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This paper uses a large vector autoregression (VAR) to measure international macroeconomic uncertainty and its effects on major economies, using two datasets, one with GDP growth rates for 19 industrialized countries and the other with a larger set of macroeconomic indicators for the U.S., euro area, and U.K. Using basic factor model diagnostics, we first provide evidence of significant commonality in international macroeconomic volatility, with one common factor accounting for strong comovement across economies and variables. We then turn to measuring uncertainty and its effects with a large VAR in which the error volatilities evolve over time according to a factor structure. The volatility of each variable in the system reflects time-varying common (global) components and idiosyncratic components. In this model, global uncertainty is allowed to contemporaneously affect the macroeconomies of the included nations—both the levels and volatilities of the included variables. In this setup, uncertainty and its effects are estimated in a single step within the same model. Our estimates yield new measures of international macroeconomic uncertainty, and indicate that uncertainty shocks (surprise increases) lower GDP and many of its components, adversely affect labor market conditions, lower stock prices, and in some economies lead to an easing of monetary policy.

Keywords: Business cycle uncertainty, stochastic volatility, large datasets.

J.E.L. Classification: F44, E32, C55, C11.

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1 Introduction

Since the seminal analysis of Bloom (2009), a large body of research has examined the measurement of macroeconomic uncertainty and its effects on the economy. Bloom (2014) surveys related work up through several years ago. Additional recent contributions include Baker, Bloom and Davis (2016), Basu and Bundick (2017), Caggiano, Castelnuovo, and Groshenny (2014), Carriero, Clark, and Marcellino (2017, 2018), Gilchrist, Sim, and Zakrajsek (2014), Jo and Sekkel (2017), Jurado, Ludvigson, and Ng (2015), Leduc and Liu (2016), Ludvigson, Ma, and Ng (2016), and Shin and Zhong (2016).

Although much of the literature has focused on uncertainty within a single economy, some work has examined common international aspects of uncertainty and its effects. Theoretical studies include Gourio, Siemer, and Verdelhan (2013) and Mumtaz and Theodoridis (2017). The former develops an international real business cycle model in which an increase in the probability of disaster leads to a decline in GDP, investment, and employment, with larger effects on the economy that would be more affected by the disaster. The latter study builds a two-economy, dynamic stochastic general equilibrium model to explain evidence of international comovement in volatilities, in a framework where cross-country risk sharing (for consumption smoothing) and trade openness help to drive such comovement of volatilities.

A larger set of studies has assessed empirical evidence of common international aspects of uncertainty and its effects. These studies have relied on a variety of models or methods, to assess sometimes different questions. In a dataset of 243 variables for 11 industrialized countries, Mumtaz and Theodoridis (2017) apply a factor model with stochastic volatility components common to the world and each country. They find the global component to be an important driver of time-varying volatility. Using GDP growth for 20 countries, Berger, Grabert, and Kempa (2016) estimate a factor model with stochastic volatility components common to the world and specific to each country; in a second step, for each country, they estimate vector autoregressions (VARs) with other variables and uncertainty to assess the effects of uncertainty. Carriere-Swallow and Cespedes (2013) and Gourio, Siemer, and Verdelhan (2013) also use simple, small VAR approaches, measuring uncertainty with the volatility of stock returns. One finding of note in Carriere-Swallow and Cespedes (2013) is that responses to uncertainty shocks differ for developed economies and emerging market economies, with larger and more persistent effects on investment and consumption for emerging markets. Using 45 variables for G-7 nations, Cuaresma, Huber, and Onorante

(2017) apply a VAR with common factors in shocks that have a time-varying variance represented with stochastic volatility. Their estimates yield a common uncertainty factor that is closely tied to the volatility of global equity prices, and shocks to that factor have significant macroeconomic and financial effects.

Some other analyses have assessed international comovement in financial uncertainty. Using data on realized stock return volatility and GDP growth in 33 countries, Cesa-Bianchi, Pesaran, and Rebucci (2017) show that return volatility is much more correlated across countries than is GDP growth, that global growth has a sizable contemporaneous impact on financial volatility, and that a common factor accounts for the bulk of the correlation between return volatility and growth. Casarin, Foroni, Marcellino, and Ravazzolo (2017) propose a Bayesian panel model for mixed frequency data, with random effects and parameters changing over time according to a Markov process, to study the effects of macroeconomic and financial uncertainty on a set of 11 macroeconomic variables per country, for a set of countries including the U.S., several European countries, and Japan. In their analysis, macroeconomic uncertainty is measured by the cross-sectional dispersion in survey forecasts of GDP growth, and financial uncertainty is measured by the VIX for the U.S. They find that, for most of the variables, financial uncertainty dominates macroeconomic uncertainty, and the effects of uncertainty differ depending on whether the economy is in a contraction or expansion regime.

Extending this prior work, in this paper we use large Bayesian VARs (BVARs) to measure international macroeconomic uncertainty and its effects on major economies. We do so for two datasets, one consisting of GDP growth for 19 industrialized economies and the other comprising of 67 variables in quarterly data for the U.S., euro area (E.A.), and U.K. from the mid-1980s through 2013. We first use the basic factor model diagnostics surveyed in Stock and Watson (2016) to assess the common factor structure of the stochastic volatilities of BVARs. Then, to estimate global uncertainty and its effects, we turn to our preferred large, heteroskedastic VAR in which the error volatilities evolve over time according to a factor structure, as developed in the U.S.-only analysis of Carriero, Clark, and Marcellino (2017). The volatility of each variable in the system reflects time-varying common (global) components and idiosyncratic components. In this model, global uncertainty is allowed to contemporaneously affect the macroeconomies of the included nations — both the levels and volatilities of the included variables. Changes in the common components of the volatilities of the VAR's variables provide contemporaneous, identifying information on uncertainty. In this setup, uncertainty and its effects are estimated in a single step within the same model.

Our results point to significant commonality in international macroeconomic volatility, with one common factor — our measure of global uncertainty — accounting for strong co-movement across economies and variables in each of our datasets. Our global uncertainty measure is strongly correlated with a comparable measure for the U.S. from Carriero, Clark, and Marcellino (2017) and to a modestly lesser extent with the Jurado, Ludvigson, and Ng (2015) estimate of U.S. macroeconomic uncertainty. This suggests that global macroeconomic uncertainty is closely related to uncertainty in the U.S., which might not seem surprising given the tie of the international economy to the U.S. economy. Our estimate of global macroeconomic uncertainty appears to be more modestly correlated with estimates of financial uncertainty from the literature and the global economic policy uncertainty measure of Davis (2016).

Our results also include impulse response functions for a surprise increase in global macroeconomic uncertainty. According to these estimates, a shock to global uncertainty reduces GDP in most industrialized countries. In the larger set of indicators for the U.S., E.A., and U.K., the surprise increase in uncertainty lowers GDP and many of its components, adversely affects labor market conditions, lowers stock prices, and in some economies leads to an easing of monetary policy. Our identified global uncertainty shock is uncorrelated with other structural (U.S.-based) shocks, such as productivity, fiscal, or monetary shocks. Hence, the responses are capturing a genuine effect from unexpected increases in uncertainty.

Historical decomposition estimates for the 19-country GDP dataset indicate that, while shocks to uncertainty can have noticeable effects on GDP growth in many countries, on balance they are not a primary driver of fluctuations in macroeconomic and financial variables. For example, over the period of the Great Recession and subsequent recovery, shocks to uncertainty made modest contributions to the paths of GDP growth in many countries (e.g., U.S., France, Spain, and Sweden) and small contributions in some countries (e.g., Japan and Norway). In the declines of GDP growth observed in a number of countries in the early 1990s and early 2000s, uncertainty shocks made small contributions in some countries (e.g., U.S., Sweden, and U.K.). Overall, shocks to the VAR's variables played a much larger role than did uncertainty shocks. However, there is a sense in which that is a natural result of considering the VAR shocks jointly as a set versus the uncertainty shock by itself; individually, some or many of the VAR shocks would also play small or modest roles.

We should also mention that, naturally, there is imprecision around both estimated uncertainty and its effects, with the extent of the imprecision generally underestimated when simpler econometric methods than ours are employed. Actually, our methodology allows us to avoid some of the limitations of previous empirical studies of the effects of international macroeconomic uncertainty (second moments) on macroeconomic fluctuations (first moments). The analysis of Mumtaz and Theodoridis (2017) is focused on international components of second moments. The model of Cuaresma, Huber, and Onorante (2017) may confound first-moment shocks with second-moment changes by imposing not only a common element of shock variances but also the same common element of shocks. In addition, in their setup, second-moment changes do not have direct effects on the levels of variables. The analysis of Berger, Grabert, and Kempa (2016) relies on a two-step approach common in the uncertainty literature, in which a measure of uncertainty is estimated in a preliminary step and then used as if it were observable data in the subsequent econometric analysis of its impact on macroeconomic variables. However, as described in Carriero, Clark, and Marcellino (2017), with such a two-step approach, it is possible that measurement error in the uncertainty estimate could lead to endogeneity bias in estimates of uncertainty's effects, and the uncertainty around the uncertainty estimates is not easily accounted for in such a setup, since the proxy for uncertainty is treated as data. Moreover, the models used in the first and second steps are somewhat contradictory, with the first step treating second moments as time-varying and the second treating them as constant over time.

Finally, in the studies that have assessed the effects of uncertainty on macroeconomic fluctuations across countries, uncertainty has commonly been measured and assessed using a small set of variables for each country. Other work in the literature, including Jurado, Ludvigson, and Ng (2015) and Carriero, Clark, and Marcellino (2017), has emphasized some benefits to using relatively large cross sections. In particular, the use of small VAR models to assess the effects of uncertainty can make the results subject to the common omitted variable bias and nonfundamentalness of the errors, and it can assess uncertainty's impacts on only a small number of economic indicators.

The paper is structured as follows. Section 2 describes the data. After presenting the BVAR model with stochastic volatility, Section 3 uses basic factor model diagnostics to assess the global factor structure in macroeconomic uncertainty. Section 4 introduces our preferred large BVAR model for measuring uncertainty and its effects and then presents results. Section 5 describes robustness checks. Section 6 summarizes our main findings and concludes. The appendix details the estimation algorithm.

2 Data

As indicated above, to assess international comovement in uncertainty and the macroeconomic effects of global uncertainty, we rely on two datasets, one consisting of GDP growth rates for a relatively large set of industrialized economies and the other consisting of a larger set of macroeconomic variables for three large economies. Although the first dataset is similar to others in the literature and helps to establish an international factor structure to uncertainty, our greater interest is in the second dataset. As noted above, for measuring uncertainty we believe it preferable to include relatively large variable sets with long time series.

More specifically, for the GDP growth analysis, we use quarterly data (quarter-on-quarter rates) in the following 19 industrialized economies, obtained from the OECD's online database (OECD 2017): United States, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom. For simplicity, in the remainder of the paper we will refer to this dataset as the *19-country GDP dataset*. For the analysis of a wider set of macroeconomic indicators across industrialized economies, long time series on large variable sets are difficult to find. Accordingly, we focus on a few major economies for which relatively large sets of long time series are available: the U.S., euro area, and U.K. For the U.S. and euro area, we obtain quarterly data on major macroeconomic indicators from the files of Jarocinski and Mackowiak (2017). After omitting their series with missing data and a few others (for various reasons, including overlap with other series), we use 51 variables from their dataset, 26 for the U.S. and the remainder for the E.A. For the U.K., we obtained comparable data on 16 variables from Haver Analytics. Table 1 lists the variables and any transformations used to achieve stationarity of the data. We will refer to this as the *3-economy macroeconomic dataset*.

In our primary results, the estimation sample starts in 1985, reflecting the availability of some of the series in the 3-economy macroeconomic dataset. The estimation sample ends in 2016:Q3 for results based on GDP growth for 19 countries and in 2013:Q3 for results with the

3-economy macroeconomic dataset (reflecting the span of the Jarocinski-Mackowiak dataset). In the 19-country GDP dataset, we also consider a sample starting in 1960; the robustness section describes these results. Following common practice in the factor model literature as well as studies such as Jurado, Ludvigson, and Ng (2015) and Carriero, Clark, and Marcellino (2017), after transforming each series for stationarity as needed, we standardize the data (demean and divide by the simple standard deviation) before estimating the model.

3 Commonality in International Macroeconomic Uncertainty

To assess the global factor structure of macroeconomic uncertainty, we use the basic factor model diagnostics surveyed in Stock and Watson (2016) to assess the common factor structure of the stochastic volatilities of BVARs. We do so for both the 19-country GDP dataset and the 3-economy macroeconomic dataset. In this section, we first present the BVAR model with stochastic volatility and then present the factor assessment results.

3.1 BVAR-SV Model

The conventional BVAR with stochastic volatility, referred to as a BVAR-SV specification, takes the following form, for the $n \times 1$ data vector y_t:

$$\begin{aligned} y_t &= \sum_{i=1}^{p} \Pi_i y_{t-i} + v_t \\ v_t &= A^{-1}\Lambda_t^{0.5}\epsilon_t, \ \epsilon_t \sim N(0, I_n), \ \Lambda_t \equiv \text{diag}(\lambda_{1,t}, \ldots, \lambda_{n,t}) \\ \ln(\lambda_{i,t}) &= \gamma_{0,i} + \gamma_{1,i}\ln(\lambda_{i,t-1}) + \nu_{i,t}, \ i = 1, \ldots, n \\ \nu_t &\equiv (\nu_{1,t}, \nu_{2,t}, \ldots, \nu_{n,t})' \sim \ N(0, \Phi), \end{aligned} \tag{1}$$

where A is a lower triangular matrix with ones on the diagonal and non-zero coefficients below the diagonal, and the diagonal matrix Λ_t contains the time-varying variances of conditionally Gaussian shocks. This model implies that the reduced-form variance-covariance matrix of innovations to the VAR is $\text{var}(v_t) \equiv \Sigma_t = A^{-1}\Lambda_t A^{-1\prime}$. Note that, as in Primiceri's (2005) implementation, innovations to log volatility are allowed to be correlated across variables; Φ is not restricted to be diagonal. For notational simplicity, let Π denote the collection of the VAR's coefficients. Note also that, to speed computation, we estimate the model with the triangularization approach developed in Carriero, Clark, and Marcellino (2016b). Estimates derived from the BVAR-SV model are based on samples of 5,000 retained draws, obtained by sampling a total of 30,000 draws, discarding the first 5,000, and retaining every 5th draw of the post-burn sample.

Regarding the priors for the BVAR-SV model, we set them to generally align with those of the baseline model with factor volatility detailed in section 4. For the VAR coefficients contained in Π, we use a Minnesota-type prior. With the variables of interest transformed for stationarity, we set the prior mean of all the VAR coefficients to 0. We make the prior variance-covariance matrix $\underline{\Omega}_{\Pi}$ diagonal. For lag l of variable j in equation i, the prior variance is $\frac{\theta_1^2}{l^2}$ for $i = j$ and $\frac{\theta_1^2 \theta_2^2}{l^2} \frac{\sigma_i^2}{\sigma_j^2}$ otherwise. In line with common settings for large models, we set overall shrinkage $\theta_1 = 0.1$ and cross-variable shrinkage $\theta_2 = 0.5$.[1] Consistent with common settings, the scale parameters σ_i^2 take the values of residual variances from AR(p) models fit over the estimation sample.

For each row a_j of the matrix A, we follow Cogley and Sargent (2005) and make the prior fairly uninformative, with prior means of 0 and variances of 10 for all coefficients. The variance of 10 is large enough for this prior to be considered uninformative. For the coefficients $(\gamma_{i,0}, \gamma_{i,1})$ (intercept, slope) of the log volatility process of equation i, $i = 1, \ldots, n$, the prior mean is $(0.05 \times \ln \sigma_i^2,\ 0.95)$, where σ_i^2 is the residual variance of an AR(p) model over the estimation sample; this prior implies the mean level of volatility is $\ln \sigma_i^2$. The prior standard deviations (assuming 0 covariance) are $(2^{0.5},\ 0.3)$. For the variance matrix Φ of innovations to log volatility, we use an inverse Wishart prior with mean of $0.03 \times I_n$ and $n+2$ degrees of freedom. For the period 0 values of $\ln \lambda_t$, we set the prior mean and variance at $\ln \sigma_i^2$ and 2.0, respectively.

3.2 Factor Structure Evidence

Beginning with commonality in uncertainty, Table 2 reports summary statistics on the factor structure of volatility estimates, relying on the main statistics described and used in the applications of Stock and Watson (2016). For consistency with the BVAR model with factor volatility we will consider below, in these factor structure results we measure volatilities by the posterior medians of $\ln \lambda_{i,t}$. For up through five principal components, we report the marginal R^2 of volatility factors estimated by principal components and the Ahn and Horenstein (2013) eigenvalue ratio.

[1] Carriero, Clark, and Marcellino (2015) find little gain from optimal determination of these parameters.

For GDP growth in 19 countries, the measures of factor structure suggest one strong factor in the international volatility of the business cycle as captured by GDP. The first factor accounts for an average of about 79 percent of the variation in volatility. The second and third factors account for about 11 and 6 percent, respectively. The Ahn-Horenstein ratio peaks at one factor with a value of 7.4, compared to 1.7 and 3.0 for the second and third factors, respectively. As reported in Table 3, the factor loadings associated with the principal components are fairly tightly clustered around 1, with a minimum of 0.751 for Denmark and a maximum of 1.114 for Sweden.

For the larger set of macroeconomic indicators for the U.S., E.A, and U.K., we use volatility estimates from BVAR-SV models fit for each economy to assess the degree of commonality — and factor structure — in volatility.[2] Figure 1 compares volatility estimates across these three economies for a subset of major macroeconomic indicators (we use a subset to limit the number of charts). In this comparison, volatility is reported in the way common in the literature, as the (posterior median of the) standard deviation of the reduced-form innovation in the BVAR, given by the square root of the diagonal elements of Σ_t. Qualitatively, these estimates suggest considerable commonality within and across countries. As the chart indicates, for a given country, there is significant comovement across variables. For example, for the U.S., most variables display a rise in volatility around the recessions of the early 1990s, 2001, and 2007-2009. For the E.A., most variables display sizable increases in uncertainty in the early and mid-1990s and again with the Great Recession. In addition, there appears to be significant comovement across economies, somewhat more so for volatility in the U.S. and E.A. than in the case of the U.K.

To more formally assess commonality in volatility in the 3-economy macroeconomic dataset, the last two columns of Table 2 report summary statistics on the factor structure of volatility estimates across countries and variables. Again, for consistency with the BVAR model with factor volatility we will consider below, in these factor structure results we measure volatilities by the posterior medians of $\ln \lambda_{i,t}$. Although we omit the results in the interest of brevity, to distinguish possible dynamic versus static factors, we have applied the same analysis to the posterior medians of the shocks to $\ln \lambda_{i,t}$ obtained in the BVAR-SV estimation. We have also applied the factor analysis metrics to the reduced-form volatilities

[2] We estimate the model separately for each country rather than as one single system to avoid an unduly informative proper prior on the log volatility innovation variance matrix Φ. With 67 variables in a joint system, a proper inverse Wishart prior on Φ would be very informative in the context of an estimation sample of fewer than 150 observations.

given by the (posterior median of the) square root of the diagonal elements of Σ_t. In both cases, we obtained results similar to those reported for the $\ln \lambda_{i,t}$ estimates.

As indicated in Table 2, for the 3-economy macroeconomic dataset, a first factor accounts for an average of about 42 percent of the variation in volatility. By comparison, the role of the first factor in volatility is much stronger in this dataset (and in the 19-country GDP dataset) than in the monthly U.S. data of Jurado, Ludvigson, and Ng (2015). Their supplemental appendix notes that a first factor accounts for an average of about 11 percent of the variation in volatility in their large dataset. In our estimates, for most variables, the estimated loadings on this factor reported in Table 4 are clustered around a value of 1. For example, the loadings on GDP growth are 1.330 for the U.S., 1.288 for the E.A., and 1.188 for the U.K. Overall, the patterns in the estimated factor loadings appear consistent with an interpretation in which the first factor is capturing a common component in macroeconomic volatilities, with most loadings clustered around values of 1, most prominently for the U.S. variables, almost as clearly for the E.A., and with modestly more dispersion in loadings on the U.K. variables. A second factor accounts for about 26 percent of the variation in international macroeconomic volatility. Together, two factors account for more than 68 percent of the variation in volatility across macroeconomic indicators and countries. Subsequent factors account for significantly smaller marginal shares of variation. The Ahn-Horenstein ratio peaks at two factors. Together, the R^2 and Ahn-Horenstein estimates suggest two factors in this larger dataset.

4 Measuring the Impact of Uncertainty

Having established evidence of common factors in international macroeconomic volatilities, we now turn to assessing the effects of global uncertainty on macroeconomic fluctuations. This section begins by detailing the Bayesian VAR with a generalized factor structure (BVAR-GFSV) we use for that purpose, first for a one-factor model we use with the 19-country GDP dataset and then for a two-factor specification we use with 3-economy macroeconomic dataset. We then present results for the uncertainty estimates and effects of shocks to uncertainty. Readers not interested in technical details can go directly to the results in section 4.4.

4.1 One-Factor BVAR-GFSV Model

With the evidence in the previous section pointing to one factor in the 19-country GDP dataset, we rely on a one-factor model in our baseline results for the dataset.

Let y_t denote the $n \times 1$ vector of variables of interest — covering multiple countries — and v_t denote the corresponding $n \times 1$ vector of reduced-form shocks to these variables. The reduced-form shocks are:

$$v_t = A^{-1}\Lambda_t^{0.5}\epsilon_t,\ \epsilon_t \sim iid\ N(0, I), \tag{2}$$

where A is an $n \times n$ lower triangular matrix with ones on the main diagonal, and Λ_t is a diagonal matrix of volatilities, $\lambda_{i,t}, i = 1, \ldots, n$. For each variable i, its log-volatility follows a linear factor model with a common uncertainty factor $\ln m_t$ that follows an AR(p_m) process augmented to include y_{t-1} and an idiosyncratic component $\ln h_{i,t}$ that follows an AR(1) process:

$$\ln \lambda_{i,t} = \beta_{m,i} \ln m_t + \ln h_{i,t},\ i = 1, \ldots, n \tag{3}$$

$$\ln m_t = \sum_{i=1}^{p_m} \delta_{m,i} \ln m_{t-i} + \delta'_{m,y} y_{t-1} + u_{m,t},\ u_{m,t} \sim iid\ N(0, \phi_m) \tag{4}$$

$$\ln h_{i,t} = \gamma_{i,0} + \gamma_{i,1} \ln h_{i,t-1} + e_{i,t},\ i = 1, \ldots, n. \tag{5}$$

The volatility factor m_t is our measure of (unobservable) *global* macroeconomic uncertainty. Note that the uncertainty shock $u_{m,t}$ is independent of the conditional errors ϵ_t, and $\nu_t = (e_{1,t}, ..., e_{n,t})'$ jointly distributed as i.i.d. $N(0, \Phi_\nu)$ and independent among themselves, so that $\Phi_\nu = diag(\phi_1, ..., \phi_n)$. For identification, we follow common practice in the dynamic factor model literature (e.g., Otrok and Whiteman 1998) and assume $\ln m_t$ to have a zero unconditional mean, fix the variance ϕ_m at 0.03, and use a simple accept-reject step to restrict the first variable's (U.S. GDP growth) loading to be positive.

The global uncertainty measure m_t can also affect the levels of the macroeconomic variables contained in y_t, contemporaneously and with lags. In particular, y_t is assumed to follow:

$$y_t = \sum_{i=1}^{p} \Pi_i y_{t-i} + \sum_{i=0}^{p_m} \Pi_{m,i} \ln m_{t-i+1} + v_t, \tag{6}$$

where p denotes the number of y_t lags in the VAR, p_m denotes the number of $\ln m_t$ lags in the conditional mean of the VAR (deliberately set, for computational convenience, to the lag order of the factor process), Π_i is an $n \times n$ matrix, $i = 1, ..., p$, and $\Pi_{m,i}$ is an $n \times 1$ vector of coefficients, $i = 0, ..., p_m$.

This model allows the international business cycle to respond to movements in global uncertainty, both through the conditional variances (contemporaneously, via movements in v_t) and through the conditional means (contemporaneously and with lag, via the coefficients collected in $\Pi_{m,i}$, $i = 0, ..., p_m$. In our implementation, we set the model's lag orders at $p = 2$ and $p_m = 2$. Note that y_t cannot contemporaneously affect uncertainty, which in this sense is treated as exogenous. (However, it is not entirely exogenous: The model allows uncertainty to respond with a lag to macroeconomic conditions.) Carriero, Clark, and Marcellino (2018) develop a model with endogenous uncertainty, but empirically they find little evidence of contemporaneous effects of y_t on macroeconomic uncertainty for the U.S.

4.2 Two-Factor BVAR-GFSV Model

With Section 2's principal component-based analysis of volatilities obtained from BVAR-SV estimates pointing to two factors in the 3-economy macroeconomic dataset, we consider specifications with two common volatility components. The natural starting point would be the model described above extended to include a second factor in both the volatility process and the VAR's conditional mean. In unreported estimates, we considered such a model, as well as a one-factor model. The estimate of the first factor in this unrestricted two-factor specification was very similar to the estimate obtained from a one-factor specification and strongly correlated with the first principal component of BVAR-SV volatilities. The estimated second factor seemed to capture (with considerable variability in the estimate from quarter to quarter) a modest low-frequency decline in volatility from the first half of the sample to the second half, with generally insignificant effects on the levels of the variables. However, these results from an unrestricted two-factor specification appear to suffer problems with the convergence of the Markov Chain Monte Carlo (MCMC) sampler with this dataset (although not with other datasets).

From this analysis, we conclude that although there are two volatility or uncertainty factors in the 3-economy macroeconomic dataset, only one bears on the levels of macroeconomic variables. As we describe in more detail in the robustness section below, we obtained a qualitatively similar result with an alternative simple approach of adding to the macroeconomic BVAR the principal components of the BVAR-SV volatilities used in this section (an approach common in the uncertainty literature, as in, e.g., Jurado, Ludvigson, and Ng 2015, though suboptimal as it ignores that uncertainty is a generated regressor).

Accordingly, for the 3-economy macroeconomic dataset, our baseline results use a two-factor model with some restrictions. In particular, the model features two common factors in volatilities but includes only one of the factors in the conditional mean of the VAR and affecting the levels of the included variables. In addition, reflecting other evidence, the idiosyncratic component of volatility is simply a constant. With the larger set of indicators for the U.S., E.A., and U.K. in our sample of quarterly data starting in the 1980s, unreported estimates of a version of the model with an AR(1) process for the idiosyncratic component of volatility — a specification that yields results very similar to those we report — display very little time variation in the idiosyncratic components. For the 3-economy macroeconomic dataset, our model estimates attribute the vast majority of time variation in volatility to the common component m_t.

With these restrictions, the model applied to the 3-economy macroeconomic dataset takes the following form, including two international uncertainty factors m_t and f_t:

$$y_t = \sum_{i=1}^{p} \Pi_i y_{t-i} + \sum_{i=0}^{p_m} \Pi_{m,i} \ln m_{t-i+1} + v_t \tag{7}$$

$$v_t = A^{-1} \Lambda_t^{0.5} \epsilon_t, \;\; \epsilon_t \sim iid\ N(0, I) \tag{8}$$

$$\ln \lambda_{i,t} = \beta_{m,i} \ln m_t + \beta_{f,i} \ln f_t + \ln h_i, \;\; i = 1, \ldots, n \tag{9}$$

$$\ln m_t = \sum_{i=1}^{p_m} \delta_{m,i} \ln m_{t-i} + \delta'_{m,y} y_{t-1} + u_{m,t}, \;\; u_{m,t} \sim iid\ N(0, \phi_m) \tag{10}$$

$$\ln f_t = \sum_{i=1}^{p_f} \delta_{f,i} \ln f_{t-i} + \delta'_{f,y} y_{t-1} + u_{f,t}, \;\; u_{f,t} \sim iid\ N(0, \phi_f). \tag{11}$$

In this case, the log-volatility of each variable i follows a linear factor model with common unobervable uncertainty factors $\ln m_t$ and $\ln f_t$, which follow independent AR processes augmented to include y_{t-1}, and a constant idiosyncratic component $\ln h_i$. The volatility factors m_t and f_t are measures of (unobservable) global macroeconomic uncertainty. However, only the first global uncertainty measure, m_t, enters the conditional mean of the VAR and affects the levels of the macroeconomic variables contained in y_t, contemporaneously and with lags.

To spell out the notation, which follows that used in the one-factor model above, A is an $n \times n$ lower triangular matrix with ones on the main diagonal; Λ_t is a diagonal matrix of volatilities, $\lambda_{i,t}, i = 1, \ldots, n$; p denotes the number of y_t lags in the VAR; p_m denotes the number of $\ln m_t$ lags in the conditional mean of the VAR; Π_i is an $n \times n$ matrix, $i = 1, ..., p$; and $\Pi_{m,i}$ is an $n \times 1$ vector of coefficients, $i = 0, ..., p_m$. The uncertainty shocks $u_{m,t}$ and $u_{f,t}$

are independent of each other and independent of the conditional errors ϵ_t. For identification, we assume that $\ln m_t$ and $\ln f_t$ have zero unconditional means, fix their variances ϕ_m and ϕ_f at 0.03, and use a simple accept-reject step to restrict the first factor's loading on U.S. GDP growth and the second factor's loading on E.A. GDP growth to be positive. In our implementation, we set the model's lag orders at $p = 2$, $p_m = 2$, and $p_f = 2$.

4.3 Priors and Estimation

For the VAR coefficients contained in Π, we use a Minnesota-type prior. With the variables of interest transformed for stationarity, we set the prior mean of all the VAR coefficients to 0. We make the prior variance-covariance matrix $\underline{\Omega}_\Pi$ diagonal. The variances are specified to make the prior on the $\ln m_t$ terms fairly loose and the prior on the lags of y_t take a Minnesota-type form. Specifically, for the $\ln m_t$ terms of equation i, the prior variance is $\theta_3^2\sigma_i^2$. For lag l of variable j in equation i, the prior variance is $\frac{\theta_1^2}{l^2}$ for $i = j$ and $\frac{\theta_1^2\theta_2^2}{l^2}\frac{\sigma_i^2}{\sigma_j^2}$ otherwise. In line with common settings, we set overall shrinkage $\theta_1 = 0.1$ and cross-variable shrinkage $\theta_2 = 0.5$; we set factor coefficient shrinkage $\theta_3 = 10$. Finally, consistent with common settings, the scale parameters σ_i^2 take the values of residual variances from AR(p) models fit over the estimation sample.

Regarding priors attached to the volatility-related components of the model, for the rows a_j of the matrix A, we follow Cogley and Sargent (2005) and make the prior fairly uninformative, with prior means of 0 and variances of 10 for all coefficients.

For the loading $\beta_{i,m}$, $i = 1, ..., n$, on the uncertainty factor $\ln m_t$, we use a prior mean of 1 and a standard deviation of 0.5. The prior is meant to be consistent with average volatility approximating aggregate uncertainty. In the two-factor model, for the loading $\beta_{i,f}$, $i = 1, ..., n$, on the uncertainty factor $\ln f_t$, we assign a lower prior mean and larger standard deviation, of 0.5 and 1.0, respectively. For the coefficients of the processes of the factors, we use priors consistent with some persistence in volatility. For the coefficients on lags 1 and 2 of $\ln m_t$ and $\ln f_t$, we use means of 0.9 and 0.0, respectively, with standard deviations of 0.2. For the coefficients on y_{t-1}, we use means of 0 and standard deviations of 0.4. For the period 0 values of $\ln m_t$ and $\ln f_t$, we set the means at 0 and in each draw use the variances implied by the AR representations of the factors and the draws of the coefficients and error variance matrix.

For the idiosyncratic volatility component, in the model for the 3-economy macroeconomic dataset in which it is constant at h_i, the prior mean is $\ln \sigma_i^2$, where σ_i^2 is the residual variance of an AR(p) model over the estimation sample, and the prior standard deviation is 2. In the model for the 19-country GDP dataset in which the idiosyncratic component is time-varying as in (5), the prior mean is ($\ln \sigma_i^2$, 0.0), where σ_i^2 is the residual variance of an AR(p) model over the estimation sample. In this specification, for the variance of innovations to the log idiosyncratic volatilities, we use a mean of 0.03 and 15 degrees of freedom.

As detailed in the appendix and Carriero, Clark, and Marcellino (2017), the BVAR-GFSV model can be estimated with a Gibbs sampler. Our reported results are based on 5,000 draws, obtained by sampling a total of 30,000 draws, discarding the first 5,000, and retaining every 5th draw of the post-burn sample.

Finally, although the model is estimated with standardized data, for comparability to previous studies the impulse responses are scaled and transformed back to the units typical in the literature. We do so by using the model estimates to: (1) obtain impulse responses in standardized, sometimes (i.e., for some variables) differenced data; (2) multiply the impulse responses for each variable by the standard deviations used in standardizing the data before model estimation; and (3) accumulate the impulse responses of step (2) as appropriate to get back impulse responses in levels or log levels. Accordingly, the units of the reported impulse responses are percentage point changes (based on 100 times log levels for variables in logs or rates for variables not in log terms).

4.4 BVAR-GFSV Estimates of Uncertainty

Although the BVAR-GFSV estimates of uncertainty reflect influence from the first moments of macroeconomic data, the estimates are also directly related to the loadings on the common factor in volatility. These loadings (for the 3-economy macroeconomic dataset, we report only the first factor's loadings for brevity) are reported in the last columns of Tables 3 and 4. In the case of the 19-country GDP dataset, the loadings are broadly centered around 1, with a minimum of 0.396 for Sweden and maximum of 1.634 for Germany. In this respect, the loadings estimated from the BVAR-GFSV model are similar to those estimated by principal components applied to log volatilities of the BVAR-SV model. In the case of the 3-economy macroeconomic dataset, most of the variables have sizable loadings on the volatility factor (keeping in mind that the scale of the loadings reflects the normalization imposed by fixing the innovation variance for identification). Across variables, the average of the loading estimates (posterior means) is 0.75, with a range of 0.12 to 1.50; more than 3/4 of the loadings are above 0.5.

Figure 2 displays the posterior distribution of the measures of uncertainty obtained from the BVAR-GFSV specification, along with corresponding measures obtained from the first principal component of the log volatilities from the BVAR-SV models. The top panel provides estimates for the 19-country GDP dataset, and the bottom panel reports estimates for the 3-economy macroeconomic dataset. In reporting the BVAR-GFSV estimates, we define uncertainty as the square root of the common volatility factor ($\sqrt{m_t}$), corresponding to a standard deviation. Figure 2 also reports the 15%-85% credible set bands around our estimated measure of uncertainty, which is correctly considered a random variable in our approach. In the case of the first principal component of BVAR-SV log volatilities (specifically, the principal component of the $\ln \lambda_{i,t}$ estimates), for scale comparability we exponentiate the principal component and then compute (and plot) its square root.

As indicated in Figure 2, the uncertainty factors show significant increases around some of the political and economic events that Bloom (2009) highlights as periods of uncertainty, including the first Gulf war, 9/11, the Enron scandal, the second Gulf war, and the recent financial crisis period. In some cases, increases in uncertainty around such events seemed to be defined somewhat more clearly in our larger variable set (bottom panel) than in the GDP-only dataset for 19 countries. But in both cases, the credible sets around the BVAR-GFSV estimates indicate that the uncertainty around uncertainty estimates is sizable. Although we believe it to be important to take account of such uncertainty around uncertainty when measuring uncertainty and its effects, the estimates obtained with our BVAR-GFSV model are significantly correlated with those obtained from the principal component of the BVAR-SV volatility estimates, more so in the 3-economy macroeconomic dataset (correlation of 0.800) than in the 19-country GDP dataset (correlation of 0.641). With the larger variable set, although we omit the results in the interest of brevity, we obtained similar estimates of common factor volatility (and reduced-form volatilities of the model's variables) in a version of the model extended to treat the idiosyncratic components as time-varying. As noted above, in the 3-economy macroeconomic dataset, essentially all of the time variation in volatilities appears to be due to common international components and not to components operating at a country or variable level.

Figure 3 compares our uncertainty estimates to each other and to other estimates in the literature. As indicated in the top left panel, even though our 3-economy macroeconomic and 19-economy GDP datasets differ significantly in composition, estimates of uncertainty obtained with our BVAR-GFSV model are quite similar, with a correlation of 0.794. The estimate from our 3-economy dataset is also strongly correlated with the estimate of U.S. macroeconomic uncertainty from Carriero, Clark, and Marcellino (2017) and to a slightly lesser extent with the Jurado, Ludvigson, and Ng (2015) estimate of U.S. macroeconomic uncertainty. This suggests that global macroeconomic uncertainty is closely related to uncertainty in the U.S., which might not seem surprising given the tie of the international economy to the U.S. economy.[3] Our estimate of global macroeconomic uncertainty appears to be modestly correlated with estimates of financial uncertainty from the literature and the global economic policy uncertainty measure of Davis (2016). Our estimate of global macroeconomic uncertainty is also only modestly correlated with the uncertainty measures of Berger, Grabert, and Kempa (2016) and Mumtaz and Theodoridis (2017), both of which display relatively sharp spikes with the Great Recession. Although the number of differences across specifications makes it difficult to identify which factor might account for the differences in uncertainty estimates, one probably important difference is that our uncertainty measure is a common factor in macroeconomic volatilities, whereas in these papers uncertainty is the volatility of common factors in the business cycle.

Here, as in the empirical literature on uncertainty more generally, an important issue is whether the unobserved uncertainty state variables merely pick up some kind of "level" shock rather than isolating uncertainty. For example, Bloom's (2009) uncertainty shocks are thought to be correlated with identified shocks to monetary policy, productivity, etc., estimated in other work. Once these "level" shocks are partialed out from Bloom's uncertainty shocks, the effects of uncertainty shocks seem to be rather reduced. To assess whether the same correlations are evident in our uncertainty estimates, we compute the correlations of our estimated global macroeconomic uncertainty shocks with some well-known and available macro shocks for the U.S. (estimates for other countries do not seem to be widely available), drawing on comparable exercises in Stock and Watson (2012), Caldara, et al. (2016), and Carriero, Clark, and Marcellino (2017). Specifically, we consider productivity shocks (Fernald's updates of Basu, Fernald, and Kimball 2006), oil supply shocks (Hamilton 2003 and Kilian 2008), monetary policy shocks (Gurkaynak, et al. 2005 and Coibion, et al. 2017), and

[3] Cesa-Bianchi, Pesaran, and Rebucci (2017) find that global volatility in stock returns is very closely related to volatility in U.S. returns.

fiscal policy shocks (Ramey 2011 and Mertens and Ravn 2012).[4]

As indicated by the results in Table 5, our international uncertainty shocks are not very correlated with "known" macroeconomic shocks in the U.S. At least in this sense, to the extent shocks in the U.S. bear on the international business cycle, our estimated uncertainty shocks seem to truly represent a second-order "variance" phenomenon, rather than a first-order "level" shock.

4.5 Measuring the Impact of Uncertainty: Impulse Response Estimates and Historical Decompositions from BVAR-GFSV Model

Figures 4 and 5 provide the BVAR-GFSV estimates of impulse response functions for a shock to international macroeconomic uncertainty, with results for the 19-country GDP dataset in Figure 4 and results for the 3-economy macroeconomic dataset in Figure 5. Starting with the 19-country results, an international shock to macroeconomic uncertainty slowly dies out over several quarters. The rise in uncertainty induces statistically significant, persistent declines in GDP in most of the countries. For example, after several quarters, GDP falls about 0.4 percentage point in countries including the U.S., Canada, France, the Netherlands, and the U.K. In general, the magnitudes of the declines are comparable across most countries, although a little less severe in some (e.g., Australia) and more severe in others (e.g., Finland and Sweden). Castelnuovo and Tran (2017) obtain a similar finding of larger uncertainty effects in some countries relative to others. Possible reasons could relate to recessions or the zero lower bound (ZLB) constraint on monetary policy: In some research, uncertainty shocks have larger effects during recessions (e.g., Caggiano, Castelnuovo, Groshenny 2014 and Caggiano, Castelnuovo, and Figures 2017) or in the presence of the ZLB (e.g., Caggiano, Castelnuovo, and Pellegrino 2017), and Australia faced neither a recession nor the ZLB in the 2007-2009 period.

As shown in Figure 5, in the 3-economy macroeconomic dataset, it is also the case that an international shock to macroeconomic uncertainty (to the factor $\ln m_t$ in the VAR's conditional mean) gradually dies out over a few quarters. For the U.S., E.A., and U.K, the heightened international uncertainty reduces GDP and components including investment, exports, and imports. In all three economies, employment falls and unemployment rises,

[4]The productivity shocks correspond to growth rates of utilization-adjusted TFP. The oil price shock measure of Hamilton (2003) is the net-oil price increase series. The monetary policy shocks of Coibion, et al. (2017) update the estimates of Romer and Romer (2004).

and some other measures of economic activity, including confidence or sentiment indicators and capacity utilization, also fall. The shock does not have any consistently significant and negative effects on producer or consumer prices, although there are some effects, such as in the case of the fall in producer prices in the E.A. Although stock prices fall in all three economies, the policy rate falls in the U.S. but is little changed in the E.A. or U.K. In general, these results line up with those obtained with monthly data for the U.S. in Carriero, Clark, and Marcellino (2017), with the exception of stock prices, which in our previous paper were essentially unchanged in response to a macro uncertainty shock but fell in response to a shock to financial uncertainty.

Although these impulse responses show that shocks to uncertainty have significant effects, they cannot provide an assessment of the broader cyclical importance of global macroeconomic uncertainty shocks. For that broader assessment, we estimate historical decompositions. In a standard linear model, a historical decomposition of the total s-step-ahead prediction error variance of y_{t+s} can be easily obtained by constructing a baseline path (forecast) without shocks, and then constructing the contribution of shocks. With linearity, the sums of the shock contributions and the baseline path equal the data. In our case, the usual decomposition cannot be directly applied because of interactions between Λ_{t+s} and ϵ_{t+s}: Shocks to log uncertainty affect the forecast errors through $\Lambda_{t+s}\epsilon_{t+s}$, and, over time, shocks ϵ_{t+s} affect Λ_{t+s} through the response of uncertainty to lagged y. However, as developed in Carriero, Clark, and Marcellino (2017), it is possible to decompose the total contribution of the shocks into three parts: (i) the direct contributions of the uncertainty shocks u_{t+s} to the evolution of y; (ii) the direct contributions of the VAR "structural" shocks ϵ_{t+s} to the path of y, taking account of movements in Σ_{t+s} that arise as uncertainty responds to y but abstracting from movements in Σ_{t+s} due to uncertainty shocks; and (iii) the interaction between shocks to uncertainty and the structural shocks ϵ_{t+s}.

To be more specific, consider a simple one-factor model with lag orders of 1:

$$\begin{cases} y_t = \Pi y_{t-1} + \Gamma_1 \ln m_t + \Gamma_2 \ln m_{t-1} + v_t \\ \ln m_t = \delta y_{t-1} + \gamma \ln m_{t-1} + u_t \end{cases} , \tag{12}$$

where v_t and u_t are independent, with variances Σ_t and Φ_u, respectively. So we can replace v_t above with $\Sigma_t^{0.5}\epsilon_t$, where $\Sigma_t^{0.5}$ is a short-cut notation for the Cholesky decomposition of Σ_t and ϵ_t is $N(0, I_n)$. The one-step-ahead forecast errors are $y_{t+1} - E_t y_{t+1} = \Sigma_{t+1}^{0.5}\epsilon_{t+1} + \Gamma_1 u_{t+1}$. Now let $\hat{\Sigma}_{t+s|t}$ denote the future error variance matrix that would prevail in the absence of future shocks to uncertainty. This would be constructed from forecasts of future uncertainty accounting for movements in y driven by ϵ shocks and the path of idiosyncratic volatility terms (incorporating shocks to these terms). The following decomposition can be obtained by adding and subtracting $\hat{\Sigma}_{t+1|t}$ terms in the forecast error:

$$y_{t+1} - E_t y_{t+1} = \Gamma_1 u_{t+1} + \hat{\Sigma}^{0.5}_{t+1|t}\epsilon_{t+1} + (\Sigma^{0.5}_{t+1} - \hat{\Sigma}^{0.5}_{t+1|t})\epsilon_{t+1}. \quad (13)$$

In this decomposition, the first term gives the direct contribution of the uncertainty shock, the second term gives the direct contribution of the structural shocks to the VAR, and the third term gives the interaction component. The third term can be simply measured as a residual contribution, as the data less the direct contributions from the uncertainty shock and the structural shocks to the VAR. We apply this basic decomposition to our more general model to obtain historical decompositions.

One potential complication with this approach is that, in the interaction components, there is not a good way to separate the roles of aggregate uncertainty and idiosyncratic volatility, because Σ_t is the product of terms containing innovations to aggregate uncertainty and innovations to idiosyncratic components. Since the terms are multiplicative and not additive, there isn't a clear way to isolate the role of aggregate uncertainty from the role of idiosyncratic components. Moreover, any attempt to do so would be dependent on the ordering of the variables within the VAR because the effect of uncertainty on the conditional variance of y_t is influenced by the matrix A^{-1}, and hence the ordering of the variables within the VAR matters. Because of these complications, and because the interaction effects are empirically much less pronounced than the direct effects, we chose to leave the interaction component as is, without attempting to separate the roles of aggregate uncertainty and idiosyncratic volatility in the interaction component.

Figures 6 (19-country GDP dataset) and 7 (3-economy macroeconomic dataset) show the standardized data series, a baseline path corresponding to the unconditional forecast, the direct contributions of shocks to macroeconomic uncertainty, and the direct contributions of the VAR's shocks. The reported estimates are posterior medians of decompositions computed for each draw from the posterior. To save space, the charts provide results for a subset of selected variables. Finally, the decomposition results start in 1987:Q1 for the 19-country GDP dataset and, for better readability, 1998:Q1 for the 3-economy macroeconomic dataset.

As indicated in Figure 6's decomposition estimates for the 19-country GDP dataset, while shocks to uncertainty can have noticeable effects on GDP growth in many countries, on balance they are not a primary driver of fluctuations in macroeconomic and financial variables. For example, over the period of the Great Recession and subsequent recovery, shocks to uncertainty made modest contributions to the paths of GDP growth in many (e.g., U.S., France, Spain, and Sweden) and small contributions in some countries (e.g., Japan and Norway). In the declines of GDP growth observed in a number of countries in the early 1990s and early 2000s, uncertainty shocks made small contributions in some countries (e.g., U.S., Sweden, and U.K.). Overall, shocks to the VAR's variables played a much larger role than did uncertainty shocks. However, there is a sense in which that is a natural result of considering the VAR shocks jointly as a set versus the uncertainty shock; individually, some or many of the VAR shocks would also play small or modest roles.

Figure 7's decomposition estimates for the 3-economy macroeconomic dataset paint a broadly similar picture. For example, around the Great Recession (2007-2009 for the U.S.), shocks to macroeconomic uncertainty (the first factor $\ln m_t$) contribute fluctuations in economic activity, including in GDP, business investment, and housing investment, but not much to inflation or stock prices. Similar patterns, albeit with similar magnitudes, are evident in the decline in GDP growth observed in the early 2000s. With this dataset, too, the effects of uncertainty shocks are generally dominated by the contributions of the VAR's shocks. Carriero, Clark, and Marcellino (2017) obtain a broadly similar result, as does Benati (2016) with a different approach.

5 Robustness

This section describes the robustness of our main results to some changes in specification or approach, including using a two-step approach to assessing the effects of uncertainty and extending the sample of the 19-country GDP growth analysis back to 1960.

5.1 Impulse Response Estimates from Two-Step Approach

As one robustness check, we compare our BVAR-GFSV estimates of impulse responses to estimates from a two-step approach similar to those used in a number of uncertainty analyses, such as Jurado, Ludvigson, and Ng (2015) and Berger, Grabert, and Kempa (2016). In the first step of the two-step approach, we obtain a measure of uncertainty as the first principal component of log volatilities ($\ln \lambda_{i,t}$, estimated as posterior medians) estimated with the BVAR-SV specification. In the second step, we added this measure of uncertainty to a conventional homoskedastic BVAR in the 67 variables of the larger dataset — hence yielding a 68-variable BVAR — and performed standard structural analysis, ordering the uncertainty measure first in the system. To be precise, this BVAR takes the following form:

$$y_t = \sum_{i=1}^{p} \Pi_i y_{t-i} + v_t, \ v_t \sim i.i.d. \ N(0, \Sigma). \tag{14}$$

To speed computation, we estimate the model with the triangularization approach developed in Carriero, Clark, and Marcellino (2016b), using an independent Normal-Wishart prior.[5] Regarding the priors on the VAR's coefficients, we set them to be the same as with the BVAR-GFSV and BVAR-SV models, with the same Minnesota-type prior. For the innovation variance matrix Σ, we use $n + 2$ degrees of freedom and a prior mean of a diagonal matrix with elements equal to 0.8 times the values of the residual variances from AR(p) models fit over the estimation sample.

Figure 8 compares the two-step (red line and the 68 percent credible set indicated by the blue lines) and BVAR-GFSV estimates (black line and gray shading). To facilitate comparison, we have scaled up the impulse responses from the two-step approach to match up to the size of the uncertainty shock that we obtain with the BVAR-GFSV model. Qualitatively, the impulse responses obtained from the two-step approach are similar to those obtained with our BVAR-GFSV model. In the two-step estimates, as in our BVAR-GFSV results, an international shock to macroeconomic uncertainty gradually dies out over several quarters. The heightened uncertainty reduces GDP and many of its components, including investment, exports, and imports, in the U.S., E.A., and U.K. (although, for the U.K., the responses of exports and imports are smaller in the two-step approach). Other components of spending (e.g., consumption) are reduced in some economies (U.S. and U.K.) but not others (E.A.). In most but not all economies, employment falls and unemployment rises, and some other measures of economic activity, including confidence or sentiment indicators and capacity utilization, also fall. In response, stock prices and policy rates move lower in all three economies (in the BVAR-GFSV estimates, policy rates do not decline uniformly across economies).

While qualitatively similar across the approaches, it is often, although not always, the case that the magnitudes of responses are smaller in the two-step estimates than in the BVAR-GFSV results. This is particularly true in the U.S. estimates, but it also applies to some degree for the E.A. and U.K. For example, in the U.S. results, the declines in

[5]Estimates derived from the BVAR are based on samples of 5,000 retained draws, obtained by sampling a total of 6,000 draws and discarding the first 1,000.

GDP, exports, and imports are smaller (in absolute value) in the two-step estimates than in the BVAR-GFSV estimates. In the U.K. results, the decline in GDP is similar across the estimates, but the estimated falloff in exports and imports is not quite as sharp in the two-step estimates as in the baseline estimates. Finally, a key difference is that the confidence bands are wider for the BVAR-GFSV estimates than for the two-step estimates; as might be expected, by treating the uncertainty measure as data rather than an estimate, the two-step approach appears to understate uncertainty around estimates of the effects of shocks to uncertainty.

In results not shown in the interest of brevity, we have also used the two-step approach to consider the effects of a second volatility or uncertainty factor, by adding the first two principal components of BVAR-SV volatilities to a homoskedastic BVAR in the macroeconomic variables, ordering the factors first in the system. These two-step estimates corroborate the difficulty of identifying a second uncertainty factor with effects on the levels of macroeconomic variables. In the two-step case, the shock to the second principal component reduces some selected measures of economic activity in the U.S. but does not have broadly significant effects across economies. In fact, in the U.K. responses, although GDP falls, employment rises and unemployment falls, contradicting most other evidence on the effects of an uncertainty shock, including our preferred BVAR-GFSV estimates presented earlier and the estimates of Jurado, Ludvigson, and Ng (2015) and Carriero, Clark, and Marcellino (2017).

5.2 Results for GDP Growth in 19 Countries over Longer Sample

Although one might be concerned with the stability of a VAR in data on GDP growth across countries extending back to 1960, as another robustness check we have examined the international factor structure of uncertainty and its effects on GDP for a sample of 1960 through 2016. According to the basic measures of a factor structure, results are very similar for the alternative 1960-2016 and the baseline 1985-2016 samples. In the longer sample, as in the baseline, the measures of factor structure suggest one strong factor in the international volatility of the business cycle as captured by GDP, with the first factor accounting for an average of about 74 percent of the variation in volatility and the second accounting for 13 percent, and the Ahn-Horenstein ratio peaking at one factor. In the longer sample, the estimated first factor displays a sizable Great Moderation component in it, declining steadily from the early 1960s through the mid-1980s.

In BVAR-GFSV estimates over the 1960-2016 sample, the influence of the Great Moderation on volatility appears to pose some challenges in estimating macroeconomic uncertainty as it relates to the business cycle. With a one-factor specification, the estimated factor contains a sizable Great Moderation component. A shock to that factor has mixed effects across countries, with GDP declining as expected in some countries but rising in others. We obtain estimates more in line with conventional wisdom on uncertainty's effects with a two-factor BVAR-GFSV specification.[6] In this case, the estimated first factor continues to have a sizable Great Moderation component in it, and a shock to that factor has essentially no effects on the levels of macroeconomic variables. The second factor looks more like a measure of business cycle-relevant uncertainty; in fact, it is very similar to the estimate from the baseline one-factor model for the 1985-2016 sample. A shock to the second factor reduces GDP across countries, with impulse responses qualitatively similar to those from the baseline one-factor model for the 1985-2016 sample.

6 Conclusions

This paper uses large Bayesian VARs to measure international macroeconomic uncertainty and its effects on major economies, using two datasets, one consisting of GDP growth for 19 industrialized economics and the other comprising 67 variables in quarterly data for the U.S., euro area, and U.K. Using basic factor model diagnostics, we first provide evidence of significant commonality in international macroeconomic volatility, with one common factor — in each of our datasets — accounting for strong comovement across economies and variables. We then turn to measuring uncertainty and its effects with a large, heteroskedastic VAR in which the error volatilities evolve over time according to a factor structure. The volatility of each variable in the system reflects time-varying common (global) components and idiosyncratic components. In this model, global uncertainty is allowed to contemporaneously affect the macroeconomies of the included nations — both the levels and volatilities of the included variables. In this setup, uncertainty and its effects are estimated in a single step within the same model. Our estimates yield new measures of international macroeconomic uncertainty, and indicate that uncertainty shocks (surprise increases) lower GDP, as well as

[6]These two-factor estimates display no evident MCMC convergence problems. In addition, we considered two-factor estimates in which a tight prior is used to effectively eliminate a second factor from the VAR's conditional mean. In this case, the estimated first factor becomes the uncertainty measure with significant macroeconomic effects, and the second factor picks up the Great Moderation's influence on volatility.

many of its components, around the world, adversely affect labor market conditions, lower stock prices, and in some economies lead to an easing of monetary policy.

Our analysis extends recent work on common international aspects of macroeconomic uncertainty and its effects in several directions. Our framework allows us to coherently estimate uncertainty and its effects in one step, rather than rely on a two-step approach common in the uncertainty literature, in which a measure of uncertainty is estimated in a preliminary step and then used as if it were observable data in the subsequent econometric analysis (ignoring time-varying second moments) of its impact on macroeconomic variables. Our approach, unlike some other analyses in the international uncertainty literature, makes use of large datasets; some other work in the U.S.-focused literature has emphasized some benefits to using relatively large cross sections. Finally, whereas some previous work in the international uncertainty literature has either focused on international components to second moments or possibly confounded first-moment shocks with second-moment changes, our paper cleanly distinguishes uncertainty as a second-moment phenomenon that can affect first moments.

Our results can be seen as providing an empirical basis for further work on structural open-economy models. As noted in the introduction, Gourio, Siemer, and Verdelhan (2013) develop a model in which one particular type of uncertainty, associated with disaster risk, leads to a broad decline in economic activity, more so in an economy more affected by the disaster. Mumtaz and Theodoridis (2017) develop a model that can explain international comovement in volatilities. Further work is needed to establish models in which an international shock to risk in the tradition of closed-economy studies such as Bloom (2009), Basu and Bundick (2017), and Leduc and Liu (2016) produces global changes in economic activity and other indicators in line with the patterns documented in this paper.

7 Appendix: MCMC Algorithm for BVAR-GFSV Model

In detailing the algorithm in this appendix, for simplicity we present the more general version with the time-varying idiosyncratic volatility component and then indicate simplifications associated with treating the idiosyncratic component as constant. For simplicity, we describe the computations for a one-factor specification; the second factor is handled with the same basic approach.

Our exposition of priors, posteriors, and estimation makes use of the following additional notation. The vector a_j, $j = 2, \ldots, n$, contains the j^{th} row of the matrix A (for columns 1 through $j-1$). We define the vector $\gamma = \{\gamma_1, ..., \gamma_n\}$ as the set of coefficients appearing in the conditional means of the transition equations for the states $h_{1:T}$, and $\delta = \{D(L), \delta_m'\}$ as the set of the coefficients in the conditional mean of the transition equation for the states $m_{1:T}$. The coefficient matrices Φ_v and Φ_u defined above collect the variances of the shocks to the transition equations for the idiosyncratic states $h_{1:T}$ and the common uncertainty factor $m_{1:T}$; for identification, the value of Φ_u is fixed. In addition, we group the parameters of the model in (2)-(6), except the vector of factor loadings β, into $\Theta = \{\Pi, A, \gamma, \delta, \Phi_v, \Phi_u\}$. Finally, let $s_{1:T}$ denote the time series of the mixture states used (as explained below) to draw $h_{1:T}$.

We use an MCMC algorithm to obtain draws from the joint posterior distribution of model parameters Θ, loadings β, and latent states $h_{1:T}$, $m_{1:T}$, $s_{1:T}$. Specifically, we sample in turn from the following two conditional posteriors (for simplicity, we suppress notation for the dependence of each conditional posterior on the data sample $y_{1:T}$): (1) $h_{1:T}$, $\beta \mid \Theta$, $s_{1:T}$, $m_{1:T}$, and (2) Θ, $s_{1:T}$, $m_{1:T} \mid h_{1:T}$, β.

The first step relies on a state space system. Defining the rescaled residuals $\tilde{v}_t = Av_t$, taking the log squares of (2), and subtracting out the known (in the conditional posterior) contributions of the common factors yields the observation equations ($\bar{c}$ denotes an offset constant used to avoid potential problems with near-zero values):

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{m,j} \ln m_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2, \; j = 1, \ldots, n. \tag{15}$$

For the idiosyncratic volatility components, the transition and measurement equations of the state-space system are given by (5) and (15), respectively. The system is linear but not Gaussian, due to the error terms $\ln \epsilon_{j,t}^2$. However, $\epsilon_{j,t}$ is a Gaussian process with unit variance; therefore, we can use the mixture of normals approximation of Kim, Shephard, and Chib (1998) to obtain an approximate Gaussian system, conditional on the mixture of states $s_{1:T}$. To produce a draw from $h_{1:T}$, $\beta \mid \Theta$, $s_{1:T}$, $m_{1:T}$, we then proceed as usual by (a) drawing the time series of the states given the loadings using $h_{1:T} \mid \beta$, Θ, $s_{1:T}$, $m_{1:T}$, following Del Negro and Primiceri's (2015) implementation of the Kim, Shephard, and Chib (1998) algorithm, and by then (b) drawing the loadings given the states using ($\beta \mid h_{1:T}$, Θ, $s_{1:T}$, $m_{1:T}$, using the conditional posterior detailed below in (25).

In specifications in which the idiosyncratic components $h_{1:T}$ are restricted to be constant over time, the algorithm simplifies as follows. In this case, the measurement equation (15) simplifies to

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{m,j} \ln m_t = \ln h_j + \ln \epsilon_{j,t}^2, \; j = 1, \ldots, n, \tag{16}$$

and we no longer have a transition equation for the idiosyncratic components. Rather, given normally distributed priors on the idiosyncratic constants of each variable and the mixture states $s_{1:T}$ and their associated means and variances, we draw the idiosyncratic constants from a conditionally normal posterior using a GLS regression based on (16).

The second step conditions on the idiosyncratic volatilities and factor loadings to produce draws of the model coefficients Θ, common uncertainty factor $m_{1:T}$, and the mixture states $s_{1:T}$. Draws from the posterior Θ, $s_{1:T} \mid h_{1:T}$, β are obtained in three substeps from, respectively: (a) $\Theta \mid m_{1:T}$, $h_{1:T}$, β; (b) $m_{1:T}$, $\mid \Theta$, $h_{1:T}$, β; and (c) $s_{1:T} \mid \Theta$, $m_{1:T}$, $h_{1:T}$, β. More specifically, for $\Theta \mid m_{1:T}$, $h_{1:T}$, β we use the posteriors detailed below, in equations (23), (24), (26), (27), and (28). For $m_{1:T} \mid \Theta$, $h_{1:T}$, β, we use the particle Gibbs step proposed by Andrieu, Doucet, and Holenstein (2010). For $s_{1:T} \mid \Theta$, $m_{1:T}$, $h_{1:T}$, β, we use the 10-state mixture approximation of Omori, et al. (2007).

7.1 Coefficient Priors and Posteriors

We specify the following (independent) priors for the parameter blocks of the model:

$$\mathrm{vec}(\Pi) \sim N(\mathrm{vec}(\underline{\mu}_{\Pi}), \underline{\Omega}_{\Pi}), \tag{17}$$

$$a_j \sim N(\underline{\mu}_{a,j}, \underline{\Omega}_{a,j}), \; j = 2, \ldots, n, \tag{18}$$

$$\beta_{m,j} \sim N(\underline{\mu}_{\beta}, \underline{\Omega}_{\beta}), \; j = 1, \ldots, n, \tag{19}$$

$$\gamma_j \sim N(\underline{\mu}_{\gamma}, \underline{\Omega}_{\gamma}), \; j = 1, \ldots, n, \tag{20}$$

$$\delta \sim N(\underline{\mu}_{\delta}, \underline{\Omega}_{\delta}), \tag{21}$$

$$\phi_j \sim IG(d_\phi \cdot \underline{\phi}, d_\phi), \quad j = 1, \ldots, n. \tag{22}$$

Under these priors, the parameters Π, A, β, γ, δ, and Φ_v have the following closed form conditional posterior distributions:

$$\begin{aligned}
\text{vec}(\Pi)|A,\beta,m_{1:T},h_{1:T},y_{1:T} &\sim N(\text{vec}(\bar{\mu}_{\Pi}),\bar{\Omega}_{\Pi}), && (23)\\
a_j|\Pi,\beta,m_{1:T},h_{1:T},y_{1:T} &\sim N(\bar{\mu}_{a,j},\bar{\Omega}_{a,j}),\ j=2,\ldots,n, && (24)\\
\beta_{m,j}|\Pi,A,\gamma,\Phi,m_{1:T},h_{1:T},s_{1:T},y_{1:T} &\sim N(\bar{\mu}_{\beta},\bar{\Omega}_{\beta}),\quad j=1,\ldots,n, && (25)\\
\gamma_j|\Pi,A,\beta,\Phi,m_{1:T},h_{1:T},y_{1:T} &\sim N(\bar{\mu}_{\gamma},\bar{\Omega}_{\gamma}),\ j=1,\ldots,n, && (26)\\
\delta|\Pi,A,\gamma,\beta,\Phi,m_{1:T},h_{1:T},y_{1:T} &\sim N(\bar{\mu}_{\delta},\bar{\Omega}_{\delta}), && (27)\\
\phi_j|\Pi,A,\beta,\gamma,m_{1:T},h_{1:T},y_{1:T} &\sim IG\left(d_{\phi}\cdot\underline{\phi}+\Sigma_{t=1}^{T}\nu_{jt}^2,\ d_{\phi}+T\right),\ j=1,\ldots,n. && (28)
\end{aligned}$$

Expressions for $\bar{\mu}_{a,j}$, $\bar{\mu}_{\delta}$, $\bar{\mu}_{\gamma}$, $\bar{\Omega}_{a,j}$, $\bar{\Omega}_{\delta}$, and $\bar{\Omega}_{\gamma}$ are straightforward to obtain using standard results from the linear regression model. To save space, we omit details for these posteriors; general solutions are readily available in other sources (e.g., Cogley and Sargent (2005) for $\bar{\mu}_{a,j}$).

In the posterior for the factor loadings β, the mean and variance take a GLS-based form, with dependence on the mixture states used to draw volatility. For the VAR coefficients Π, with smaller models it is common to rely on a GLS solution for the posterior mean (e.g., Carriero, Clark, and Marcellino 2016a). However, with large models it is far faster to exploit the triangularization — obtaining the same posterior provided by standard system solutions — developed in Carriero, Clark, and Marcellino (2016b) and estimate the VAR coefficients on an equation-by-equation basis.

Specifically, using the factorization given below allows us to draw the coefficients of the matrix Π in separate blocks. Let $\pi^{(j)}$ denote the j-th column of the matrix Π, and let $\pi^{(1:j-1)}$ denote all the previous columns. Then draws of $\pi^{(j)}$ can be obtained from:

$$\begin{aligned}
\pi^{(j)} \quad | \quad & \pi^{(1:j-1)},A,\beta,m_{1:T},h_{1:T},y_{1:T}\sim N(\bar{\mu}_{\pi^{(j)}},\overline{\Omega}_{\pi^{(j)}}), && (29)\\
\bar{\mu}_{\pi^{(j)}} \quad = \quad & \overline{\Omega}_{\pi^{(j)}}\left\{\Sigma_{t=1}^{T}X_t\lambda_{j,t}^{-1}y_{j,t}^{*\prime}+\underline{\Omega}_{\pi^{(j)}}^{-1}(\underline{\mu}_{\pi^{(j)}})\right\}, && (30)\\
\overline{\Omega}_{\pi^{(j)}}^{-1} \quad = \quad & \underline{\Omega}_{\pi^{(j)}}^{-1}+\Sigma_{t=1}^{T}X_t\lambda_{j,t}^{-1}X_t', && (31)
\end{aligned}$$

where $y_{j,t}^{*}=y_{j,t}-(a_{j,1}^{*}\lambda_{1,t}^{0.5}\epsilon_{1,t}+\cdots+a_{j,,j-1}^{*}\lambda_{j-1,t}^{0.5}\epsilon_{j-1,t})$, with $a_{j,i}^{*}$ denoting the generic element of the matrix A^{-1} and $\underline{\Omega}_{\pi^{(j)}}^{-1}$ and $\underline{\mu}_{\pi^{(j)}}$ denoting the prior moments on the j-th equation, given by the j-th column of $\underline{\mu}_{\Pi}$ and the j-th block on the diagonal of $\underline{\Omega}_{\Pi}^{-1}$.

7.2 Unobservable States

For the unobserved common volatility states m_t, given the law of motion in (4) and priors on the period 0 values, draws from the posteriors can be obtained using the particle Gibbs sampler of Andrieu, Doucet, and Holenstein (2010). In the particle Gibbs sampler of the uncertainty factors, we use 50 particles, which appears sufficient for efficiency and mixing.

For the unobserved idiosyncratic volatility states $h_{j,t}$, $j = 1, ..., n$, given the law of motion for the unobservable states in (5) and priors on the period 0 values, draws from the posteriors can be obtained using the algorithm of Kim, Shephard, and Chib (1998). As noted above, in specifications in which the idiosyncratic components $h_{1:T}$ are restricted to be constant over time, the algorithm simplifies. In this case, given normally distributed priors on the idiosyncratic constants of each variable and the mixture states $s_{1:T}$ and their associated means and variances, we draw the idiosyncratic constants from a conditionally normal posterior using a GLS regression based on (16).

7.3 Drawing the Loadings

Finally, we note that in drawing the loadings, we make use of the information in the observable $\ln(\tilde{v}_{j,t}^2)$, with the following transformation of the observation equations:

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \ln h_{j,t} = \beta_{m,j} \ln m_t + \ln \epsilon_{j,t}^2, \; j = 1, \ldots, n.$$

With the conditioning on $h_{1:T}$ and $s_{1:T}$ in the posterior for β, we use this equation, along with the mixture mean and variance associated with the draw of $s_{1:T}$, for sampling the factor loadings with a conditionally normal posterior with mean and variance represented in a GLS form. The same applies in the specifications in which the idiosyncratic volatilities $h_{j,t}$ are restricted to be constant over time.

7.4 Triangularization for Estimation

In this subsection we briefly summarize the VAR triangularization that is needed to handle a large system with asymmetric priors and time-varying volatilities, such as the model used here.[7] More details can be found in Carriero, Clark, and Marcellino (2016b). With the triangularization, the estimation algorithm will block the conditional posterior distribution

[7] Since the triangularization obtains computational gains of order n^2, the cross-sectional dimension of the system can be extremely large, and indeed Carriero, Clark, and Marcellino (2016b) present results for a VAR with 125 variables.

of the system of VAR coefficients in n different blocks. In the step of the typical Gibbs sampler that involves drawing the set of VAR coefficients Π, all of the remaining model coefficients are given. Consider again the reduced-form residuals:

$$\begin{bmatrix} v_{1,t} \\ v_{2,t} \\ ... \\ v_{n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & ... & 0 \\ a^*_{2,1} & 1 & & ... \\ ... & & 1 & 0 \\ a^*_{n,1} & ... & a^*_{n,n-1} & 1 \end{bmatrix} \begin{bmatrix} \lambda^{0.5}_{1,t} & 0 & ... & 0 \\ 0 & \lambda^{0.5}_{2,t} & & ... \\ ... & & ... & 0 \\ 0 & ... & 0 & \lambda^{0.5}_{n,t} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ ... \\ \epsilon_{n,t} \end{bmatrix}, \tag{32}$$

where $a^*_{j,i}$ denotes the generic element of the matrix A^{-1}, which is available under knowledge of A. The VAR can be written as:

$$\begin{aligned} y_{1,t} &= \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{1,l}y_{i,t-l} + \sum_{l=0}^{p_m}\pi^{(m)}_{l,1}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi^{(f)}_{l,1}\ln f_{t-l} + \lambda^{0.5}_{1,t}\epsilon_{1,t} \\ y_{2,t} &= \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{2,l}y_{i,t-l} + \sum_{l=0}^{p_m}\pi^{(m)}_{l,2}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi^{(f)}_{l,2}\ln f_{t-l} + a^*_{2,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \lambda^{0.5}_{2,t}\epsilon_{2,t} \\ & ... \\ y_{n,t} &= \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{n,l}y_{i,t-l} + \sum_{l=0}^{p_m}\pi^{(m)}_{l,N}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi^{(f)}_{l,N}\ln f_{t-l} + a^*_{n,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \cdots \\ & ... + a^*_{n,n-1}\lambda^{0.5}_{n-1,t}\epsilon_{n-1,t} + \lambda^{0.5}_{n,t}\epsilon_{n,t}, \end{aligned}$$

with the generic equation for variable j:

$$\begin{aligned} & y_{j,t} - (a^*_{j,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \cdots + a^*_{j,,j-1}\lambda^{0.5}_{j-1,t}\epsilon_{j-1,t}) \\ = & \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{j,l}y_{i,t-l} + \sum_{l=0}^{p_m}\pi^{(m)}_{l,j}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi^{(f)}_{l,j}\ln f_{t-l} + \lambda_{j,t}\epsilon_{j,t}. \end{aligned} \tag{33}$$

Consider estimating these equations in order from $j = 1$ to $j = n$. When estimating the generic equation j, the term of the left-hand side in (33) is known, since it is given by the difference between the dependent variable of that equation and the estimated residuals of all the previous $j - 1$ equations. Therefore we can define:

$$y^*_{j,t} = y_{j,t} - (a^*_{j,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \cdots + a^*_{j,,j-1}\lambda^{0.5}_{j-1,t}\epsilon_{j-1,t}), \tag{34}$$

and equation (33) becomes a standard generalized linear regression model for the variable in equation (34) with Gaussian disturbances with mean 0 and variance $\lambda_{j,t}$.

Accordingly, drawing on results detailed in Carriero, Clark, and Marcellino (2016b), the posterior distribution of the VAR coefficients can be factorized as:

$$
\begin{aligned}
p(\Pi|A,\beta,m_{1:T},h_{1:T},y_{1:T}) \;=\;& p(\pi^{(n)}|\pi^{(n-1)},\pi^{(n-2)},\ldots,\pi^{(1)},A,\beta,m_{1:T},h_{1:T},y_{1:T}) \\
& \times p(\pi^{(n-1)}|\pi^{(n-2)},\ldots,\pi^{(1)},A,\beta,m_{1:T},h_{1:T},y_{1:T}) \\
& \times \ldots \times p(\pi^{(1)}|A,\beta,m_{1:T},h_{1:T},y_{1:T}), \qquad (35)
\end{aligned}
$$

where the vector β collects the loadings of the uncertainty factors and $m_{1:T}$, $h_{1:T} = (h_{1,T}, ..., h_{n,T})$, and $y_{1:T}$ denote the history of the states and data up to time T.[8] As a result, we are able to estimate the coefficients of the VAR on an equation-by-equation basis. This greatly speeds estimation and permits us to consider much larger systems than we would otherwise be able to consider.

Importantly, although the expression (32) and the following triangular system are based on a Cholesky-type decomposition of the variance Σ_t, the decomposition is simply used as an estimation device, not as a way to identify structural shocks. The ordering of the variables in the system does not change the joint (conditional) posterior of the reduced-form coefficients, so changing the order of the variables is inconsequential to the results.[9] Moreover, since a shock to uncertainty is uncorrelated with shocks to the conditional mean of the variables, the ordering of the variables in the system has no influence on the shape of impulse responses in our application.

[8]Note we have implicitly used the fact that the matrix $\underline{\Omega}_{\Pi}^{-1}$ is block diagonal, which is the case in our application, as our prior on the conditional mean coefficients is independent across equations, with a Minnesota-style form.

[9]This statement refers to drawing from the conditional posterior of the conditional mean parameters, when Σ_t belongs to the conditioning set. One needs also to keep in mind that the joint distribution of the system might be affected by the ordering of the variables in the system due to an entirely different reason: the diagonalization typically used for the error variance Σ_t in stochastic volatility models. Since priors are elicited separately for A and Λ_t, the implied prior of Σ_t will change if one changes the equation ordering, and therefore different orderings would result in different prior specifications and then potentially different joint posteriors. This problem is not a feature of our triangular algorithm, but rather it is inherent to all models using the diagonalization of Σ_t. As noted by Sims and Zha (2006) and Primiceri (2005), this problem will be mitigated in the case (as the one considered in this paper) in which the covariances A do not vary with time, because the likelihood information will soon dominate the prior.

8 References

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Table 1: Variables in the 3-economy macroeconomic dataset

U.S. variables	*E.A. variables*	*U.K. variables*
real GDP ($\Delta \ln$)	real GDP ($\Delta \ln$)	real GDP ($\Delta \ln$)
real consumption ($\Delta \ln$)	real consumption ($\Delta \ln$)	real consumption ($\Delta \ln$)
real government consumption ($\Delta \ln$)	real government consumption ($\Delta \ln$)	real government consumption ($\Delta \ln$)
real investment ($\Delta \ln$)	real investment ($\Delta \ln$)	real investment ($\Delta \ln$)
real exports ($\Delta \ln$)	real exports ($\Delta \ln$)	real exports ($\Delta \ln$)
real imports ($\Delta \ln$)	real imports ($\Delta \ln$)	real imports ($\Delta \ln$)
real inventories	real inventories	unit labor costs ($\Delta \ln$)
unit labor costs ($\Delta \ln$)	unit labor costs ($\Delta \ln$)	industrial confidence
employment ($\Delta \ln$)	employment ($\Delta \ln$)	consumer confidence
hours worked ($\Delta \ln$)	unemployment rate	employment ($\Delta \ln$)
unemployment rate	Eonia rate	unemployment rate
Federal funds rate	2-year bond yield	producer prices ($\Delta \ln$)
2-year bond yield	10-year bond yield	retail price index ($\Delta \ln$)
10-year bond yield	M3 ($\Delta \ln$)	official bank rate
M2 ($\Delta \ln$)	GDP deflator ($\Delta \ln$)	10-year bond yield
oil price ($\Delta \ln$)	consumer prices ($\Delta \ln$)	stock price index ($\Delta \ln$)
commodity prices ($\Delta \ln$)	core consumer prices ($\Delta \ln$)	
consumer prices ($\Delta \ln$)	producer prices ($\Delta \ln$)	
core consumer prices ($\Delta \ln$)	real housing investment ($\Delta \ln$)	
producer prices ($\Delta \ln$)	stock price index ($\Delta \ln$)	
real housing investment ($\Delta \ln$)	capacity utilization	
stock price index ($\Delta \ln$)	consumer confidence	
capacity utilization	industrial confidence	
consumer confidence	purchasing managers' index	
industrial confidence	labor shortages	
purchasing managers' index		

Note: For those variables transformed for use in the model, the table indicates the transformation in parentheses following the variable description.

Table 2: Summary statistics on commonality in volatility

	19-country GDP dataset		3-economy macroeconomic dataset	
Prin. comp.	R^2	*A-H ratio*	R^2	*A-H ratio*
1	0.786	7.431	0.417	1.621
2	0.106	1.746	0.258	2.452
3	0.061	3.041	0.105	1.789
4	0.020	1.905	0.059	1.193
5	0.010	1.296	0.049	1.275

Table 3: Factor loadings: 19-country GDP dataset

Country	Principal component loading	GFSV loading posterior mean (st. dev.).
U.S.	0.939	0.925 (0.347)
Australia	1.051	0.695 (0.383)
Austria	1.093	1.060 (0.374)
Belgium	0.978	1.390 (0.395)
Canada	1.103	1.004 (0.392)
Denmark	0.751	0.505 (0.446)
Finland	1.062	1.007 (0.333)
France	1.079	0.718 (0.399)
Germany	1.105	1.634 (0.362)
Italy	1.106	1.169 (0.371)
Japan	1.065	0.915 (0.408)
Luxembourg	0.939	0.985 (0.362)
Netherlands	0.889	0.966 (0.396)
Norway	0.780	0.515 (0.395)
Portugal	1.003	1.287 (0.401)
Spain	0.943	1.415 (0.382)
Sweden	1.114	1.065 (0.382)
Switzerland	0.769	0.396 (0.388)
U.K.	1.097	1.130 (0.413)

Table 4: Loadings on first factor: 3-economy macroeconomic dataset

Country	Principal component loading	GFSV loading posterior mean (st. dev.)	Country	Principal component loading	GFSV loading posterior mean (st. dev.)
U.S. real GDP	1.330	0.455 (0.274)	E.A. employment	0.799	0.845 (0.411)
U.S. real consumption	1.239	0.640 (0.318)	E.A. unemployment rate	0.652	1.002 (0.371)
U.S. real government consumption	1.281	0.563 (0.316)	E.A. Eonia rate	0.846	1.460 (0.369)
U.S. real investment	1.246	0.211 (0.342)	E.A. 2-year bond yield	1.321	0.665 (0.364)
U.S. real exports	1.265	0.516 (0.327)	E.A. 10-year bond yield	0.290	0.558 (0.384)
U.S. real imports	1.291	0.678 (0.334)	E.A. M3	1.164	0.866 (0.355)
U.S. real inventories	1.328	0.326 (0.361)	E.A. GDP deflator	0.955	0.966 (0.400)
U.S. unit labor costs	0.915	0.579 (0.316)	E.A. consumer prices	1.331	0.824 (0.380)
U.S. employment	1.032	0.125 (0.376)	E.A. core consumer prices	-0.559	0.449 (0.394)
U.S. hours worked	-1.168	0.299 (0.323)	E.A. producer prices	1.213	0.696 (0.426)
U.S. unemployment rate	1.324	0.772 (0.372)	E.A. real housing investment	1.180	1.341 (0.385)
U.S. Federal funds rate	1.353	1.239 (0.333)	E.A. stock price index	0.613	0.579 (0.399)
U.S. 2-year bond yield	0.902	0.335 (0.337)	E.A. capacity utilization	0.390	0.629 (0.389)
U.S. 10-year bond yield	0.462	0.414 (0.349)	E.A. consumer confidence	0.836	0.574 (0.405)
U.S. M2	0.822	0.604 (0.363)	E.A. industrial confidence	1.007	0.386 (0.407)
oil price	1.344	1.245 (0.317)	E.A. purchasing managers' index	-0.952	0.449 (0.402)
commodity prices	1.347	1.030 (0.287)	E.A. labor shortages	0.719	1.368 (0.392)
U.S. consumer prices	1.194	1.006 (0.351)	U.K. real GDP	1.188	0.736 (0.406)
U.S. core consumer prices	1.186	0.797 (0.313)	U.K. real consumption	0.615	0.881 (0.391)
U.S. producer prices	1.069	0.605 (0.367)	U.K. real government consumption	0.059	0.386 (0.397)
U.S. real housing investment	0.880	0.896 (0.403)	U.K. real investment	1.105	0.526 (0.379)
U.S. stock price index	1.208	1.174 (0.395)	U.K. real exports	0.007	0.644 (0.387)
U.S. capacity utilization	1.360	0.728 (0.374)	U.K. real imports	0.641	0.729 (0.406)
U.S. consumer confidence	1.319	0.899 (0.363)	U.K. unit labor costs	0.018	0.522 (0.404)
U.S. industrial confidence	1.269	0.559 (0.375)	U.K. industrial confidence	-1.129	0.588 (0.401)
U.S. purchasing managers' index	1.363	0.896 (0.351)	U.K. consumer confidence	0.875	0.846 (0.392)
E.A. real GDP	1.288	1.497 (0.335)	U.K. employment	0.164	0.775 (0.391)
E.A. real consumption	0.701	0.961 (0.370)	U.K. unemployment rate	0.165	0.721 (0.410)
E.A. real government consumption	0.437	0.685 (0.416)	U.K. producer prices	1.096	0.816 (0.414)
E.A. real investment	0.817	0.259 (0.376)	U.K. retail price index	0.945	1.048 (0.425)
E.A. real exports	1.038	1.045 (0.387)	U.K. official bank rate	0.876	0.987 (0.412)
E.A. real imports	1.090	0.686 (0.386)	U.K. 10-year bond yield	0.252	0.906 (0.404)
E.A. real inventories	1.059	0.840 (0.363)	U.K. stock price index	0.483	0.875 (0.414)
E.A. unit labor costs	0.689	0.849 (0.366)			

Table 5: Correlations of uncertainty shocks with other shocks

known shock	19-country GDP dataset uncert. shock	3-economy macro dataset uncert. shock
Productivity: Fernald TFP	-0.097	-0.049
(1985:Q1-2016:Q3, 1985:Q4-2013:Q3)	(0.279)	(0.496)
Oil supply: Hamilton (2003)	0.056	-0.017
(1985:Q1-2016:Q3, 1985:Q4-2013:Q3)	(0.561)	(0.812)
Oil supply: Kilian (2008)	-0.038	0.022
(1985:Q1-2004:Q3, 1985:Q4-2004:Q3)	(0.776)	(0.834)
Monetary policy: Guykaynak, et al. (2005)	-0.070	-0.112
(1990:Q1-2004:Q4, 1990:Q1-2004:Q4)	(0.359)	(0.284)
Monetary policy: Coibion, et al. (2016)	-0.181	-0.046
(1985:Q1-2008:Q4, 1985:Q4-2008:Q4)	(0.036)	(0.589)
Fiscal policy: Ramey (2011)	-0.175	0.050
(1985:Q1-2008:Q4, 1985:Q4-2008:Q4)	(0.239)	(0.649)
Fiscal policy: Mertens and Ravn (2012)	0.198	0.013
(1985:Q1-2006:Q4, 1985:Q4-2006:Q4)	(0.002)	(0.845)

Notes: The table provides the correlations of the shocks to uncertainty (measured as the posterior medians of $u_{m,t}$) with selected macroeconomic shocks for the U.S. Entries in parentheses provide (in column 1) the sample periods of the correlation estimates, first for the 19-country GDP dataset and then for the 3-economy macroeconomic dataset and (in columns 2 and 3) the p-values of t-statistics of the coefficient obtained by regressing the uncertainty shock on the macroeconomic shock (and a constant). The variances underlying the t-statistics are computed with the prewhitened quadratic spectral estimator of Andrews and Monahan (1992).

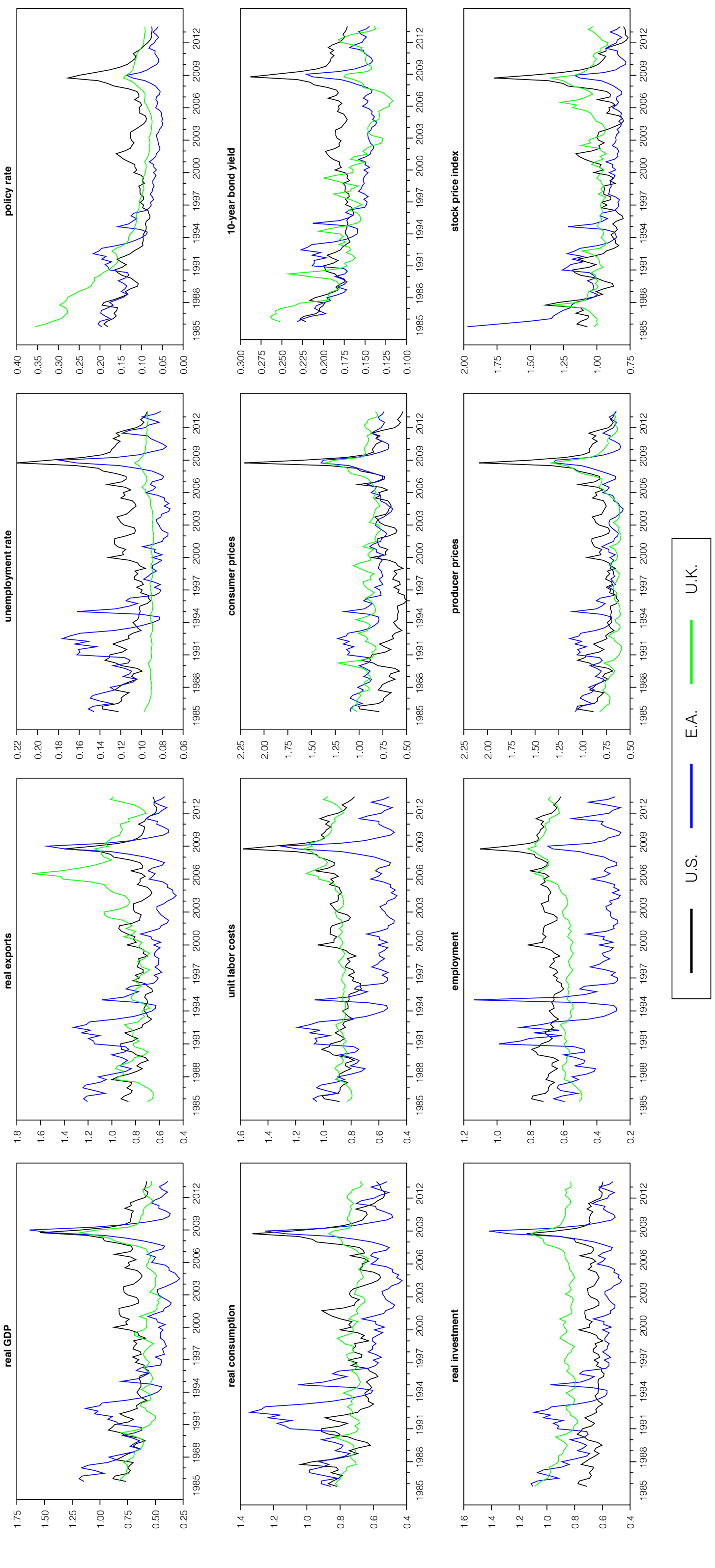


Figure 1: BVAR-SV estimates of volatilities (standard deviations), selected variables

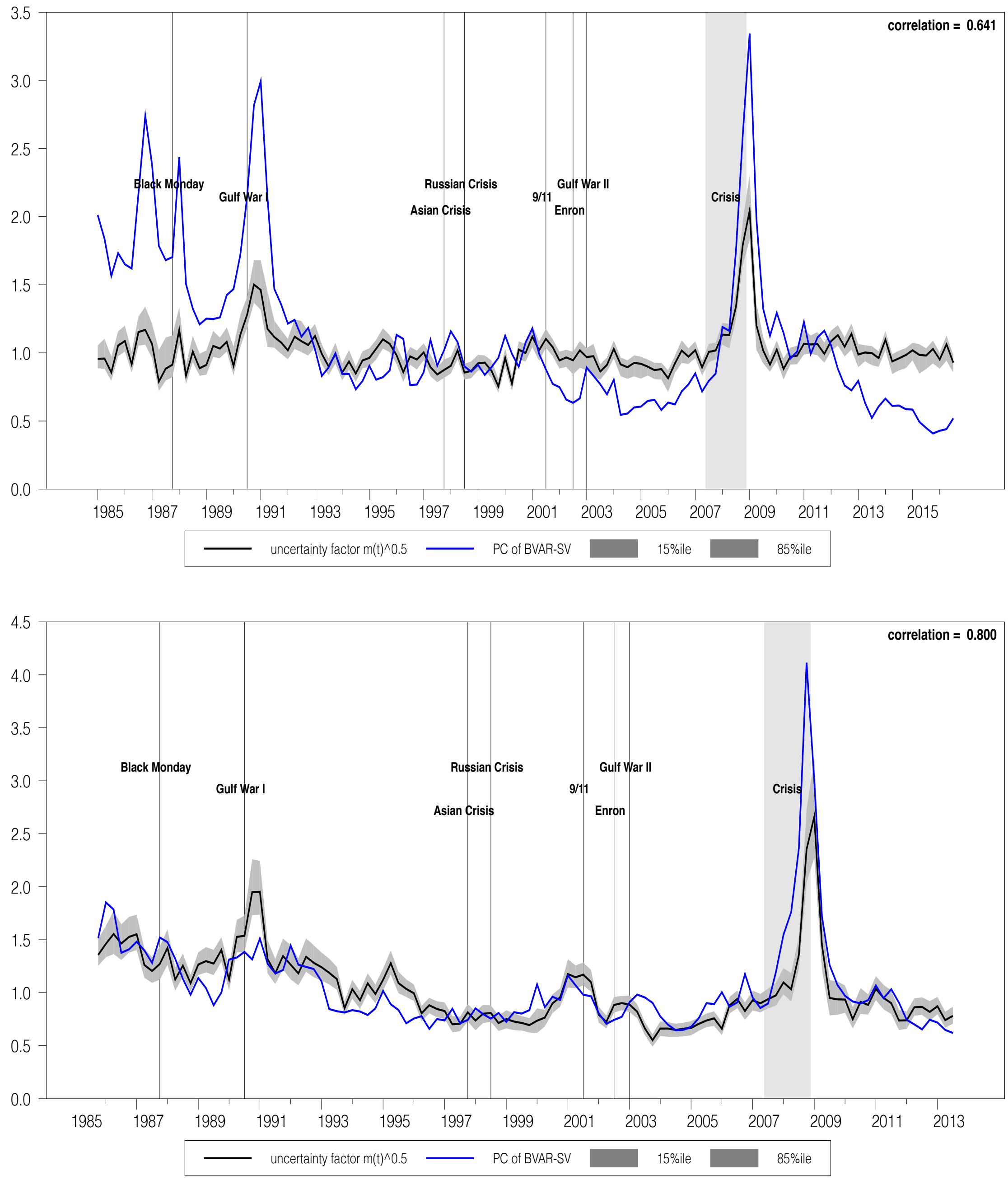


Figure 2: Uncertainty estimates for 19-country GDP dataset in the top panel and for 3-economy macroeconomic dataset in the bottom panel. In each panel, the blue line provides an estimate obtained from the first principal component of the BVAR-SV estimates of log volatility. The solid black line and gray-shaded regions provide the posterior median and 15%/85% quantiles of the BVAR-GFSV estimate of macroeconomic uncertainty ($m_t^{0.5}$). The periods indicated by black vertical lines or regions correspond to the uncertainty events highlighted in Bloom (2009). Labels for these events are indicated in text horizontally centered on the event's start date.

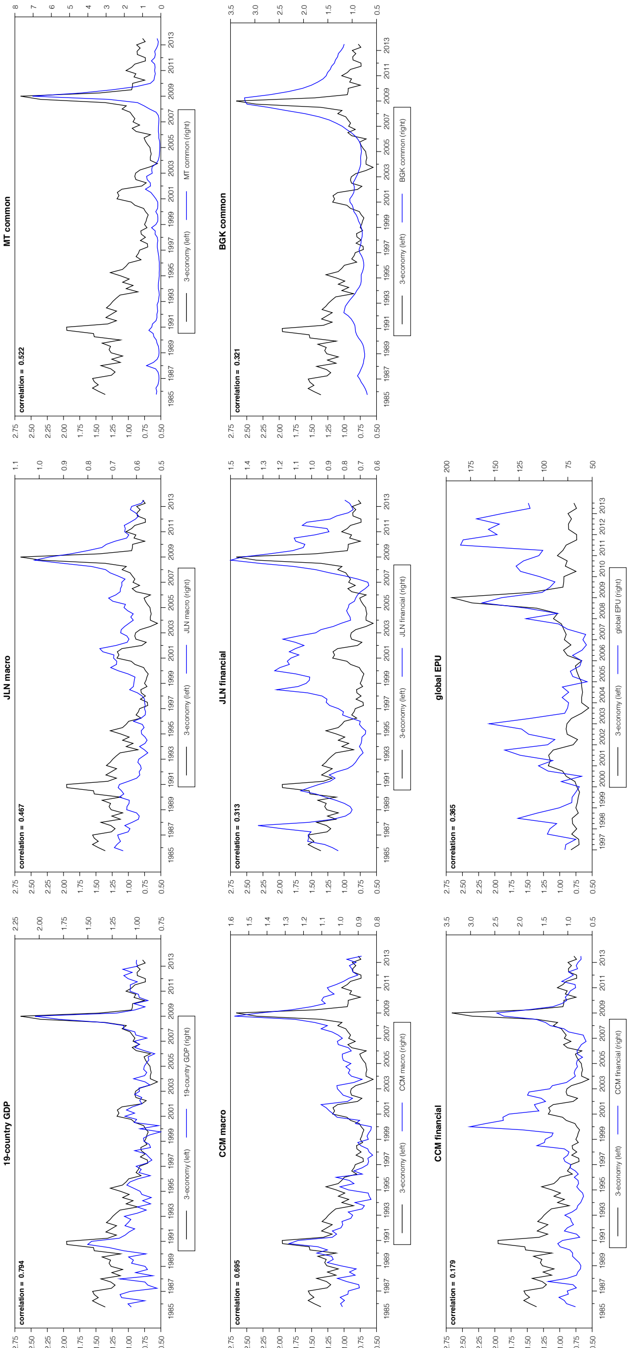


Figure 3: Comparison of uncertainty estimates to others in the literature. The top left panel compares the uncertainty estimate obtained from the 3-economy macroeconomic dataset (black line) to that obtained with the 19-country GDP dataset (blue line). Other panels compare the 3-economy macroeconomic dataset estimate (black line) to a different estimate (blue line) from the literature, including: CCM macro and financial uncertainty from Carriero, Clark, and Marcellino (2017a); JLN macro and financial uncertainty, 1-step ahead, from Jurado, Ludvigson, and Ng (2015); global economic policy uncertainty (EPU) from Davis (2016); common uncertainty from Mumtaz and Theodoridis (2017); and common uncertainty from Berger, Grabert, and Kempa (2016).

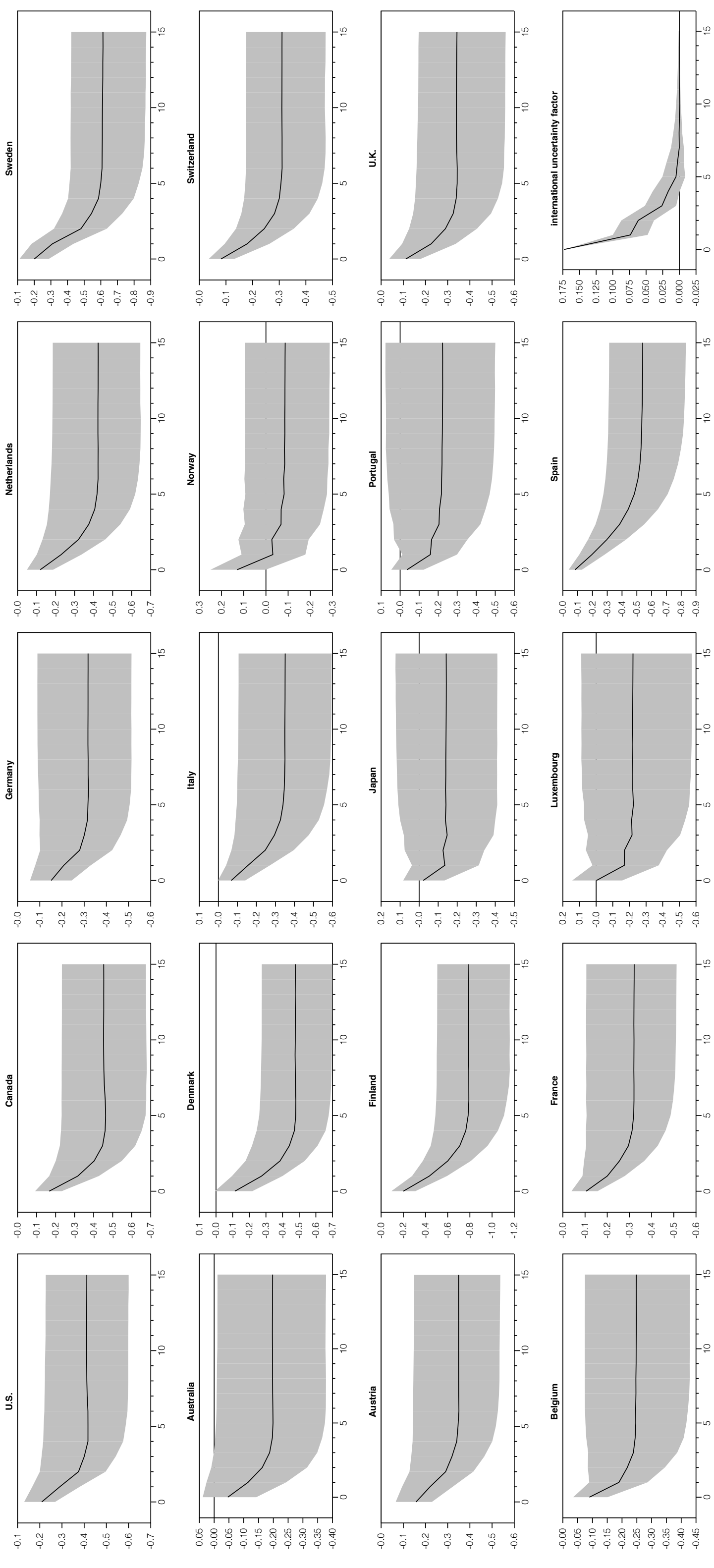


Figure 4: Impulse responses for international uncertainty shock: BVAR-GFSV estimates for 19-country GDP dataset

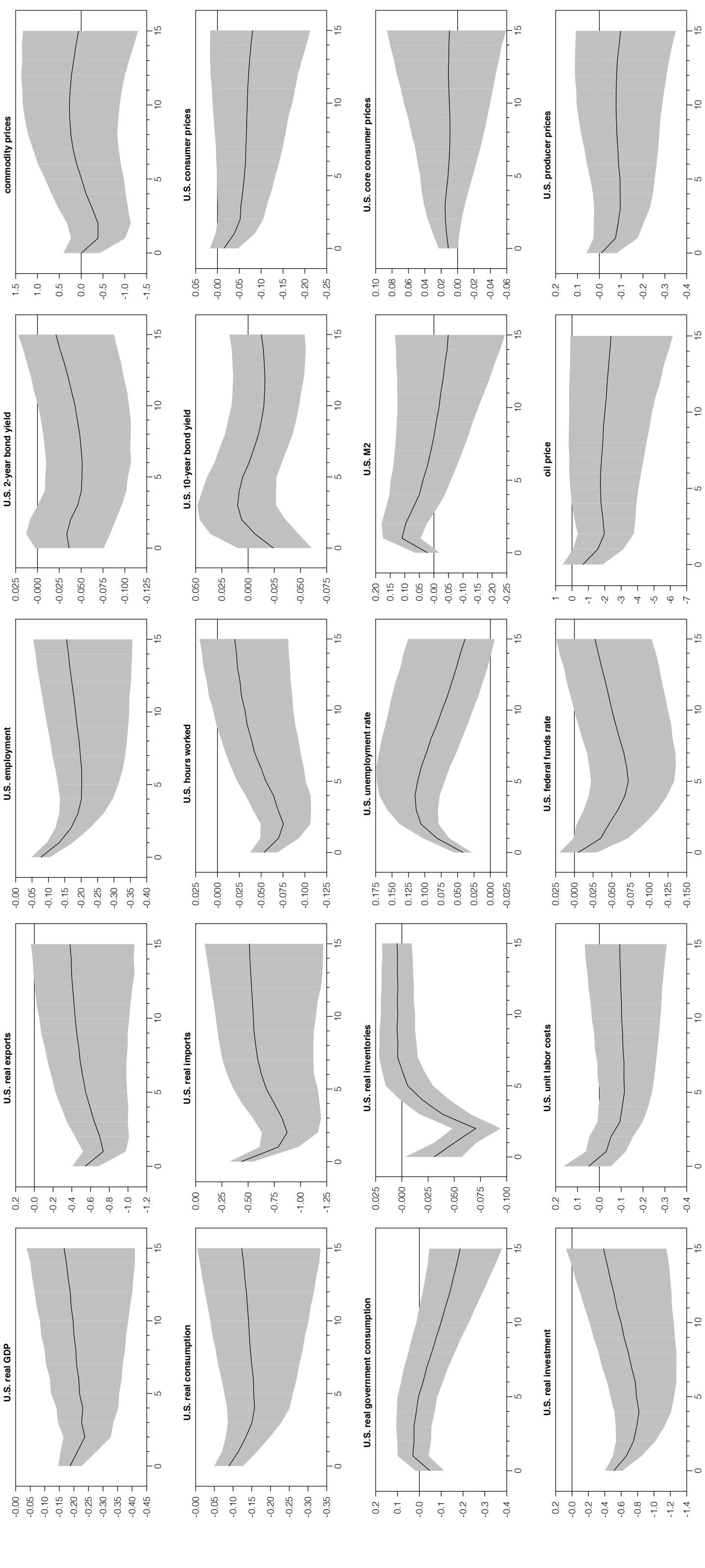


Figure 5: Impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset

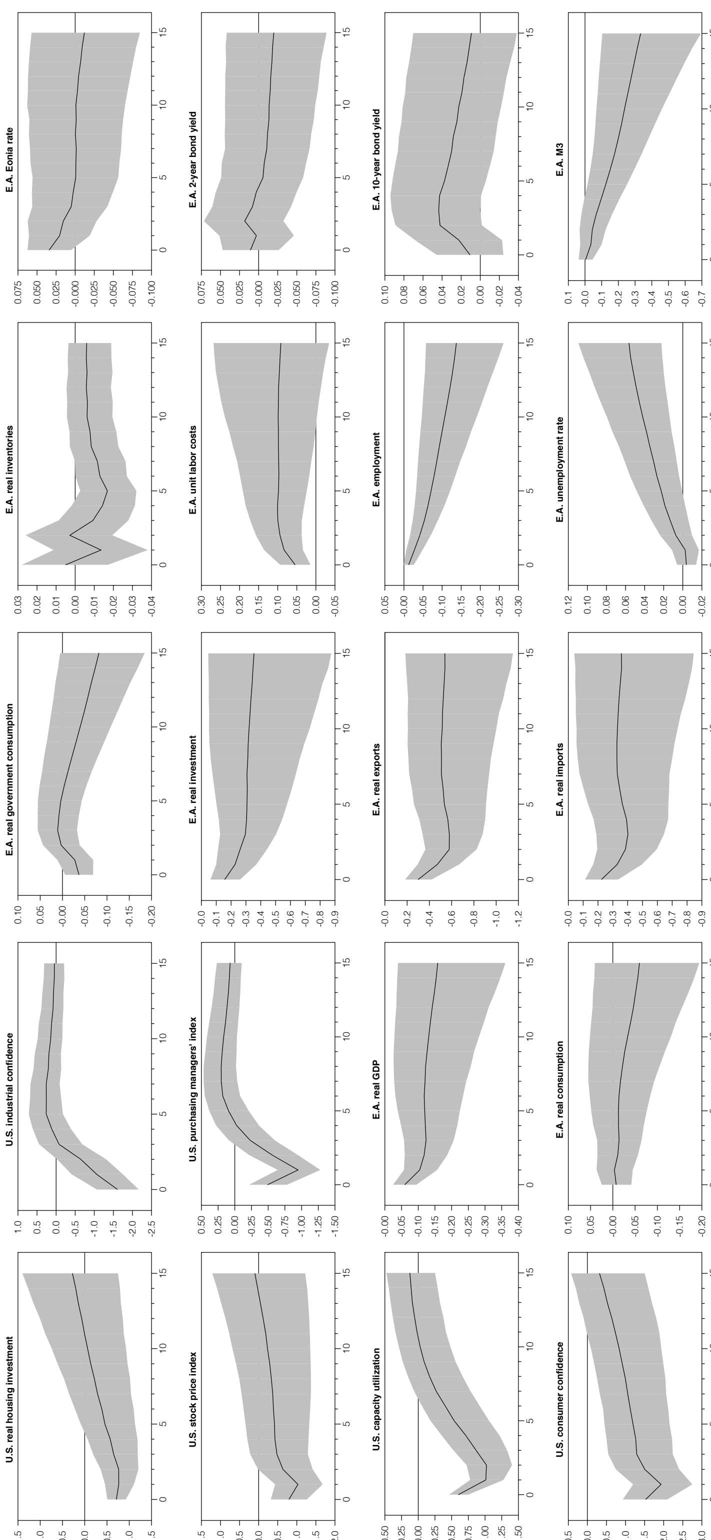


Figure 5: Continued, impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset

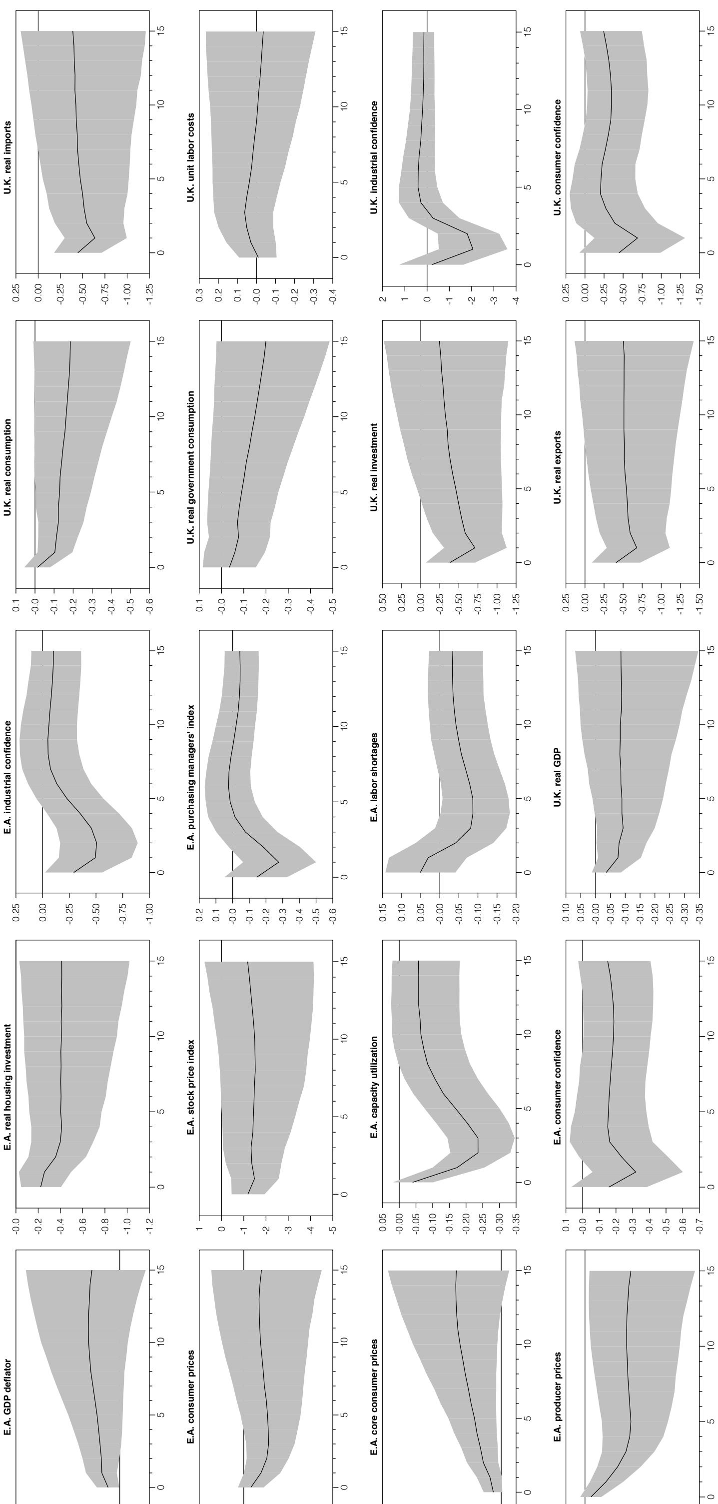


Figure 5: Continued, impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset

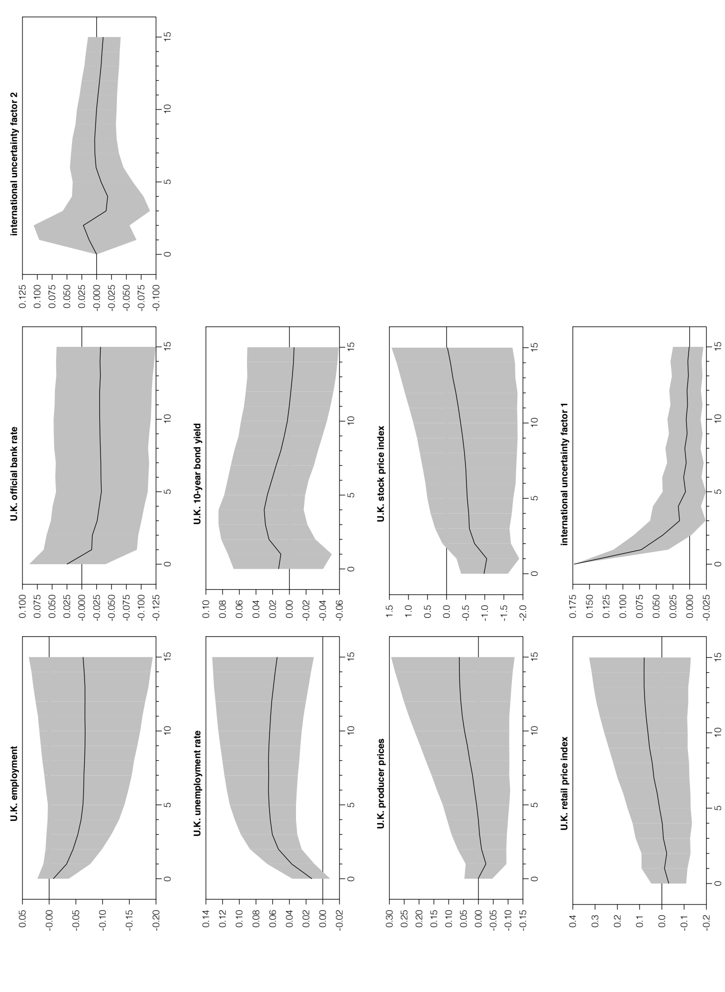


Figure 5: Continued, impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset

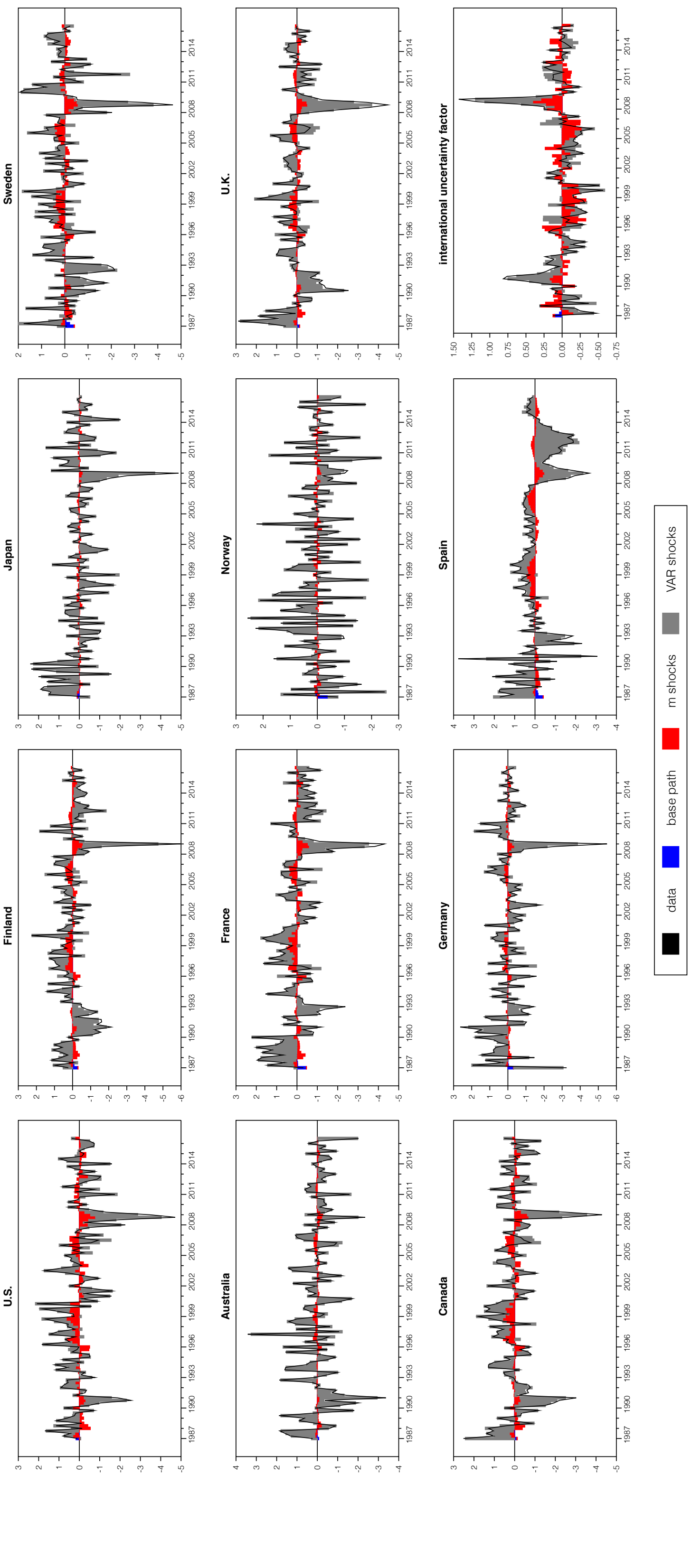


Figure 6: Historical decomposition: BVAR-GFSV estimates for 19-country GDP dataset, selected variables, posterior medians

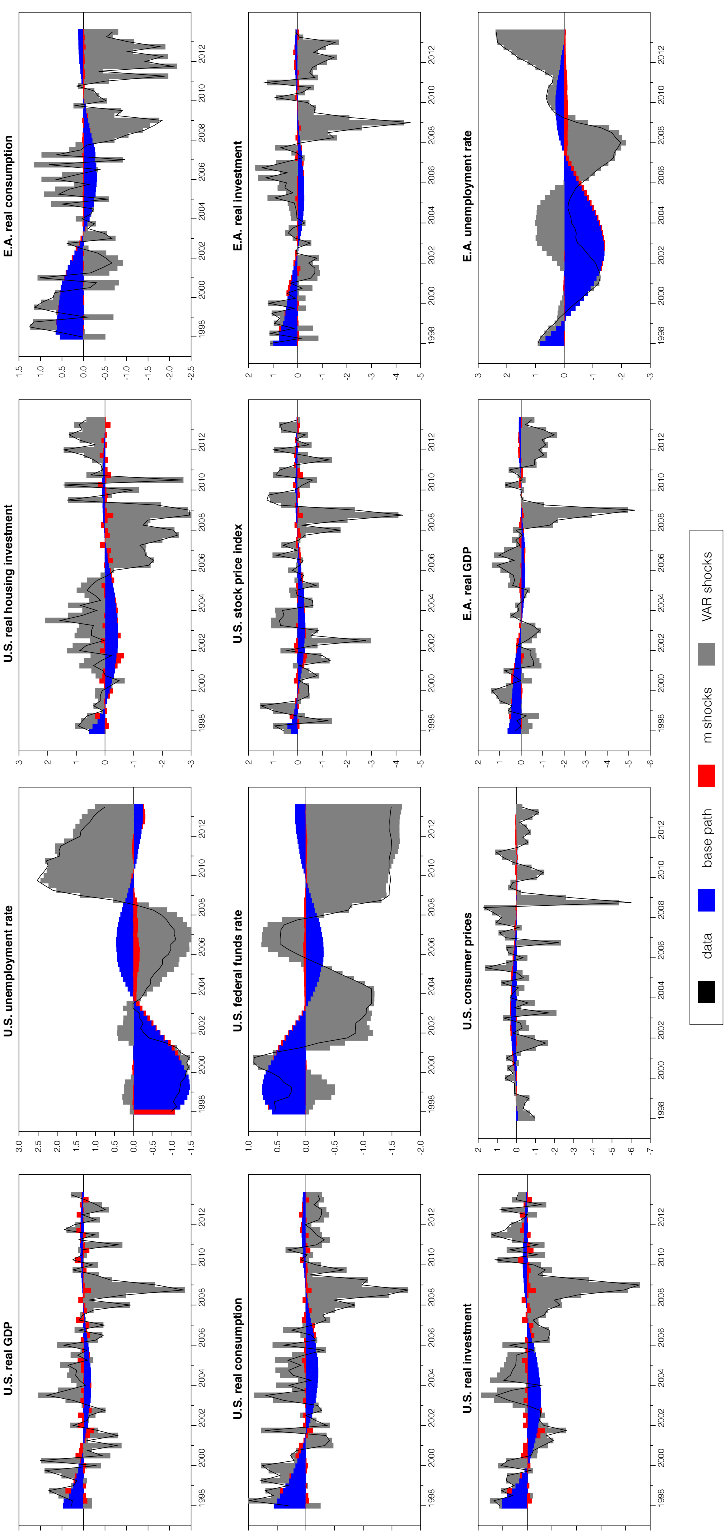


Figure 7: Historical decomposition: BVAR-GFSV estimates for 3-economy macroeconomic dataset, selected variables, posterior medians

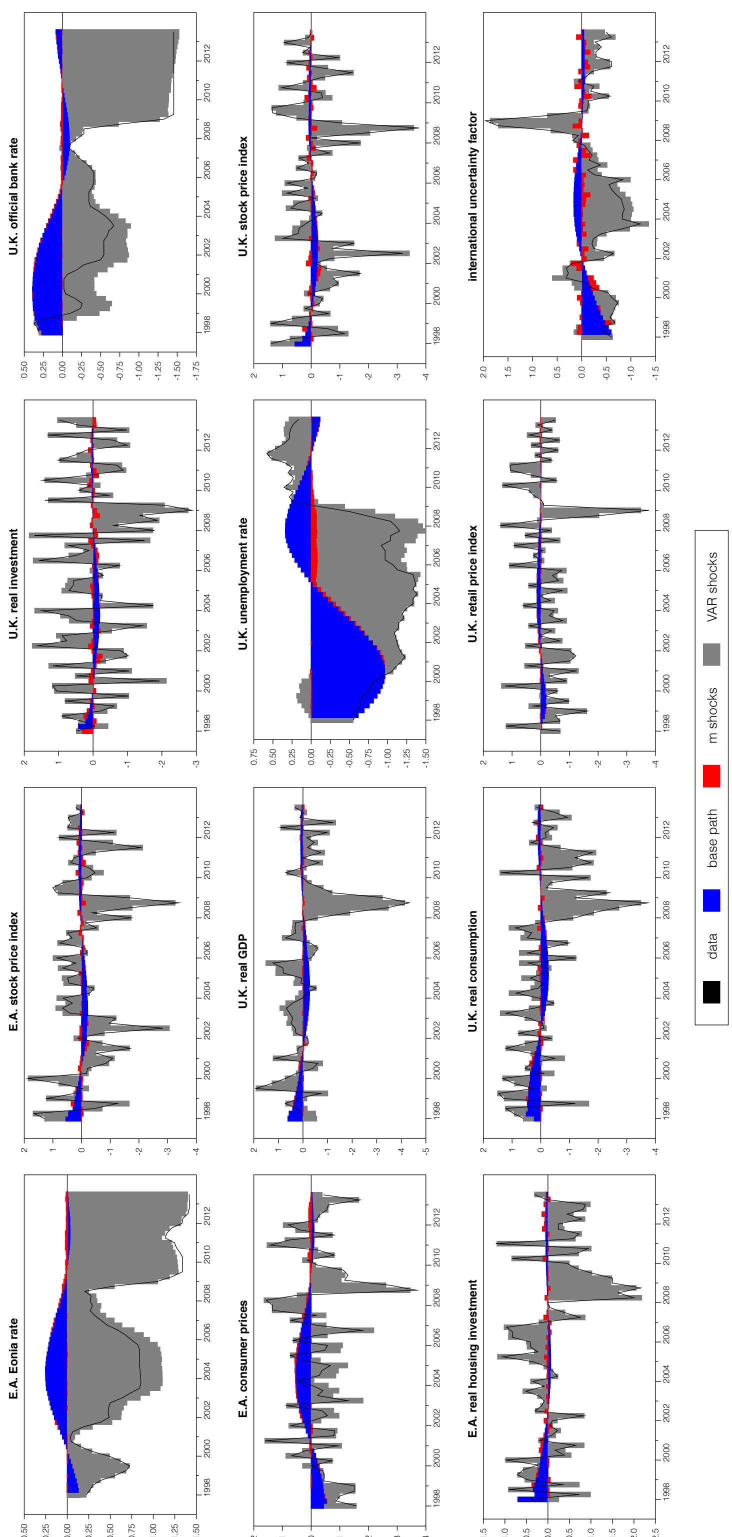


Figure 7: Continued, historical decomposition: BVAR-GFSV estimates for 3-economy macroeconomic dataset, selected variables, posterior medians

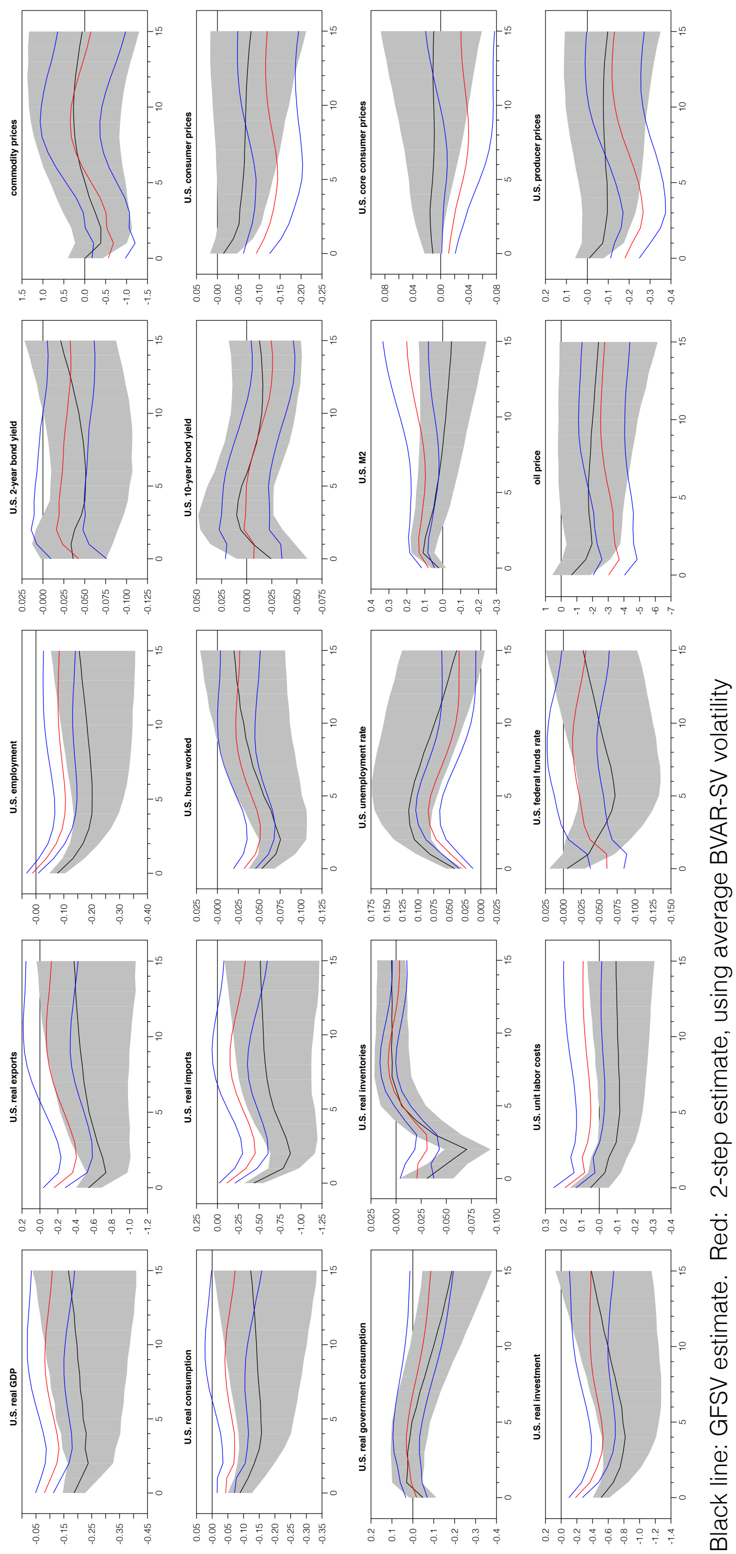


Figure 8: Impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates

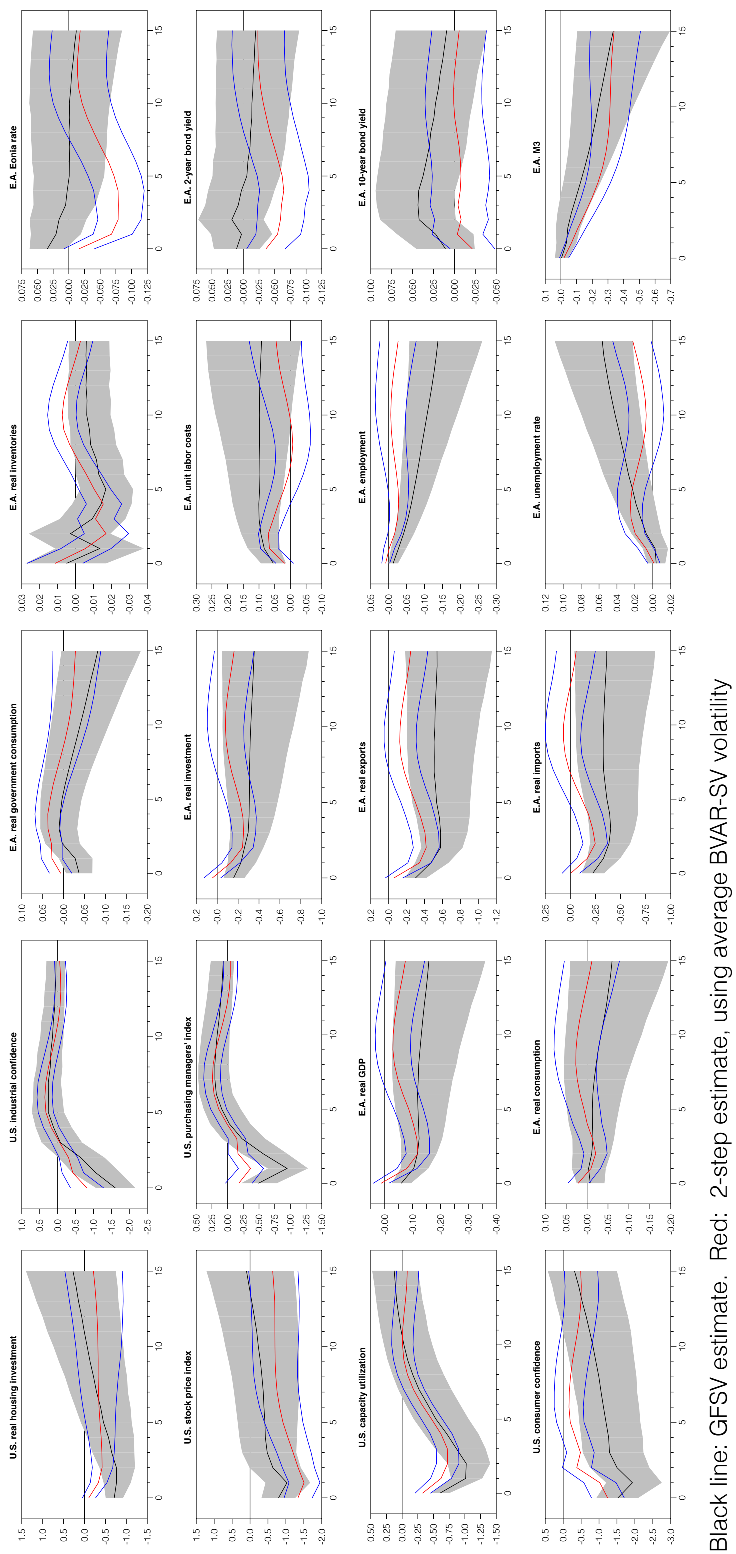


Figure 8: Continued, impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates

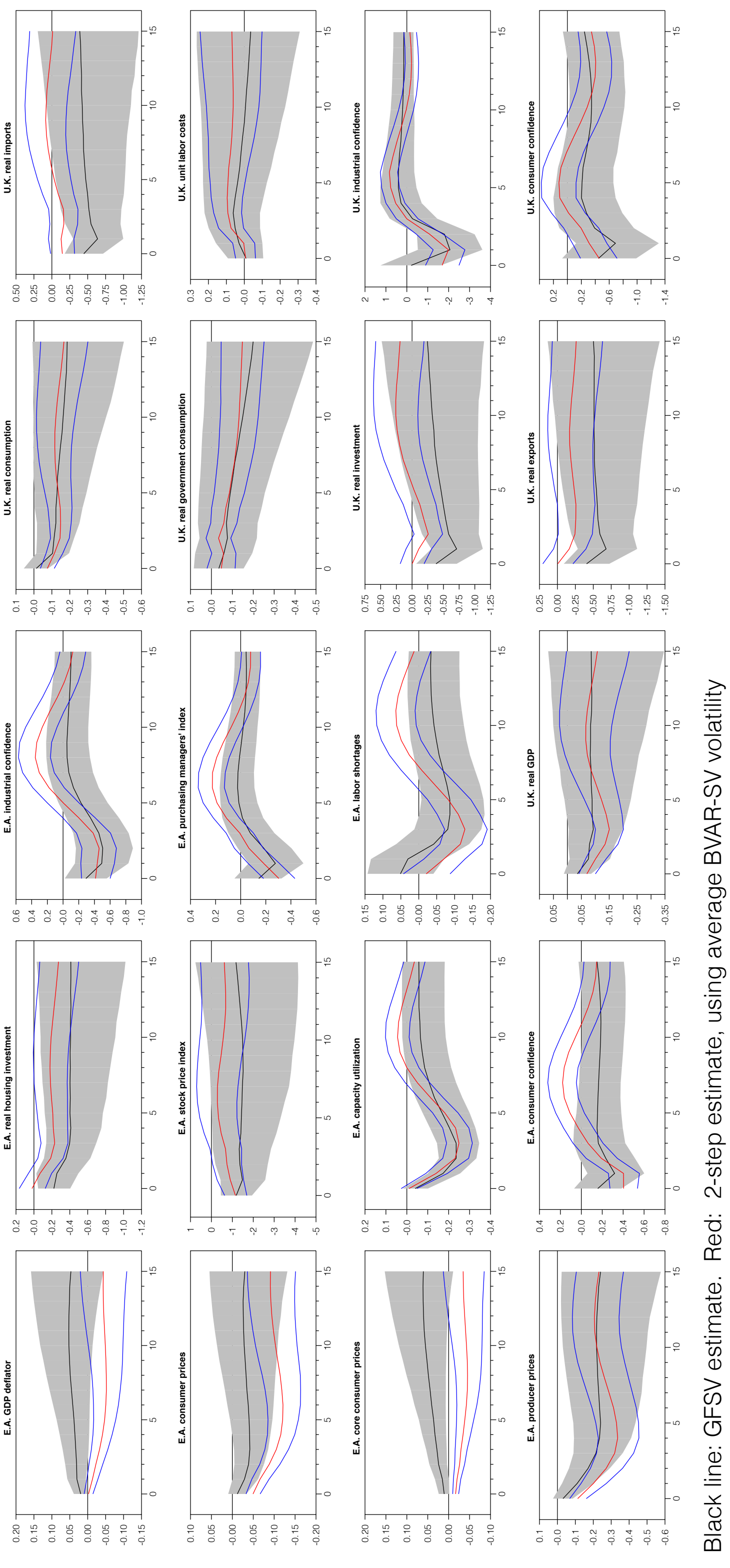
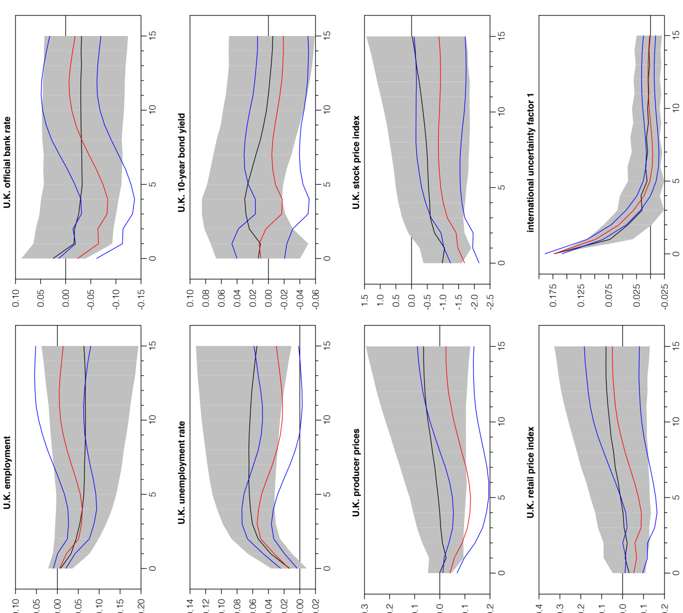


Figure 8: Continued, impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates



Black line: GFSV estimate. Red: 2-step estimate, using average BVAR-SV volatility

Figure 8: Continued, impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates