro area. However, it identifies the European block as slightly more affected by global uncertainty shocks. For Japan, consistently with the results presented for exchange rates and the considerations put forward about the centrality of the Japanese equity



Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. Results are based on 35,000 posterior draws. The red line indicates the zero line.

Fig. 2: Responses of equity prices to an uncertainty shock across the G7 countries

markets for Asia, the impact response is comparably weaker when compared to the other economies in our panel.

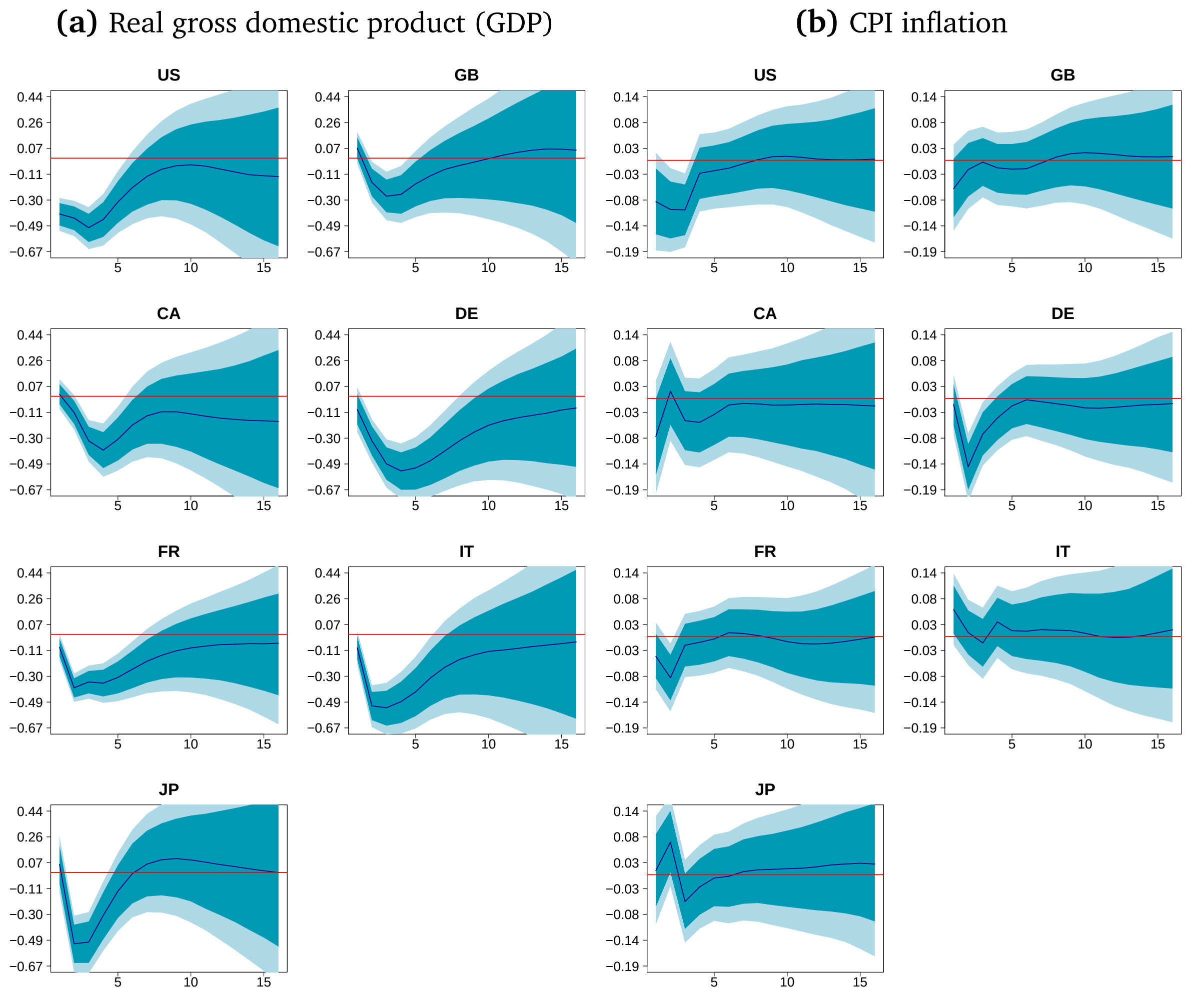
The responses of the other quantities, shown in Figs. 3 to 6, provide indications about how the macroeconomy of different countries react to uncertainty shocks and how persistent are such effects. Of particular interest are the reactions of real activity, measured through real GDP, and shown in Fig. 3 (a). Across all countries considered, an increase in uncertainty leads to a significant decline in output after a few quarters. US is often the source of global shocks. Output reactions in the US, therefore, are different in the sense that the reaction is immediate and peaks after approximately two quarters. Apart from the US, most economies considered feature a similar shape of the dynamic responses, with a rather weak initial decrease in output that subsequently reaches its peak after around four quarters. When looking at the maximum impact , we find higher values for the US, Germany, Italy and Japan. The peak output response after around one year is consistent with the structural VAR findings of Gilchrist et al. (2014).

Looking at the speed of adjustment, we identify a European group, including Germany, France and Italy, where the impact of a shock appears to be longer than for the average country, suggesting higher economic rigidities. After around seven quarters, the central 68 percent mass of the posterior distribution of the impulses contains zero for the majority of G7 countries.

A common result in the literature is the ”volatility overshoot”, a significant rebound in economic activity following an increase in economic uncertainty (e.g. Bloom, 2009), generally explained with the reallocation of resources from low to high-productivity firms after an exogenous increase in uncertainty. Our results are closer to those described in Jurado et al. (2015) and Bachmann et al. (2013), and we do not find systematic evidence of economic rebounds. A possible explanation for the absence of the overshoot in real activity can be found in Caggiano et al. (2014), who report that once the sample is extended to include the period after 2008 (i.e. when most developed central banks switched to unconventional monetary policy measures in the presence of the effective zero lower bound) the overshoot vanishes.

Figure 3(b) shows the responses of inflation. From a theoretical perspective, changes in inflation following an uncertainty shock are the result of the operation of two channels acting in opposite directions (Fernández-Villaverde et al., 2011): the aggregate demand channel (that tends to reduce inflation as households reduce consumption when facing higher levels of uncertainty) and the upward pricing bias channel (which leads to firms increasing prices to improve profits). The responses of inflation (see Fig. 3(b)) suggests that inflation drops in the US, France, and Germany while displaying no significant reactions in the remaining countries. The drop in inflation mirrors the findings presented in Bloom (2009). Inflation reactions are, however, only of transitory nature, usually fading out within three to five quarters.

Figure 4 depicts the responses of exports and the real exchange rate against the US dollar. Two findings are worth emphasizing. First, an increase in international

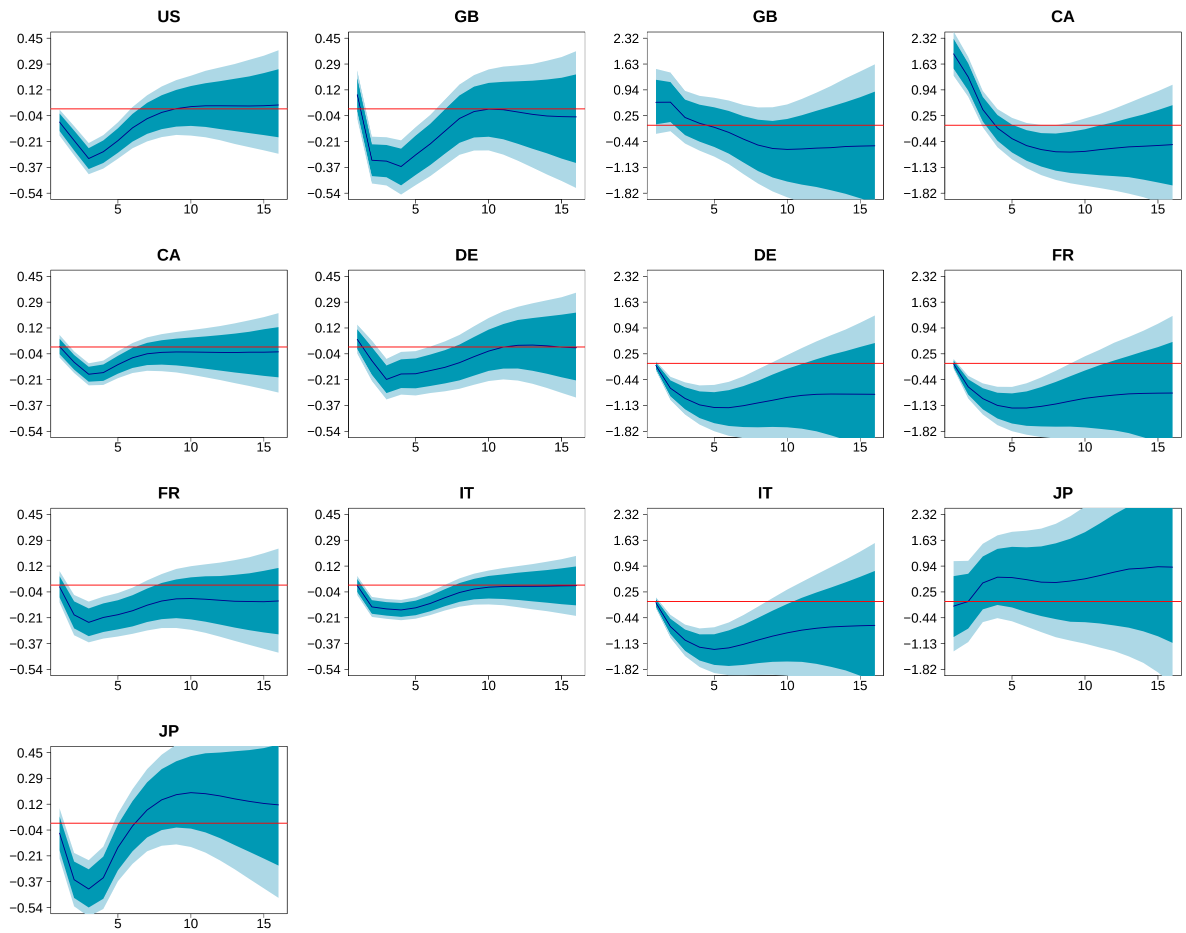


Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. The red line indicates the zero line.

Fig. 3: Responses of real output and inflation to an uncertainty shock across the G7 countries

uncertainty leads to a significant decline in exports for all countries. Second, and unsurprisingly given the tight relationship between global risk and international trade, responses appear to be remarkably strong for all countries. The shape of the responses is also similar for all countries. Our findings closely mirror the actual decline in world trade experienced during the global financial crisis, with the largest drop in international trade since the Great Depression. Finally, Fig. 4 (b) focuses on exchange rates

(a) Exports **(b)** Real exchange rates



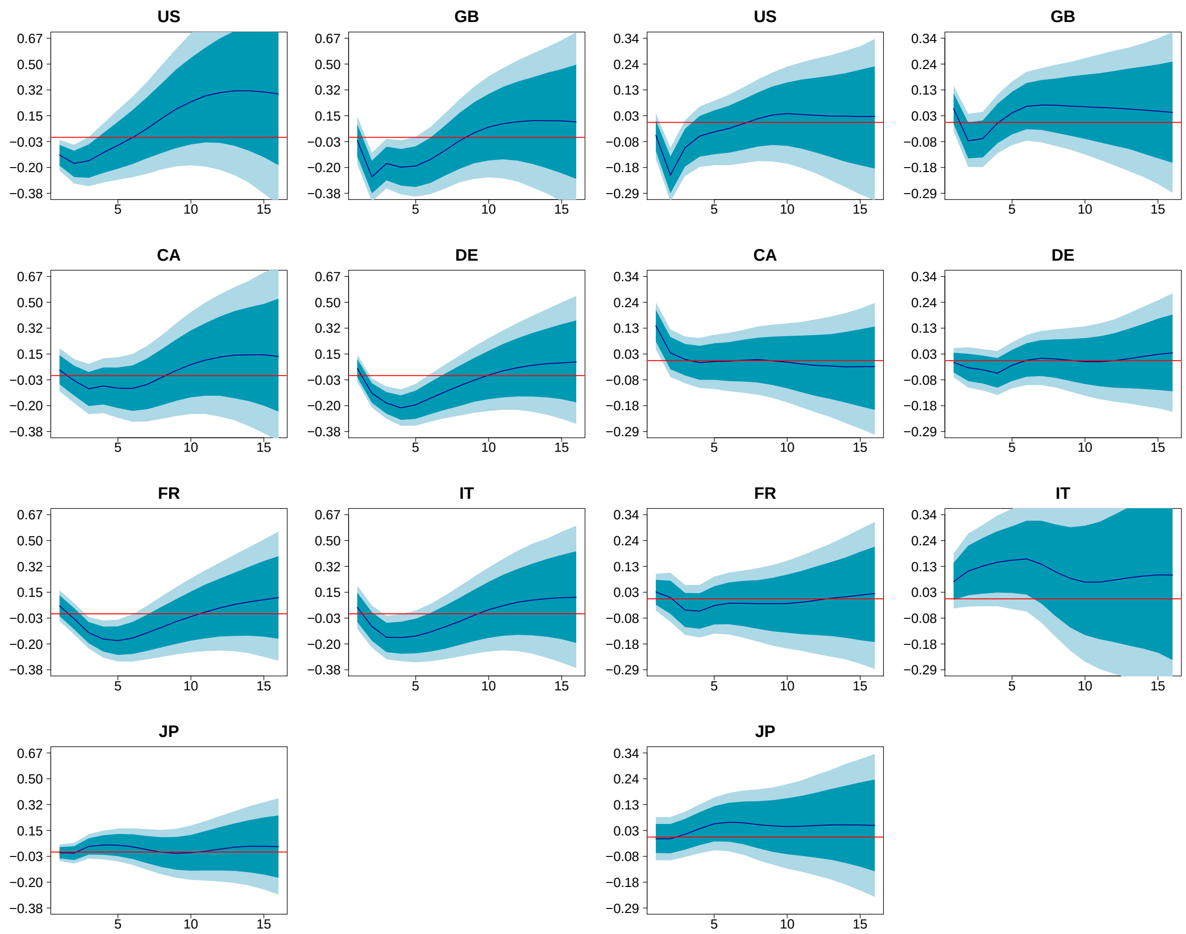
Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. Results are based on 35,000 posterior draws. The red line indicates the zero line.

Fig. 4: Responses of exports and real exchange rates to an uncertainty shock across the G7 countries

and suggests that the British pound and the Canadian dollar directly depreciate vis-á-vis the US dollar. Interestingly, countries that share the Euro display a slower reaction of their real exchange rate and tend to display an appreciation.

Inspection of the dynamic responses of short-term interest rates in Fig. 5(a) shows declining interest rates in response to an unexpected increase in uncertainty. The European Central Bank responds to uncertainty shocks and the accompanying decline

(a) Short-term interest rates **(b)** Long-term interest rates

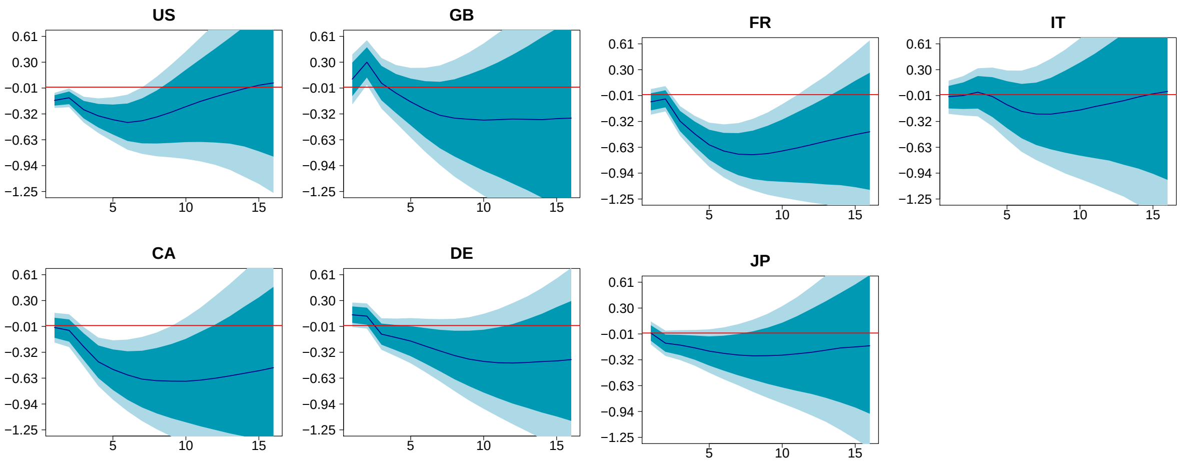


Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. The red line indicates the zero line.

Fig. 5: Responses of short-term and long-term interest rates to an uncertainty shock across the G7 countries

in output and inflation by lowering the policy rate. This is consistent with the VAR-based findings in Bekaert et al. (2013), who report falling interest rates in response to an uncertainty shock in the US. However, for Canada and Japan we find only limited evidence that central banks decrease interest rates, providing a puzzle that could be due to the fact that our sample also includes the periods characterized by the zero lower bound on interest rates. Exclusion of the observations from the 2008Q2 onwards provides clearer evidence that central banks lower their policy rates in the short-run. For the same reason we observe increases in interest rates after around one year in Japan, where rates are close to zero since 1999.

While short-term interest rates are closely related to central bank activities, long-term interest rates on government bonds are determined by market forces and their perception of uncertainty. Figure 5(b) shows that an increase in uncertainty leads to positive reactions of long-term rates in countries that have higher levels of debt (see, for instance, the responses in Italy and Japan). A more general reallocation of international investors' portfolios also increases long-term rates in Canada, while at the same time reducing rates in safe havens such as Germany and US.



Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. The red line indicates the zero line.

Fig. 6: Responses of total credit to an uncertainty shock across the G7 countries

Finally, Fig. 6(b) presents the dynamic responses of total credit. Since economic agents value projects by discounting future (uncertain) cash flows, we expect that increases in uncertainty naturally translate into more uncertain future cash flows, leading to a lower net present value of a given project and to a fall in available credit to the private sector (Krishnamurthy, 2010). The evidence is consistent with the actual developments during the recent crisis, where elevated levels of uncertainty led to a contraction in available credit in some countries. We find that credit reacts with a lag, falling significantly after around three quarters for the majority of countries considered. The credit channel adds to the equity channel described above and helps explaining the lower investment and the protracted reduction in output that characterized the aftermath of the crisis.

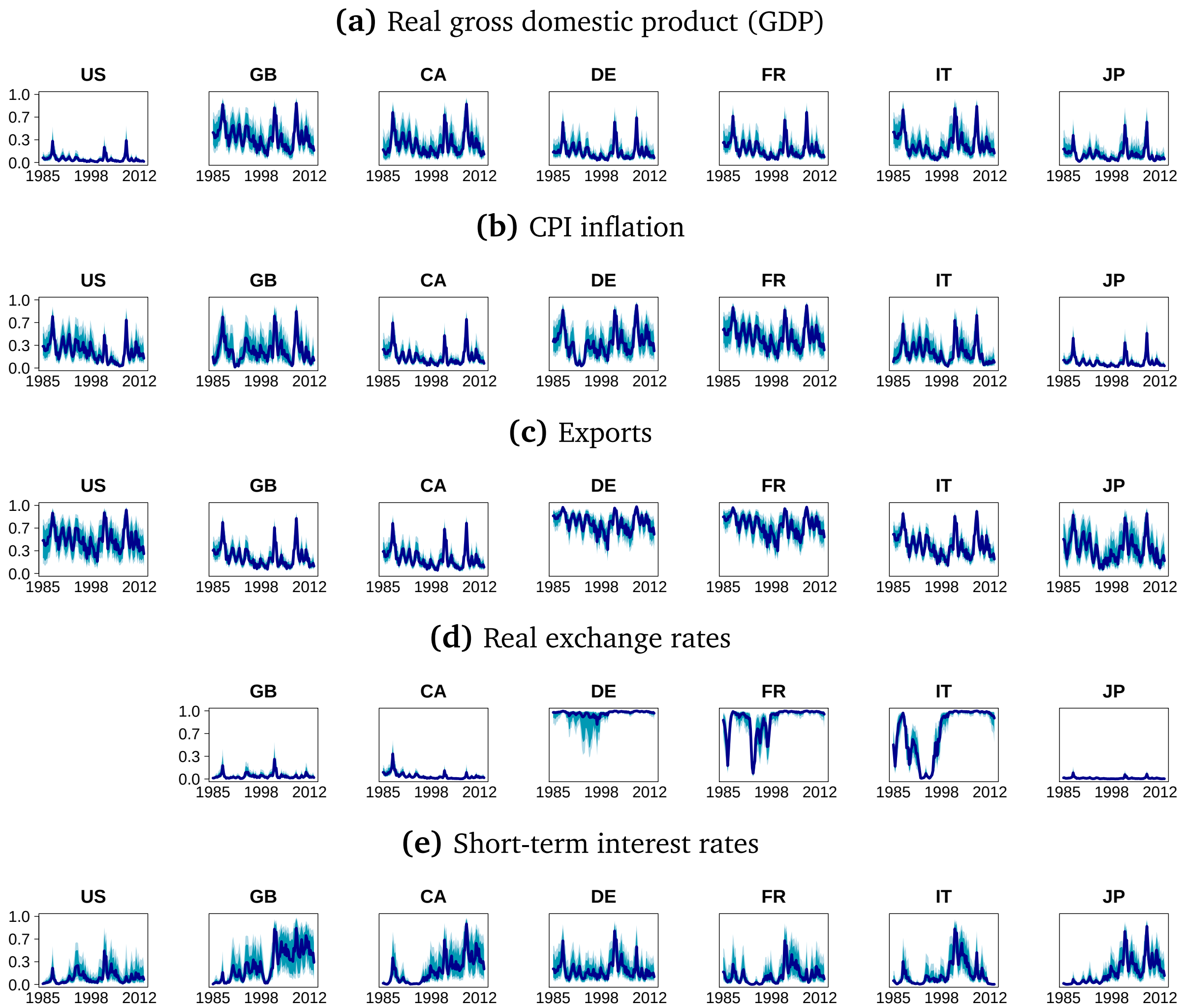
4.3 Variance decompositions

To investigate the importance of the common shocks, Fig. 7 displays the forecast error variance explained by the common uncertainty factor over time for selected variables and countries. The first row in Fig. 7 (a) shows the decomposition for GDP. Concentrating on the average behavior of the shares across time reveals that global uncertainty plays a rather limited role during tranquil periods for most countries under consideration. On the other hand, global uncertainty plays an important role during economic downturns, explaining between 50 and 75 percent of the variance for all countries.

Figure 7 (b) presents the share of forecast error variance explained by the uncertainty factor for CPI inflation. We expect uncertainty to be a major determinant of inflation in crisis times, as the negative effect of low demand should lead firms away from the production frontier and towards low price strategies. This is visible in the charts following 2008. Somewhat more surprisingly, the contribution of uncertainty is strong across the whole sample, again with the exception of Japan where inflation has been close to zero for domestic reasons. Differences in price stickiness, reflecting different institutional structures, and in the policy reaction of central banks to inflation may also explain the differences across countries. The common monetary policy and the strong economic ties determine a similar variability of inflation in the Eurozone countries during the great recession.

It is to be expected that international uncertainty strongly contributes to the forecast error variance of exchange rates and exports, by negatively affecting global trade and determining exchange rate adjustments via international capital flows. Figures 7 (c) and 7 (d) display the shares of explained variance for exports and real exchange rates. The impulse responses confirmed that high uncertainty reduces exports across all countries and appreciated the dollar. The variance decomposition further supports the intuition, highlighting that uncertainty shocks strongly determine export dynamics. The effect is particularly visible in the US and in the euro area countries, and the introduction of the euro increases the overall contribution. Our explanation largely hinges on the corresponding behavior of the exchange rate. The euro and the US Dollar being the two dominant world currencies, the exchange rate between the two is the most responsive to global uncertainty and to the policy measure implemented on the two sides of the Atlantic. In the other countries, being somewhat more "peripheric", the effect is less important as other (more local) shocks are more important drivers of exchange rate gyrations.

The last row of Fig. 7 show the corresponding shares of explained variance for short-term interest rates (Fig. 7 (e)). Short-term interest rates are closely related to policy rates. If we interpret each short-term interest rate equation as a monetary policy rule, the large shares indicate that especially during crisis episodes, central banks tend to react to global movements in uncertainty. For the ECB, this finding is particularly pronounced since the contributions across Germany, France, and Italy are similar since 1998. Note that for some countries, we observe a small increase after 2008. This could point towards increased relevance of uncertainty once the zero lower bound of interest rates is reached.



Notes: The figure display the share of innovation variance explained by the uncertainty factor across all variables and countries considered over the period from 1980Q1 to 2013Q4.

Fig. 7: Fraction of innovation variance explained by the global uncertainty factor across the G7 countries

5 Closing remarks

In this paper we empirically investigate economic uncertainty and its impact on the G7 economies. We propose a large-scale Bayesian vector autoregression with factor stochastic volatility to investigate the macroeconomic consequences of international uncertainty shocks on the G7 countries. Compared to existing approaches, our modeling framework enables the simultaneous estimation of the autoregressive parameters and the uncertainty measure, implying that uncertainty is a latent quantity and depends on systematic failures of economic agents to form correct expectations about future macroeconomic developments. Since the model is heavily parameterized we adopt novel adaptive shrinkage priors that push unnecessary coefficients towards zero while still providing enough flexibility to allow for non-zero regression coefficients.

Our measure of uncertainty compares well with other (US based) measures commonly adopted to measure economic uncertainty. Our estimates are strongly correlated with the VIX, the VXO, the national financial conditions index and the financial stress index. This suggests that US-based uncertainty shapes global uncertainty.

To assess the quantitative implications of a global uncertainty shock we perform impulse response analysis and investigate how the G7 economies react. Our findings are largely consistent with the existing literature on the impact of uncertainty on the US economy. However, we do not find the common result that uncertainty ultimately leads to a rebound in economic activity in the medium run, thus corroborating the findings in the recent work by Jurado et al. (2015).

We find that output, prices, short and long-term interest rates, and exports drop on impact after an uncertainty shock. On the other hand, total credit reacts only modestly on impact, displaying a more pronounced decline after around four quarters. Most exchange rates depreciate relative to the US dollar, reproducing the common empirical finding that investors shift assets in US-dollar denominated assets in times of elevated uncertainty. These movements are largely consistent with the actual pattern of macroeconomic time series experienced during the height of the recent financial crisis in 2008. The variance decomposition emphasizes that global uncertainty is an important driver in several macroeconomic variables, and possibly a major contributor to the dynamics of global trade and investment.

Our considerations link to the concept of economic fragility and of relative performance of different countries facing global uncertainty. Building on a common normalization, we find that countries belonging to the Euro area are similarly (and more) affected than the average G7 economy. The speed of adjustment criterion, again, identifies two groups: the US, the UK, Canada and Japan recover quickly, while in Germany, France and Italy the impact of a shock is longer than average, suggesting higher economic rigidities.

This paper focuses on the joint measurement of international shocks and national responses. As such, we do not adventure into policy prescriptions. However, this type of analysis can be useful when thinking about robust policy making. Global shocks can severely impact quantities monitored by policy makers in central banks and governmental institutions. Additionally, structural reforms and their implementation also can greatly benefit from an appropriate monitoring of relative exposure of different countries to global uncertainty and of the evolution of uncertainty over time. These are interesting themes for future research.

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