Department of Economics
Working Paper No. 245

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March 2017

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The macroeconomic effects of international uncertainty shocks

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Abstract

We propose a large-scale Bayesian VAR model with factor stochastic volatility to investigate the macroeconomic consequences of international uncertainty shocks on the G7 countries. The factor structure enables us to identify an international uncertainty shock by assuming that it is the factor most correlated with forecast errors related to equity markets and permits fast sampling of the model. Our findings suggest that the estimated uncertainty factor is strongly related to global equity price volatility, closely tracking other prominent measures commonly adopted to assess global uncertainty. The dynamic responses of a set of macroeconomic and financial variables show that an international uncertainty shock exerts a powerful effect on all economies and variables under consideration.

Keywords:	Factor stochastic volatility, vector autoregressive models, global propagation of shocks
JEL Codes:	C30, E52, F41, E32.

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1 Introduction

The deepening of economic and financial integration over the last 30 years has led to a situation where individual countries appear to be particularly exposed to common shocks. Such global shocks can severely impact quantities monitored by policy makers in central banks and governmental institutions (Leduc and Liu, 2012). 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 originated in the US housing market but quickly spread internationally, eventually leading to a severe global decline in real activity, asset prices and trade. Additionally, the crisis has been accompanied by a particularly sharp increase in uncertainty and thus lends itself as a case study on the impact of uncertainty on the real and financial sectors of the economy. 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) forced many 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 monetary policy shocks, which are typically modeled as an unpredictable uncorrelated innovation to the policy rate, a simple definition for measures of uncertainty shocks 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 shocks 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; Bachmann et al., 2013; Fernandez-Villaverde et al., 2011) rely on similar types of proxy based on stock market volatility or information on the cross-sectional dispersion of corporate profits.[1] Studies that simultaneously estimate uncertainty and its macroeconomic consequences are, however, relatively scarce (for some exceptions, see, Jurado et al., 2015; Shin and Zhong, 2016; Mumtaz and Theodoridis, 2016; Mumtaz et al., 2016; Carriero et al., 2016)

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

Recently, Jurado et al. (2015) obtain a time-varying 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. As opposed to the findings of Bloom (2009), their VAR analysis 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 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 and generalize the setting of Bloom (2009) to a larger set of countries. 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 contrary, emerging economies do not display a similar pattern, exhibiting more persistent declines in real activity over the forecast horizon.

The present contribution combines both strands of the literature mentioned above. First, we define uncertainty as a latent quantity to be estimated jointly with the model parameters in a unified framework. To this end, we assume that the reduced form errors of a Bayesian VAR with stochastic volatility (BVAR-SV) feature a factor structure. This implies that spikes in uncertainty are measured by imposing a factor structure on the one-step-ahead forecast error of the VAR. Second, the assessment of a broad range of macroeconomic and financial quantities for the G7 countries within this model framework allows us to recover an international uncertainty factor that drives the variance-covariance matrix of the full system. As a consequence, we can trace the effects of an increase in global uncertainty, as measured by the common factor that is most strongly loaded by forecast errors related to equity markets, on a broad range of macroeconomic and financial variables.

Our main findings can be summarized as follows. First, our measure of global uncertainty displays a similar pattern to other (mostly US based) measures adopted, producing 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. 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 a 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. On the other hand, almost all exchange rates tend to depreciate with respect to the US dollar after such an uncertainty shock. Such results replicate almost perfectly the actual developments of the aforementioned variables during the financial crisis of 2008/2009. Fourth, assessing whether there exist regional differences in responses to global uncertainty reveals that the magnitude of the reactions differs between a group consisting of the US, Canada and the UK and a group featuring Germany, Italy, France and Japan.

The remainder of the paper is structured as follows. Section 2 introduces the econometric framework adopted in our analysis, discusses the prior specification and provides a brief overview on the estimation method employed. Section 3 discusses the data set used, identification issues related to the factor model and several specification choices. Section 4 presents the main empirical results of the application of our mdel and section 5 concludes.

2 Econometric framework

Our modeling approach rests on the assumption that the innovations in a VAR of macroeconomic variables possess a factor structure and may thus be described by relatively few latent factors with stochastic volatility. These factors are then used to identify a global uncertainty factor, whose effects on the economy can be analyzed making use of impulse response analysis.

2.1 The vector autoregressive model with factor stochastic volatility

We are interested in modeling the dynamic responses of a vector of time series for a country 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 y_t is assumed to follow a VAR(p) process[2],

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t, \tag{2.1}$$

where A_j $(j = 1, \ldots, p)$ are $M \times M$ dimensional matrices of regression coefficients and, following Stock and Watson (2005), we assume that the VAR residuals follow a

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

factor stochastic volatility (FSV) model (Pitt and Shephard, 1999; Aguilar and West, 2000),

$$\varepsilon_t = L f_t + \eta_t \tag{2.2}$$

where L is a $M \times q$ matrix of factor loadings and $f_t \sim \mathcal{N}_q(0, V_t)$ is a vector containing q normally distributed static factors, representing a zero mean risk factor, in order to capture periods of high and low uncertainty with a diagonal variance-covariance matrix V_t given by

$$V_t = \text{diag}(\exp(v_{1t}), \ldots, \exp(v_{qt})). \tag{2.3}$$

The scalar processes v_{jt}, the logarithm of the factor variance, are assumed to follow AR(1) processes,

$$v_{jt} = \mu_j + \rho_j(v_{jt-1} - \mu_j) + u_{jt}, \tag{2.4}$$

where μ_j denotes the unconditional mean of the corresponding log volatility, ρ_j is the autoregressive parameter with support between -1 and 1 and $u_{jt} \sim \mathcal{N}(0, \vartheta_j^2)$ is a white noise error with variance ϑ_j^2. Finally, $\eta_t \sim \mathcal{N}_M(0, \Sigma)$ is a normally distributed vector error term with time-invariant variance-covariance matrix $\Sigma = \text{diag}(\sigma_1^2, \ldots, \sigma_M^2)$.

Equation (2.2) implies that the variance-covariance matrix of ε_t is given by

$$\Omega_t = L V_t L' + \Sigma. \tag{2.5}$$

We introduce time-variation in Ω_t exclusively through the stochastic volatility specification of the factors in f_t. The assumption of a constant Σ leads to significant computational gains. Our model assumes that each shock series features some equilibrium long-run level of volatility given by σ_i^2, with mean reverting deviations from that equilibrium value being driven by the stochastic volatility specification of the q latent factors.

Our model nests several specifications that are commonly adopted in applications for economics and finance. Assuming a constant V_t yields the model proposed in Stock and Watson (2005). If we set $q = 1$ we obtain a specification that is comparable to the model of Carriero et al. (2015a), albeit with a particular factor structure on the covariances. Our model framework, however, allows for a larger number of factors to summarize the dynamics of Ω_t.

2.2 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 loading and factors, our model consists of a relatively standard VAR model, we specify a variant of the well-known Minnesota prior (Litterman, 1986; Sims and Zha, 1998) that assumes a multivariate random walk model *a priori*.

We impose a Gaussian prior on the autoregressive coefficients, stored in a $M \times K$ matrix $A = (A_1, \ldots, A_p)$, with $K = pM$,

$$\text{vec}(A)|\Sigma \sim \mathcal{N}_K(\text{vec}(\Phi), \Sigma \otimes \Psi). \tag{2.6}$$

The matrix of prior expected values, Φ, is of dimension $M \times K$ and Ψ is a $K \times K$ diagonal prior variance matrix. The prior dependence between A and Σ implies that the likelihood of the model features a convenient Kronecker structure that permits equation by equation estimation and thus significantly simplifies the computational load associated with Bayesian inference for the model.

For the prior expected value and variance we implement a combination of the Minnesota prior (Litterman, 1986; Kadiyala and Karlsson, 1997; Sims and Zha, 1998) with the sum of coefficients prior (Bańbura et al., 2010). We specify the prior mean $\mathbf{\Phi}$ such that

$$\mathbb{E}([A_j]_{ik}) = \begin{cases} 1, & \text{for } i = k; j = 1 \\ 0, & \text{for } i \neq j; j > 1 \end{cases} . \tag{2.7}$$

The expectation operator is denoted by $\mathbb{E}(\bullet)$ and $[\bullet]_{ij}$ selects the i, jth element of a given matrix. Equation (2.7) 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.

The prior variance of A is specified such that the parameters associated to higher lag orders are more strongly shrunk towards zero, i.e.

$$\text{var}([A_j]_{ik}) = \begin{cases} \frac{\theta^2}{j^2}, & \text{for } i = k \\ \frac{\theta^2}{j^2}\frac{s_i}{s_k}, & \text{for } i \neq j; j \geq 1 \end{cases} . \tag{2.8}$$

Here, θ is a hyperparameter controlling the overall tightness of the prior and s_j $(j = 1, \ldots, m)$ denotes a prior scaling factor, typically chosen to be the standard deviation of an autoregressive model estimated over the full sample (Sims and Zha, 1998). Low values of θ place more weight on the prior relative to the likelihood information, whereas large values render the prior relatively non-informative. The term j^2 pushes the coefficients of more distant lags sharply towards zero a priori, capturing the notion that the more recent past is more relevant than the distant past when it comes to explaining the dynamics of the series.

The Minnesota prior described above is extended to perform ”soft” differencing using a set of dummy observations in the spirit of the so-called *sum of coefficients* prior or no-cointegration prior (Doan et al., 1984). Both priors can be implemented in a straightforward manner by concatenating the following set of dummy observations to the actual full-data matrices $\boldsymbol{Y}$ and $\boldsymbol{X}$ (Bańbura et al., 2010),

$$\underline{Y} = \begin{pmatrix} \text{diag}(s_1, \dots, s_M)/\theta \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \mathbf{0}_{M(p-1)\times M} \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \text{diag}(s_1, \dots, s_M) \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \text{diag}(\mu_1, \dots, \mu_M)/\tau \end{pmatrix}, \tag{2.9}$$

$$\underline{X} = \begin{pmatrix} J_p \otimes \text{diag}(s_1, \dots, s_M)/\theta \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ 0_{M\times pM} \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ (1, \dots, p) \otimes \text{diag}(\mu_1, \dots, \mu_M)/\tau \end{pmatrix}. \tag{2.10}$$

J_p is set equal to $\text{diag}(1, \dots, p)$, implementing shrinkage on the lagged endogenous variables, μ_j is set to the sample average of y_{jt} and τ is a hyperparameter that controls the tightness of the sum of coefficients prior. The first two blocks implement the prior on the coefficients related to the lagged endogenous variables, the third block implements the prior on the variance-covariance matrix of ε_t and the final block implements the sum of coefficients prior.

For the factor loadings we impose normally distributed priors on each element l_{ij} of L,

$$l_{ij} \sim \mathcal{N}(0, v) \tag{2.11}$$

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

For the log-volatility equation, following Kastner and Frühwirth-Schnatter (2014), we impose a normally distributed prior on μ_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 $\frac{\rho_j+1}{2} \sim \mathcal{B}(25, 5)$, placing significant prior mass on high persistence regions of ρ_j. Using a (relatively non-standard) Gamma prior on $\vartheta_j^2 \sim G(1/2, 1/(2B_\vartheta))$ with $B_\vartheta = 1$ translates into a normally distributed prior on ϑ_j with mean zero and variance given by B_ϑ. This choice provides more shrinkage capabilities as traditional inverted Gamma priors since a value of zero for ϑ_j is not ruled out a priori.[3] Finally, inverted Gamma priors are specified for each $\sigma_j^2 \sim \mathcal{IG}(0.01, 0.01)$.

[3]Using different values for B_ϑ (as long as they are not too small) yields similar results in our empirical study.

2.3 The Markov chain Monte Carlo algorithm

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

$$\hat{y}_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \eta_t \tag{2.12}$$

with $\hat{y}_t = y_t - Lf_t$. Since the covariance matrix of η_t is diagonal, inference on the parameters of Eq. (2.12) 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. Moreover, the assumption that Σ is time invariant implies that inversion of the design matrix can be placed outside the main loop of the MCMC algorithm, leading to substantial computational gains. In addition, estimating the M equations can, in principle, be straightforwardly parallelized. Our MCMC design is composed by the following steps:

1. Conditional on L and $f^T = (f_1, \dots, f_T)'$ as well as the full history of log volatilities $v^T = (v_1, \dots, v_T)$ with $v_t = (v_{1t}, \dots, v_{qt})'$, 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).

2. 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.

3. 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)

4. Finally, we sample the full history of log volatilities using the algorithm proposed in Kastner and Frühwirth-Schnatter (2014).[4]

2.4 Model identification

Since Eq. (2.2) is not identified, we follow Aguilar and West (2000) and identify the factors and associated loadings by specifying the upper $q \times q$ block of L to be a lower triangular matrix with unit diagonals. This identification scheme implies that the specific ordering of the variables in y_t may affect our results, an issue we deal with in the robustness section. In order to ensure the economic interpretation of an

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

international risk factor, we assume that the uncertainty factor is the one where the one-step-ahead forecast errors of equity prices load most strongly.[5]

3 Data and model specification

Our dataset is quarterly 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 several 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 the inflation rate enter the model in log levels.

Given the quarterly frequency of our data we include $p = 4$ lags[7] in the model. We choose θ to maximize the marginal likelihood of VAR models where the factor is estimated using principal components and without stochastic volatility. For the tightness of the sum of coefficient prior we set $\tau = 3\theta$, a somewhat more informative setting as that used in Bańbura et al. (2010). The results presented are based on 15,000 MCMC draws after discarding the first 10,000 draws as burn-in. Running the chain several times from different initial conditions and comparing the corresponding posterior draws gives clear indications of convergence.

Selecting the number of latent factors

Following Mumtaz and Theodoridis (2016), we select the appropriate number of latent factors by choosing the value of q that minimizes the deviance information criterion (DIC) (Spiegelhalter et al., 2002). The DIC is defined as

$$DIC = D + P \tag{3.1}$$

with

$$D = \frac{1}{R}\sum_{r=1}^{R}\{-2\ln\mathcal{L}(\gamma_i)\} \tag{3.2}$$

$$P = D + 2\ln\mathcal{L}(\overline{\gamma}) \tag{3.3}$$

[5]This assumption might be questionable but as we will show in the robustness section our findings are remarkably robust with respect to competing identification schemes that impose more structure on L. Furthermore, using a single factor model (i.e. $q = 1$) also yields results that are similar to those presented in the empirical application.

[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 $p = 5$.

where γ is a generic vector containing all parameters of the model and the index i denotes the ith draw of γ. Moreover, $\mathcal{L}(\bullet)$ denotes the (conditional) likelihood function, $\overline{\gamma}$ is the posterior mean of γ and R denotes the number of MCMC draws saved. Loosely speaking, the first term D is a measure of fit of the model and the second term P penalizes model complexity. We evaluate the DIC over a grid of possible values for $q = 1, \ldots, 6$ and pick the q that minimizes the DIC. Table 3 presents our findings. The second column presents the DIC and the following two columns present the measure of in-sample fit and the complexity penalty, respectively. The number of factors that minimizes the DIC is $q^* = 9$.

Table 1: Model comparison based on the deviance information criterion (DIC)

q	DIC	P	D
1	-17370.79	1508.83	-18879.63
2	-18350.71	1639.58	-19990.29
3	-19052.31	1732.54	-20784.86
4	-19523.76	1758.53	-21282.29
5	-19602.68	1843.95	-21446.63
6	-19672.81	1754.46	-21427.26
7	-19932.72	1833.87	-21766.60
8	-20003.29	1843.76	-21847.05
9	**-20528.47**	**1844.43**	**-22372.90**
10	-20264.62	1888.25	-22152.87

It is worth mentioning that using the conditional likelihood, as opposed to the integrated likelihood[8], leads to relatively unreliable estimates of the DIC. Thus, we also compute classical information criteria (namely optimal coordinates and parallel analysis) to select the number of factors . These measures confirm the findings based on the DIC and also select $q^* = 9$.[9]

4 Empirical results

In this section we present the main findings of the paper concerning the quantitative assessment of global uncertainty. In the next subsection we briefly summarize the key properties of our estimated global risk factor and how it relates to traditional measures adopted in the literature. We also report a variance decomposition over time

[8]The integrated likelihood is obtained by integrating out the latent states of the model, a computationally intensive task for the present model.

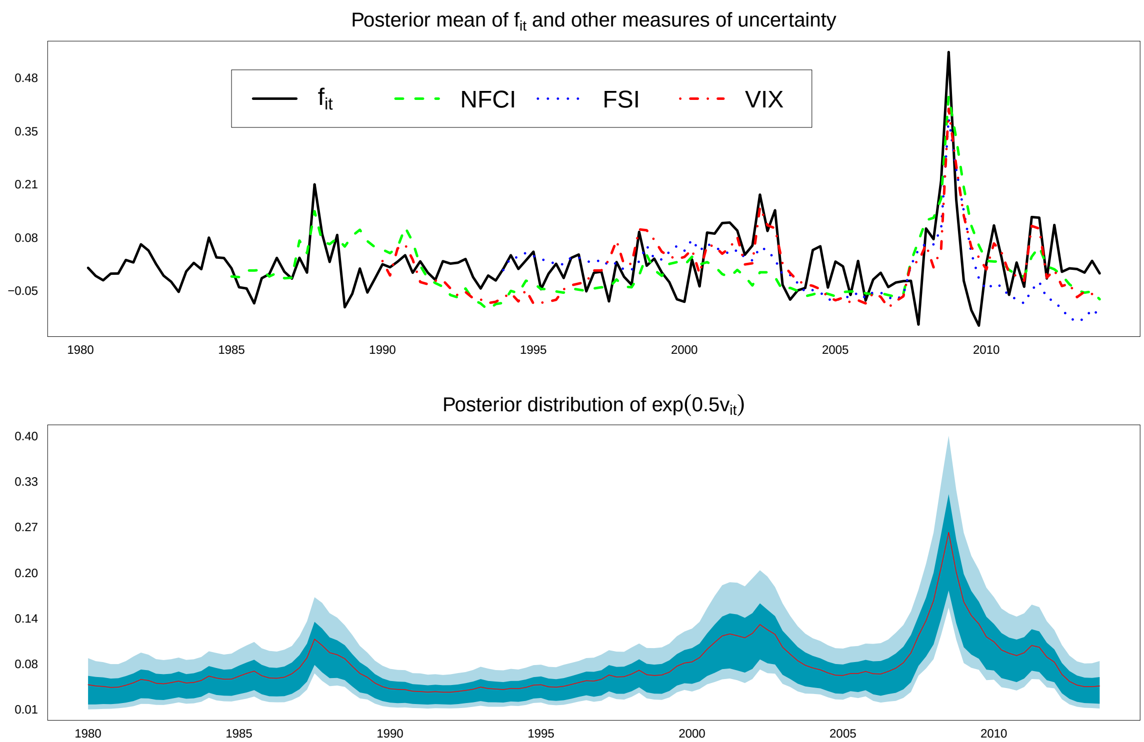
[9]We also perform a robustness check and compare the impulse responses presented in the next subsection for q ranging from one to ten, leading to similar results throughout.

aimed at gaining insights into the differential importance of global risk to explain macroeconomic dynamics over time. We then proceed to the findings of our impulse response exercise, where we investigate the macroeconomic impact of an global uncertainty shock. Finally, we assess whether there are relevant asymmetries in the responses when comparing the group of anglo-saxon countries (US, Canada, and the UK) to the rest of the sample (Germany, France, Italy and Japan).

4.1 An estimated global risk factor and its explanatory power

Figure 1 shows the mean of the posterior distribution of the uncertainty factor alongside three commonly used measures of economic and financial uncertainty: the national financial conditions index (NFCI), the financial stress index (FSI) and the volatility index (VIX). The lower panel of the figure depicts the posterior distribution of the stochastic volatility component of the uncertainty factor.

Our measure of international uncertainty closely tracks all three indices used for the US. All four measures display a sharp increase in uncertainty during the 1987 stock market crash, the East Asian currency crisis and the sovereign default of Russia, the mild recession following the 9/11 terrorist attacks and, most notably, the recent financial crisis. The strong correlation of the international factor with selected US-based uncertainty measures follows from our identification strategy and the economic linkages they represent. By construction, we identify the uncertainty factor to be the factor that is most strongly loaded by forecast errors associated with one-step-ahead prediction errors of equity prices. These series are strongly correlated with the US stock market, whose volatility plays an important role in shaping the global uncertainty factor. In addition, the estimated loadings suggest that US inflation and short-term interest rates also load heavily on the uncertainty factor, thereby identifying monetary policy as an important determinant of international uncertainty. Finally, the last set of variables that drive the factor are real exchange rates relative to the US dollar.



Notes: The top panel presents the posterior mean of the uncertainty factor (in solid black), the national financial conditions index (NFCI) for the US (in dashed green), the financial stress index (FSI, in dotted blue) and the volatility index (VIX, in dot-dashed red).

Fig. 1: Posterior median of the latent factor alongside the NFCI, the FSI and the VIX (top panel) and its corresponding volatility (bottom panel)

The lower panel of Fig. 1 shows the posterior distribution of the stochastic volatility component of the uncertainty factor. Pronounced increases in volatility are also found in 1987, the period surrounding 9/11 and, in particular, the recent financial crisis.

To investigate how global uncertainty drives the forecast error variance of different variables, Fig. 2 displays the forecast error variance explained by the common uncertainty factor over time for all variables and countries included in the estimation. The first row in Fig. 2 (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 all the countries under consideration. For the US, for instance, the average share of forecast variance explained by the global uncertainty factor is around 6 percent, whereas for all other countries it explains between 1.6 (UK) and 4.6 (Japan) percent. On the other hand, global uncertainty plays an important role during economic downturns, explaining between 20 and 45 percent for the US and slightly lower values for most other countries except Japan.

Figure 2 (b) presents the share of forecast error variance explained by the uncertainty factor for CPI inflation. Forecast errors for US inflation are strongly driven by global uncertainty during crisis periods. However, even during normal times, the share of US inflation forecast variance explained by global uncertainty reaches around 10 percent, averaging 16 percent over the full sample. This result reflects the fact that US inflation loads strongly on global uncertainty, and thus significantly shapes the global uncertainty factor. For all other countries, inflation forecast variance is mostly driven by other factors and overall global uncertainty only explains around 1 percent of the forecast error variance across the full sample. Differences in price stickiness, reflecting different institutional structures, and in the policy reaction of central banks to inflation may help explain the differences across countries. ECB monetary policy, traditionally oriented towards price stability, results in a smaller variability of inflation in the eurozone countries during the great recession.

Figures 2 (c) and 2 (d) display the corresponding shares of explained variance for exports and real exchange rates. For both quantities, the shares appear to be significantly higher as compared to output and inflation, reaching around 20 percent and 30 percent for exports and exchange rates, respectively. The prompt reaction of exchange rates and subsequently exports to global shocks explains such differences in the explanatory power of the global uncertainty factor for these variables. The pattern of increasing shares of explained variation during crises can again be found for all countries for these variables. The final column of Fig. 2 (d) shows that the share of forecast variance explained by the uncertainty factor for Japan tends to be low, reaching only 0.62 percent on average.

The last three rows of Fig. 2 show the corresponding shares o explained variance for short-term interest rates (Fig. 2 (e)), equity prices (Fig. 2 (f)) and total credit (Fig. 2 (g)). The share of forecast error variance explained by the global uncertainty factor in short-term interest rates appears large for the US, Canada and Germany, whereas for the other economies the average share explained is comparatively low. During recessions the shares reach values of 50 percent for the US and 30 percent for Canada. Finally, for equity prices global uncertainty plays a dominant role in explaining forecast variance, which is not surprising given the fact that we identify global uncertainty by assuming that forecast errors associated with equity prices load most strongly on this factor. For total credit, the shares are rather low.

Summing up, we generally find that international uncertainty explains a large fraction of forecast error variance for equity prices, exchange rates and exports, the first mostly because they strongly react to economic information and risk signals, the last two because such variables are directly affected by global economic developments in general. Most importantly, we find that global uncertainty strongly affects GDP and high values of uncertainty are associated with recessions in all countries. Looking at the differences, we observe that for some countries (most notably the US and Japan), global uncertainty proves to be a particular important driver of systematic forecast errors during recessions. This is presumably due to their role as ”safe havens” for the global economy in periods of turmoil.

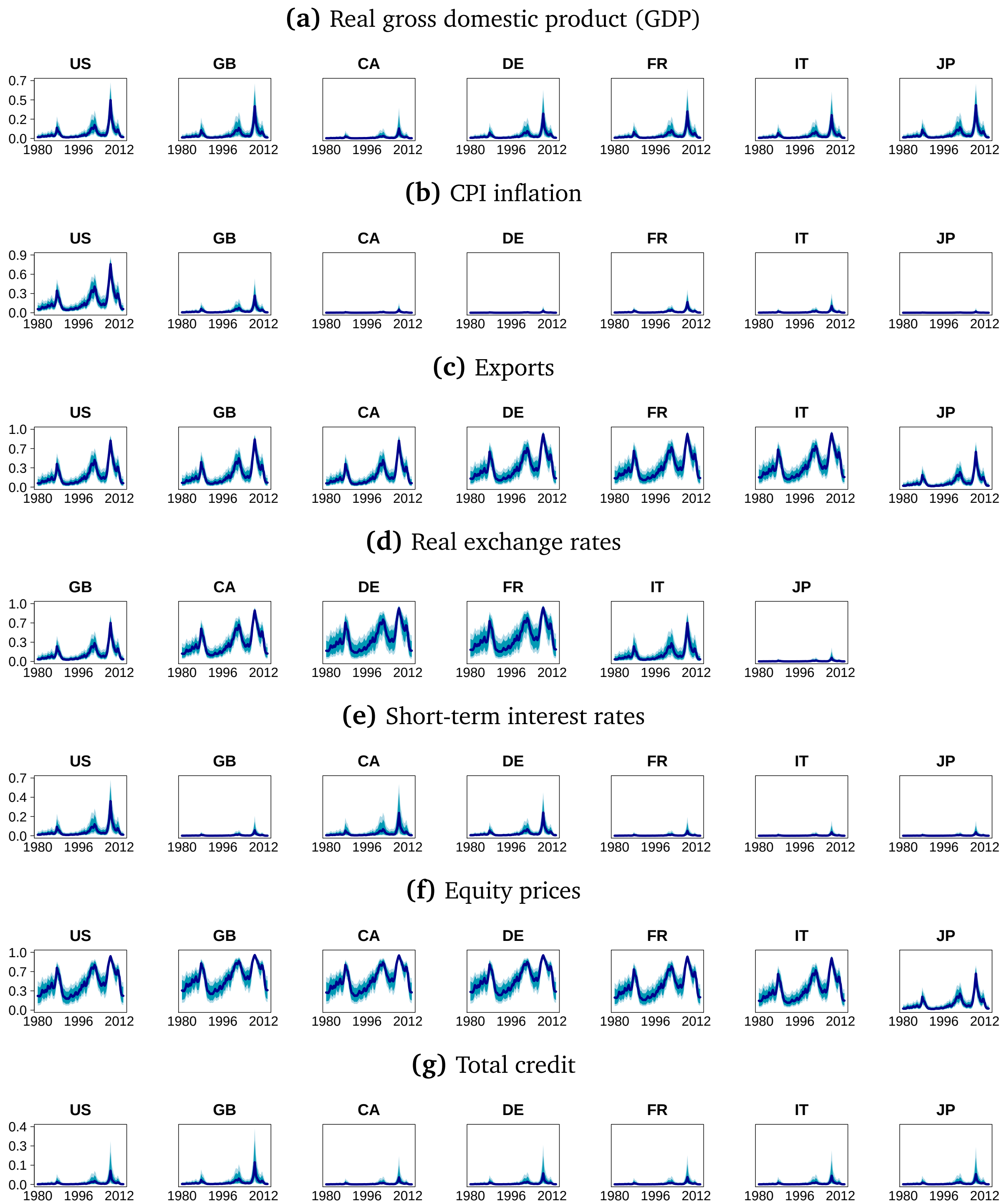
4.2 The transmission of global uncertainty shocks

This section shows that the impact of an increase in global uncertainty has substantially the same effect of a negative demand shock on macroeconomic variables. We compute impulse responses to a shock in global uncertainty normalized to create a 10% *average* decline in equity prices across all countries considered.

Figures 3 to 4 display the responses across countries for real variables. The range of values between the 16th and 25th percentile, as well as between the 75th and 84th percentile of the posterior distribution of the response is depicted in light blue, the range of values in dark blue represents those between the 25th and 75th percentile. Fig. 3 depicts the impulse responses of real GDP and inflation, while Fig. 4 present the responses of exports and exchange rates against the US dollar.

The reactions of real activity measured through GDP are shown in Fig. 3 (a). Across all countries considered, output declines significantly on impact. No country displays a ”volatility overshoot” that translates into a significant rebound in economic activity following an increase in economic uncertainty (a phenomenon prominently reported in Bloom, 2009), a result which is consistent with established findings in Jurado et al. (2015) and Bachmann et al. (2013). This provides some evidence that the traditional ”wait and see” mechanism that states that firms postpone investments and hiring until economic conditions improve and uncertainty dissipates, leading to a rebound in real activity, is not present in the estimates based on our framework. The impact magnitudes tend to be quite similar across G7 economies, with slightly lower impact reactions in France and the UK. After around five quarters, the central 70 percent mass of the posterior distribution of the impulses contains zero for the majority of G7 countries. Among all countries considered, Canada displays the strongest and longest lasting response of output. The economic integration of Canada with the US has been often been found to result on stronger (cumulated) responses in this economy as the US itself (Feldkircher and Huber, 2016; Crespo Cuaresma et al., 2016). The maximum response is reached after around one year for all countries except the UK and Canada, thus being consistent with the structural VAR findings of Gilchrist et al. (2014).

The responses of inflation (see Fig. 3(b)) suggests that inflation drops for all countries following the uncertainty shock. The fall in inflation is most pronounced in the US, mirroring the findings presented in Bloom (2009). Inflation reactions are, however, only of transitory nature, usually fading out within three to four quarters. From a theoretical point of view, 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

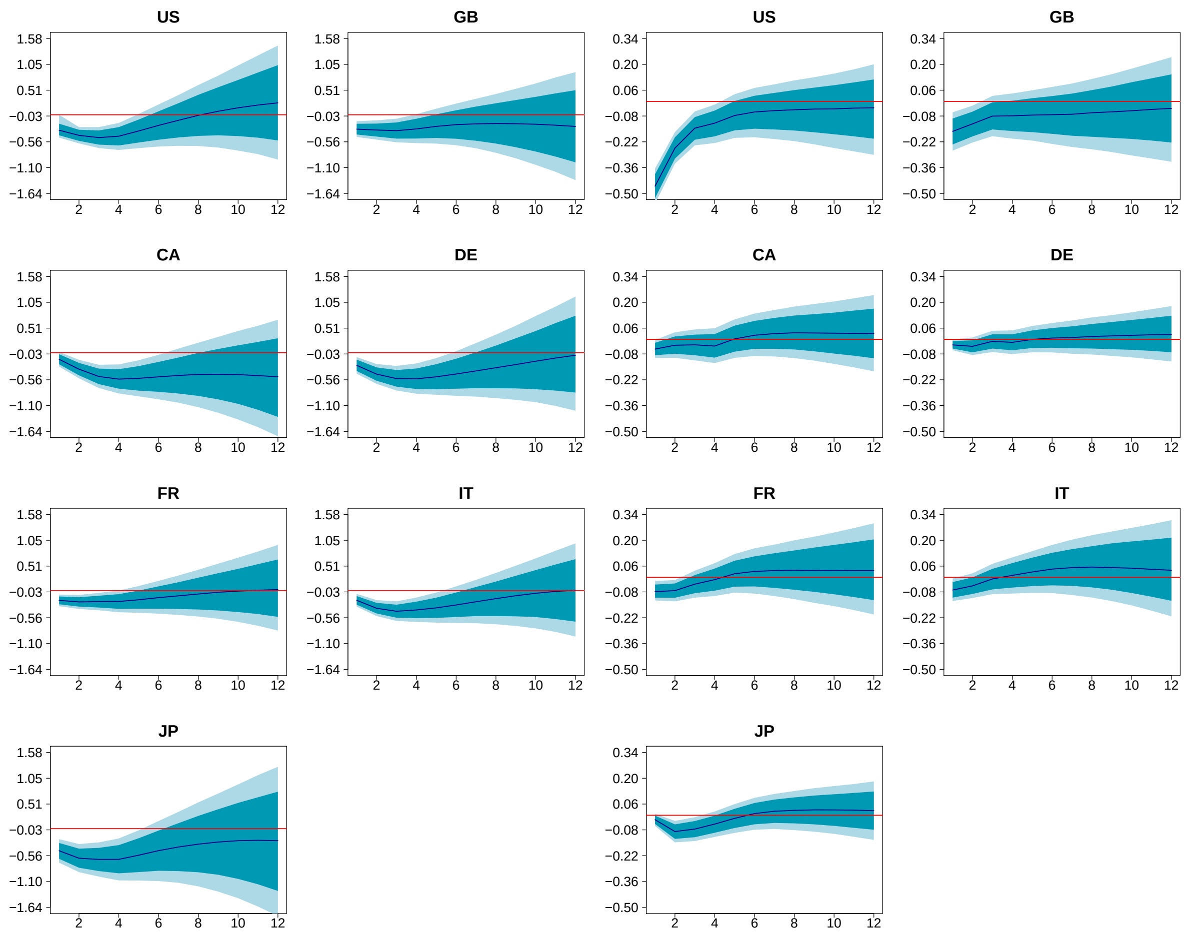


Notes: The figure display the share of innovation variance explained by the uncertainty factor across all variables and countries considered over the period from 1980Q1 to 2013Q4.

Fig. 2: Fraction of innovation variance explained by the global uncertainty factor across the G7 countries

as households reduce consumption when faced with more uncertainty) and the upward pricing bias channel (which leads to firms increasing prices to improve profits). For the UK and Canada the posterior is strongly skewed towards positive values of inflation after around three quarters, pointing towards a more dominant role of the upward pricing bias channel.

(a) Real gross domestic product (GDP) **(b)** CPI inflation

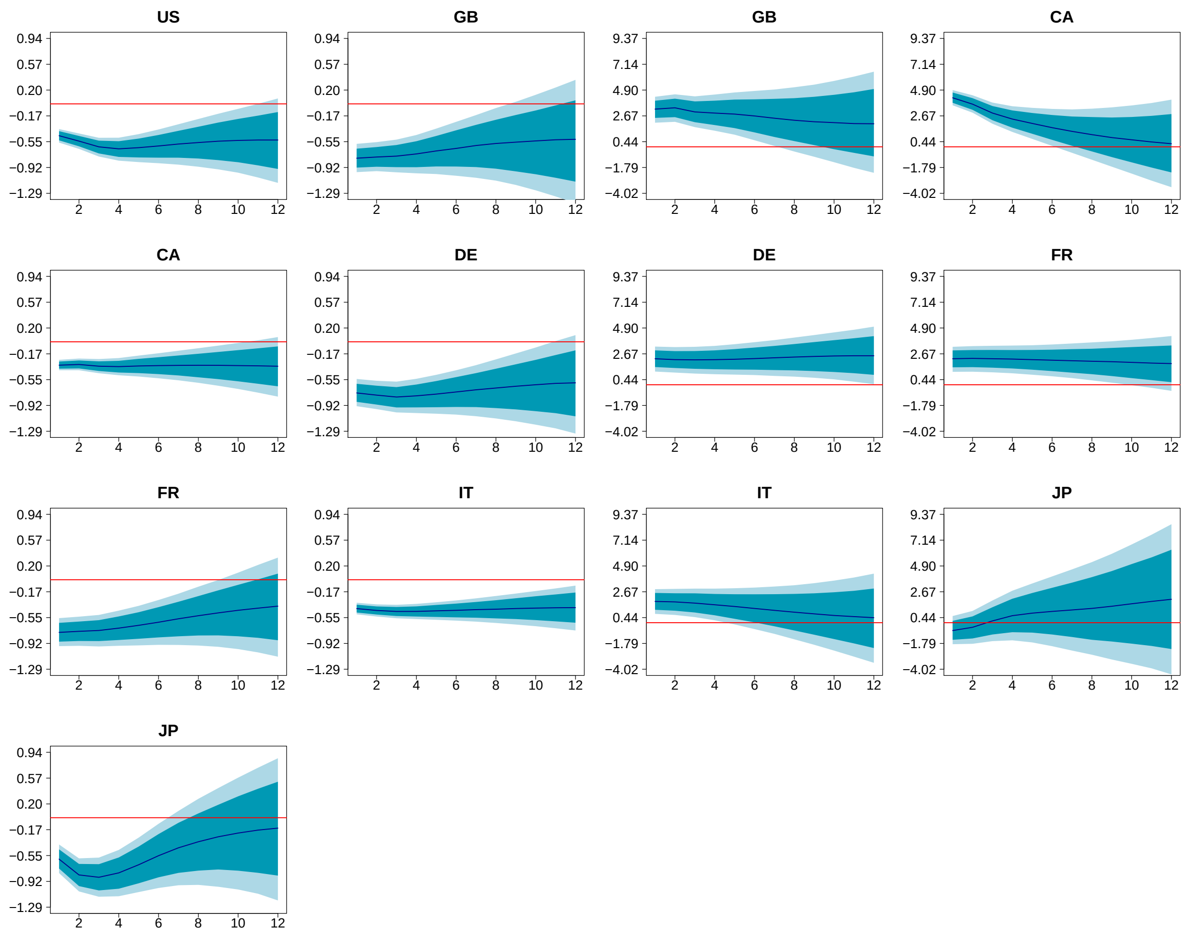


Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. Results are based on 35,000 posterior draws. The red line indicates the zero line.

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

Figure 4 depicts the responses of exports and the real exchange rate against the US dollar. Two findings are worth emphasizing. First, as in the results presented in Fig. 3, an increase in international uncertainty leads to a significant drop in exports

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



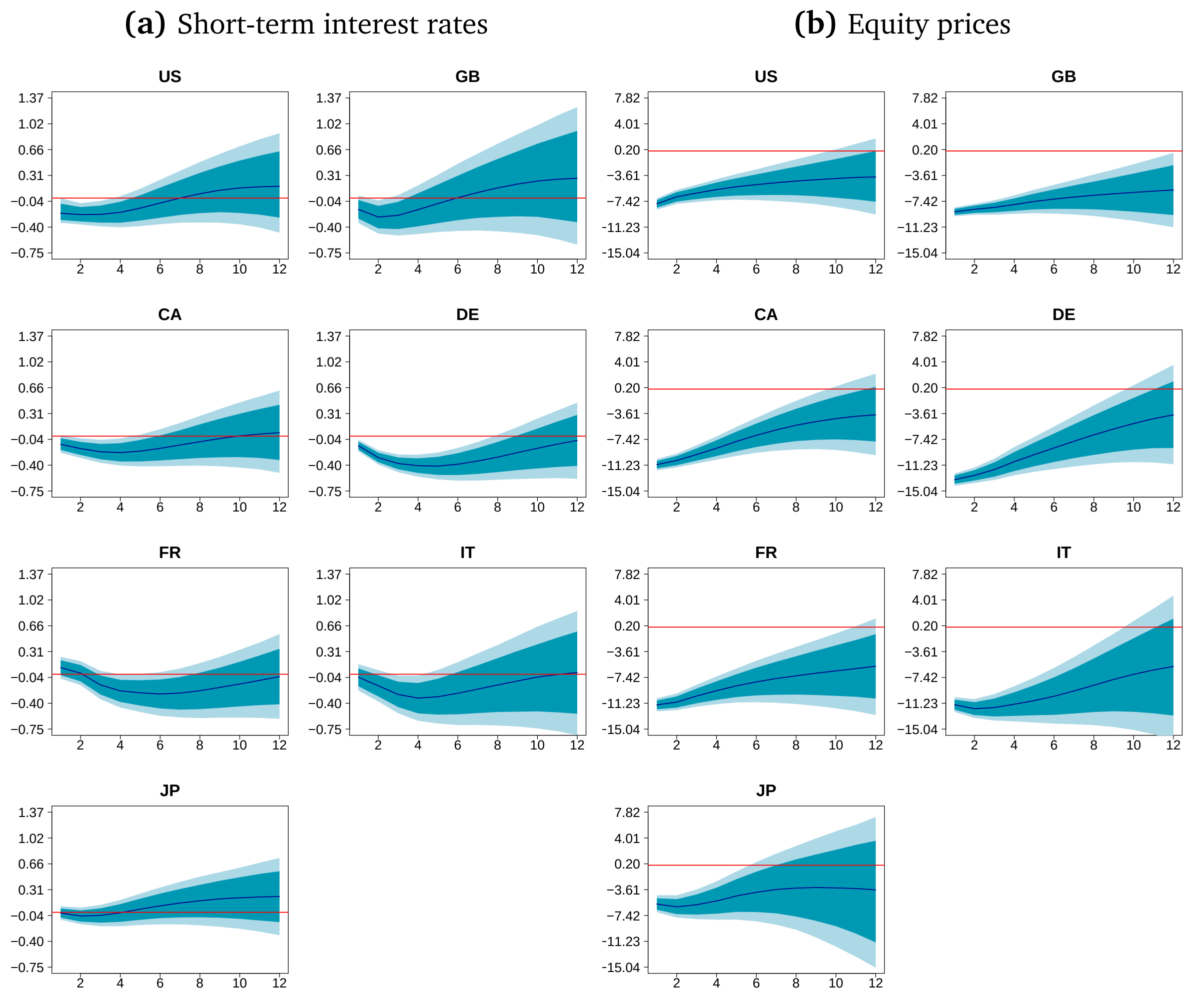
Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. Results are based on 35,000 posterior draws. The red line indicates the zero line.

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

for all countries. Total exports drop by around 0.5% on impact in the US, Canada, Japan, Italy and France and by around 0.7% in the UK and Germany. Second, and unsurprisingly given the tight relationship between global risk and international trade, responses appear to be remarkably persistent for all countries. Our findings closely resemble 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) suggests that all currencies depreciate with respect to the US dollar. This can be explained by international investors diversifying their portfolios away from more risky assets into US dollar denominated securities (most notable US treasury bonds). Such a ”flight to safety” leads to a pronounced appreciation of the dollar, where most countries display similar responses . The use of simple carry trade strategies that exploit differences in returns across economies may also explain such a phenomenon. Such a strategy works well in times of low uncertainty, typically associated with low risk premia and stable expectations about future exchange rates. However, if uncertainty increases, risk premia rise and exchange rate expectations become more volatile, leading to higher risk premia and thus effectively rendering traditional carry trade strategies less profitable (Gourio et al., 2013). Inspection of the dynamic responses of short-term interest rates reveals declining interest rates in response to an unexpected increase in uncertainty. Central banks appear to respond to uncertainty shocks and the accompanying decline in output and inflation by lowering interest rates. 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. Note, however, that the drop in interest rates is not precisely estimated within the first four quarters for most economies under consideration, with zero falling within the central 50 percent of the posterior over the impulse response function. The shape of the responses indicates a different speed of adjustment across central banks, with the US Fed reacting almost instantaneously (see Fig. 5(b)), while central banks in other G7 economies adjust interest rates somewhat sluggishly, reaching a negative peak after around three quarters on average.

The effects on equity prices, presented in Fig. 5 (b), 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. US equity prices drop by around 8 percent on impact, whereas the impact effects materialize in falls of equity prices of around 10 percent for all other countries except Japan. For Japan, consistently with the results presented for exchange rates and the considerations put forward about the centrality of the Japanese equity markets for Asia, the impact response is comparable to that of the US. This suggests that both of these equity markets tend to be less dependent on international asset markets.

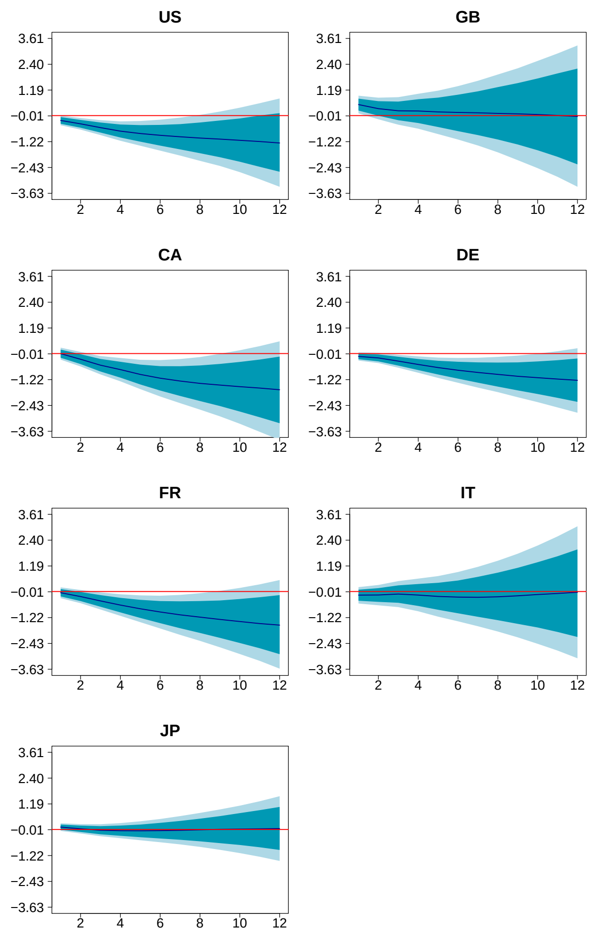
Finally, Fig. 6 presents the dynamic responses of total credit. Since economic agents value projects by discounting future (uncertain) cash flows, we expect that increases in uncertainty naturally translate into more uncertain future cash flows, leading to a lower net present value of a given project and to a sharp 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 practice we find that credit reacts with a lag, falling significantly after around three quarters for the majority of countries considered.



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

(a) Total credit

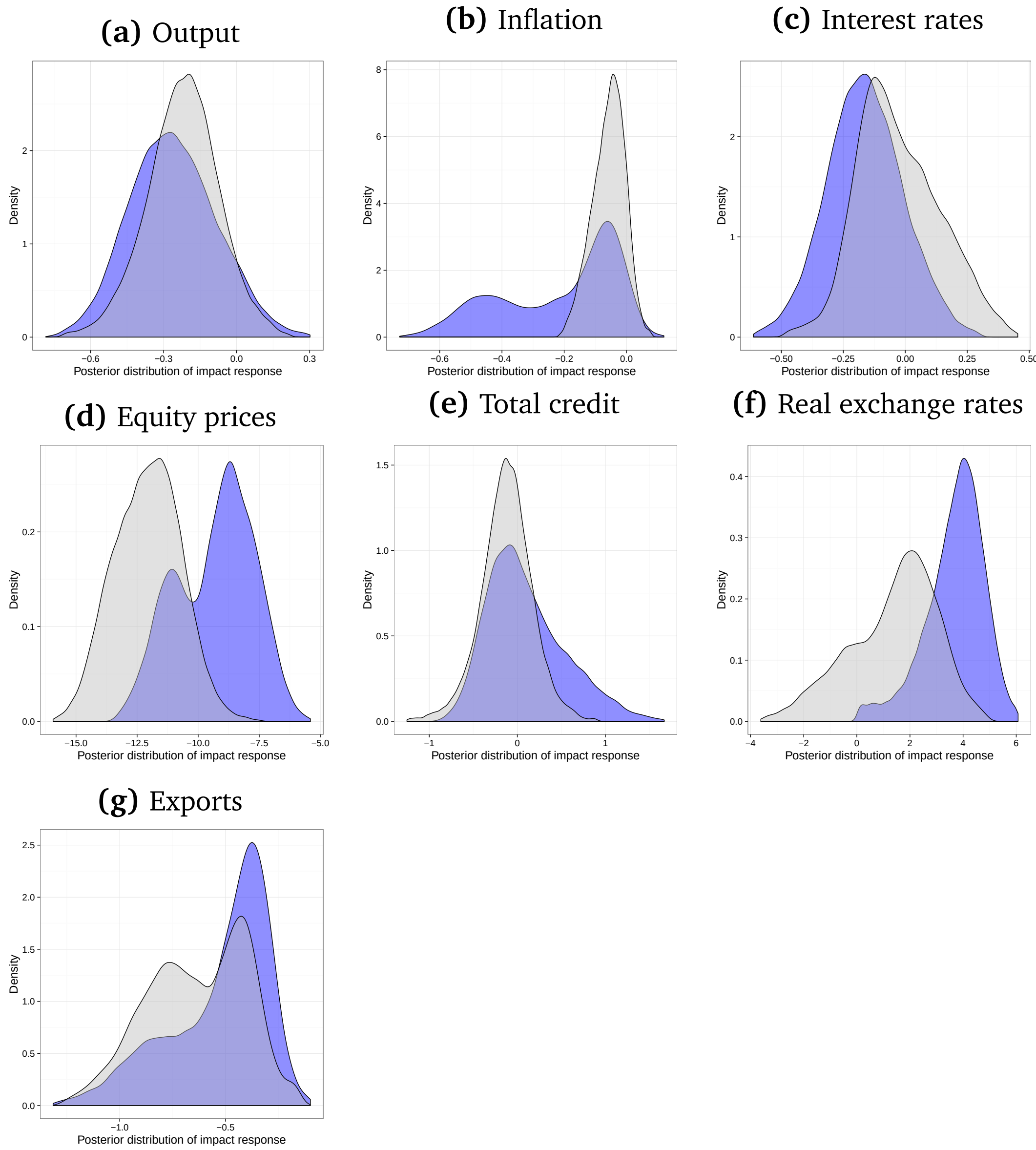


Notes: Posterior distribution of impulse responses in percentage points. Median in black. Shades of blue correspond to probabilities delimited by 16th, 25th, 75th and 84th percentiles. Results are based on 35,000 posterior draws. The red line indicates the zero line.

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

Two general conclusions emerge. First, international uncertainty shocks exert a powerful effect on macroeconomic and financial variables. Second, the responses to uncertainty shocks differ markedly across economies. In particular, Japan stands out as an outlier due to its position as a central economy in the Asian continent. To gain further quantitative insights on the differences across the remaining economies, Fig. 7 depicts the posterior distribution of impact responses for two groups: the group of anglo-saxon economies, consisting of the US, the UK and Canada (labeled as Group 1, in blue) and a second group that features the euro area countries: Germany, France and Italy (labeled Group 2, in gray).

For output, interest rates and total credit, no discernible differences can be found between the two groups. Both densities have a similar shape, mean and median. The unimodal shape of the posterior distribution of the impact responses for these variables suggests that within-group responses appear to be rather similar. The dispersion of the impact distributions tend to be comparable across groups. For the other quantities considered, several interesting differences arise. First, while the median of impact estimates for inflation is similar in both groups, the dispersion is much higher in the first group. We interpret this result as underlining the importance of economic integration and common monetary policy in the eurozone. In addition, while the impact distribution of inflation is clearly unimodal in group 2, the shape in group 1 is multimodal, pointing towards more heterogeneity in inflation responses across the group of anglo-saxon economies. Second, the responses of equity prices to the uncertainty shock depicted in Fig. 7 (d) suggest that the reaction of European equity markets is significantly stronger than in the rest of G7 economies, an event possibly caused by lower trading volumes and the strong dependence on US stock markets. Third, Fig. 7 (f) leads to the conclusion that the appreciation of real exchange rates in Canada and the UK tends to be stronger than that in their European counterparts. In parts, this may well reflect the fact that the introduction of the Euro helped to increase the resilience of European currencies with respect to international uncertainty shocks. Finally, while the median of impact responses for exports appears to be similar between both groups, the shape of the distributions differs, with the second group possessing a much larger variance that can be traced back to both more within-group variation and higher estimation uncertainty.



Notes: The figure shows the posterior distribution of impact responses for two country groups. The first group (blue density) includes the US, the UK and Canada while the second group (gray density) includes Germany, France and Italy.

Fig. 7: Posterior distribution of impact responses between countries

5 Robustness

The main identifying assumptions in our model rest on the lower triangular structure of the upper $q \times q$ block of L in Eq. (2.2). We identify the uncertainty factor as the factor that most heavily loads on one-step-ahead forecast errors of equity prices.

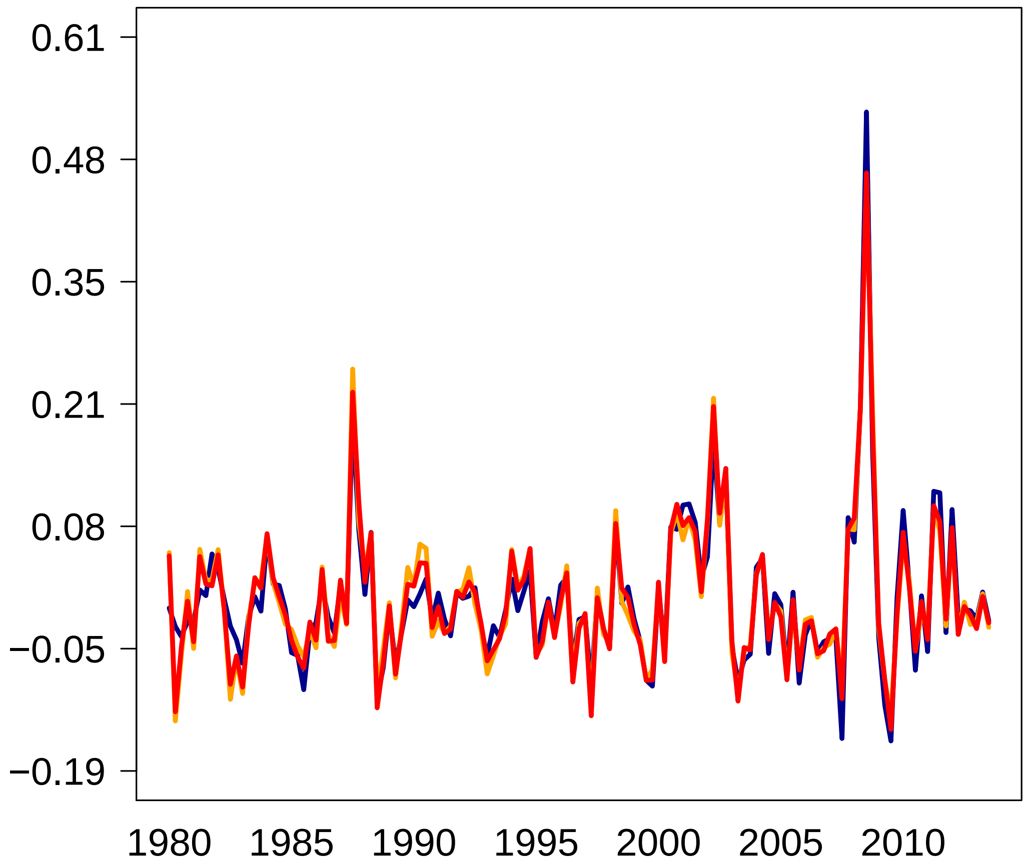
In this section we assess the robustness of our findings with respect to a different identifying assumption and examine whether the results obtained differ from those obtained using a simple single factor model (that is, setting $q = 1$ in Eq. (2.2).

We repeat the estimation of the model using an alternative identification strategy based on interpreting the factors as measuring a global uncertainty factor and a set of seven country-specific uncertainty factors. This identifying assumption assumes that, while global uncertainty shocks affect all variables in the system instantaneously, country-specific uncertainty shocks influence variables in a different economy with a one quarter lag. Under this identification scheme, the errors of a given country only load on the corresponding country-specific factor and the global factor. While this identifying assumption may have some theoretical appeal, its empirical support based on the DIC is less convincing than that for the model we consider.[10] In addition to this alternative identification scheme, we also entertain a specification based on a single factor, that is $q = 1$. This model assumes that the covariances of the full system are driven by a single latent factor that captures the bulk of macroeconomic fluctuations.

We start by comparing the estimated uncertainty factor from our baseline specification (with $q = 9$), with the factors obtained from the model with country-specific uncertainty factors and the single factor model. Figure 8 presents all three factors, with the baseline in dark blue, the single factor model in orange and the model featuring country-specific uncertainty factors in red. All three factors display a correlation of around 0.99, suggesting that the global uncertainty factor and its evolution over time are robustly identified independently of the identification used to extract it.

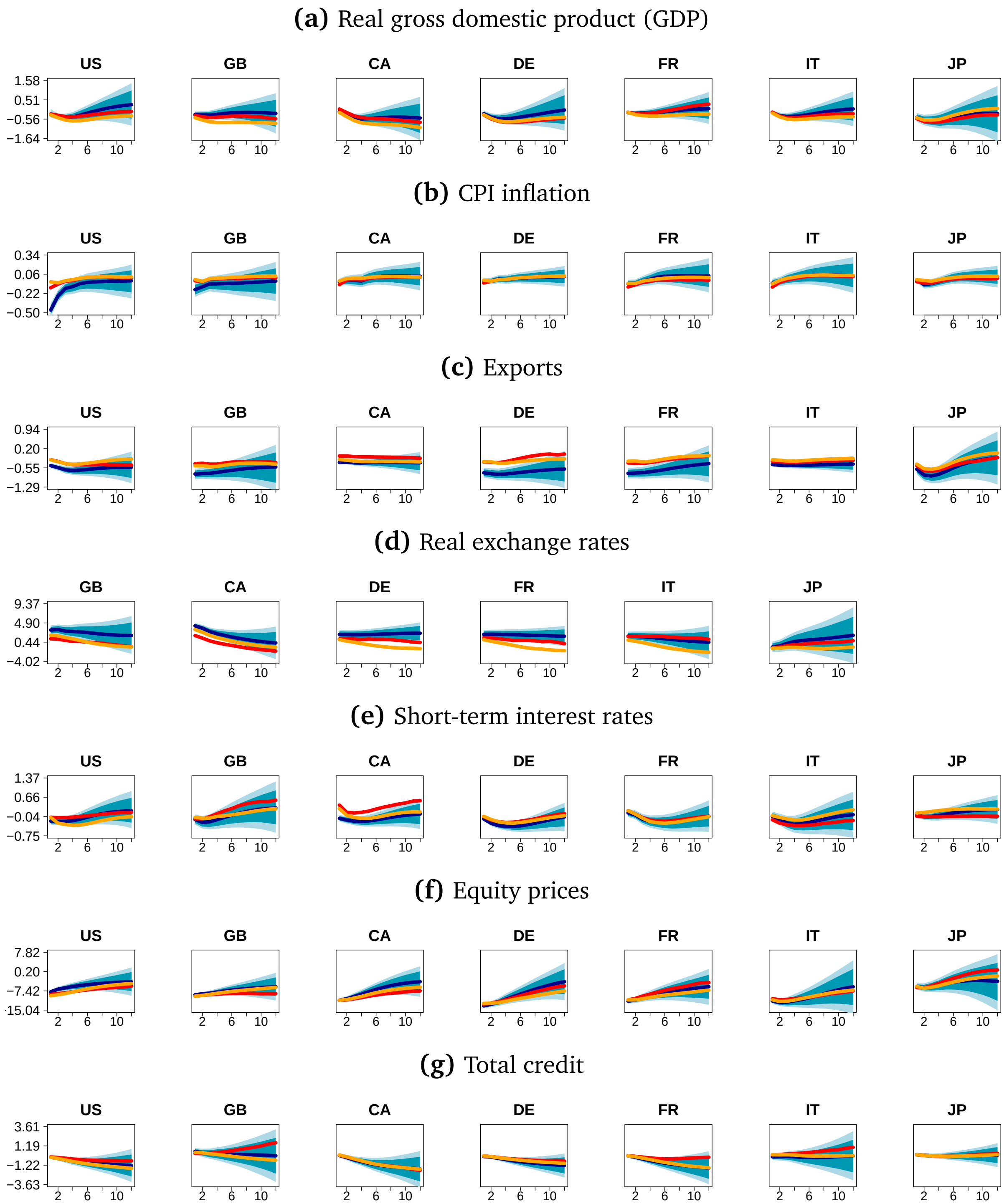
The median impulse responses for the alternative specifications are presented in Fig. 9 together with the posterior of our baseline model. Fig. 9 shows that for all countries and variables under scrutiny, impulse responses do not tend to differ much. The posterior medians of the competing specifications closely track the impulses of the baseline model for most countries and variables. In addition, the responses of the alternative models only rarely leave the credible sets. The overall correlation between the median of responses across models reaches around 0.78, providing further confidence that our results are robust with respect to alternative identification schemes.

[10] In fact, this specification is also inferior to the single factor model as measured by DIC.



Notes: Posterior median of the uncertainty factor with $q = 6$ in dark blue, $q = 1$ in orange and a model that features a global and a set of country-specific uncertainty factors, in red.

Fig. 8: Posterior median of uncertainty factors associated with different identification schemes



Notes: The figure is the same as Fig. 4, Fig. 5 and Fig. 6 alongside the corresponding posterior medians of impulse responses associated with a single factor (in orange) and a model with global and country-specific uncertainty factors (in red).

Fig. 9: Robustness of impulse responses

6 Closing remarks

In this paper we propose a VAR model for the G7 economies whose shocks are driven by relatively few latent factors that exhibit stochastic volatility and can be interpreted as international uncertainty factors. Compared to existing approaches, we are able to simultaneously estimate the autoregressive parameters and the uncertainty index, indicating that uncertainty is, to some extent, endogenous in our system and depends on systematic failures of economic agents to form correct expectations about future macroeconomic developments. The uncertainty factor is compared with other (US based) measures commonly adopted to measure economic uncertainty. Our estimates are strongly correlated with the VIX, the national financial conditions index and the financial stress index.

In the empirical application, we simulate the effects of uncertainty shocks on the G7 countries. 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 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 and short-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 heightened uncertainty.

Using two alternative specifications of the model reveals that our main results are broadly robust to changes in the identification strategy, as well as to the number of factors used to elicit uncertainty shocks. Uncertainty estimates are highly correlated across competing specifications, providing further confidence in our findings.

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