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ASSESSING INTERNATIONAL COMMONALITY IN MACROECONOMIC UNCERTAINTY AND ITS EFFECTS

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Abstract

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Assessing International Commonality in Macroeconomic Uncertainty and Its Effects[*]

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Abstract

This paper uses a large vector autoregression to measure international macroeconomic uncertainty and its effects on major economies. We provide evidence of significant commonality in macroeconomic volatility, with one common factor driving strong comovement across economies and variables. We measure uncertainty and its effects with a large model in which the error volatilities feature a factor structure containing time-varying global components and idiosyncratic components. Global uncertainty contemporaneously affects both the levels and volatilities of the included variables. Our new estimates of international macroeconomic uncertainty indicate that surprise increases in uncertainty reduce output and stock prices, adversely affect labor market conditions, 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

1 Introduction

Since the seminal analysis of Bloom (2009), a large body of research has examined the measurement of macroeconomic uncertainty and its effects. Bloom (2014) surveys related work up through several years ago. Additional recent contributions include, among others, Baker, Bloom and Davis (2016), Basu and Bundick (2017), Caggiano, Castelnuovo, and Groshenny (2014), Carriero, Clark, and Marcellino (2018, 2019), Gilchrist, Sim, and Zakrajsek (2014), Jurado, Ludvigson, and Ng (2015), Leduc and Liu (2016), and Ludvigson, Ma, and Ng (2019).

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. Among studies of economic models, Gourio, Siemer, and Verdelhan (2013) develop 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. After developing economic evidence of international comovement in volatilities (discussed in more detail below, in a separate section on empirical evidence), Mumtaz and Theodoridis (2017) build a two-economy, dynamic stochastic general equilibrium (DSGE) model in which cross-country risk sharing (for consumption smoothing) and trade openness help to drive such comovement of volatilities. Cross, Kam, and Poon (2018) develop a two-economy DSGE model in which level and volatility shocks can have real effects.

Other studies take a comparative international perspective, while not allowing for cross-country interactions. For example, Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011) focus on the effects of changes in the stochastic volatility of the real interest rate in small EMEs. After estimating the volatility process, they insert it in a small open economy DSGE model, and obtain that a increase in the real interest rate volatility leads to a decrease in output, consumption, investment, hours, and debt.

Extending prior empirical work on international aspects of uncertainty (as detailed below), in this paper we use large Bayesian vector autoregressions (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 comprised of 67 variables in quarterly data for the U.S., euro area (E.A.), and U.K. We first use basic factor model diagnostics 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 (2018). 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. 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 comovement 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 (2018) 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.

The paper is structured as follows. Section 2 reviews related empirical literature and explains our contributions. Section 3 describes the data. Section 4 uses basic factor model diagnostics to assess the global factor structure in macroeconomic volatility. Section 5 introduces our preferred large BVAR model for measuring uncertainty and its effects and then presents results. Section 6 describes some robustness checks. Section 7 summarizes our main findings. The supplemental appendix details the estimation algorithm and priors and provides additional results.

2 Relationship to Prior Work

To make clear our contributions, in this section we first briefly summarize the most closely related empirical studies of common international aspects of uncertainty and its effects. We then detail key differences in our analysis compared to the most closely related prior work. In broad terms, our work extends the literature by a combination of the use of a large dataset for each economy considered, the inclusion of uncertainty (volatility factors) in the conditional mean of the VAR, and the joint, one-step estimation of uncertainty and its first-moment macroeconomic effects. Our approach also differs from some others in that our uncertainty measure is a common factor in macroeconomic volatilities, whereas in some research uncertainty is measured with the volatility of common factors in the business cycle (i.e., factors in first moments).

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 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. 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 factor that is closely tied to the volatility of global equity prices, and shocks to that factor have significant macroeconomic and financial effects. Cross, Hou, and Poon (2018) use a VAR with common stochastic volatility in mean to estimate the effects of domestic and international uncertainty in three small open economies,

finding that international uncertainty spillovers have important effects in all countries.

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 (2019) 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 (2018) 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.

Other research has focused on the international transmission of policy uncertainty.[1] From a nonlinear (smooth transition) VAR, Caggiano, Castelnuovo, and Figueres (2019) find significant asymmetries, with Canadian (and U.K.) unemployment increasing after a U.S. uncertainty shock in recessions but not expansions. Their interpretation of the results is that higher U.S. policy uncertainty leads to higher uncertainty in Canada and the U.K., and this in turn affects economic activity. Belke and Osowski (2019) compare the transmission of U.S. and E.A. policy uncertainty using a large-scale FAVAR model with data for 18 OECD countries. Their results are broadly in line with those of Caggiano, Castelnuovo, and Figueres (2019), in the sense that the effects of both U.S. and E.A. uncertainty shocks are generally negative on all countries, with stronger effects for the former than for the latter, and with uncertainty shocks originating in one country quickly increasing uncertainty in the other countries.

As to the relationship of our paper to prior studies focused on macroeconomic uncertainty related to time-varying second moments, our model is closely related to that developed in the U.S.-only analysis of Carriero, Clark, and Marcellino (2018). In this paper, we exploit the flexi-

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[1]Bhattarai, Chatterjee, and Park (2019) examine the transmission of U.S. uncertainty as measured with the VIX to emerging market economies, finding significant effects with some heterogeneity across countries tied to differences in monetary policy responses. Still other studies have examined other global aspects of uncertainty with network-based approaches: Klossner and Sekkel (2014) find evidence of significant spillovers of policy uncertainty from one advanced economy to policy uncertainty in another, and Rossi and Sekhposyan (2017) find spillovers of macroeconomic uncertainty among Euro area countries.

bility of the underlying framework of our earlier work to adjust it to fit our international context. For example, as detailed below, in our two factor implementation, only one (this paper) rather than both factors (earlier paper) enter the conditional mean, and the idiosyncratic components are constant (this paper) rather than time-varying (earlier paper). This paper's primary contribution is empirical, adapting our previous U.S.-only framework to assess the commonality in macroeconomic uncertainty across countries and its effects on major economies.

As a general matter, we believe that our approach and analysis has some possible advantages over some prior work on international uncertainty by allowing and making use of more variables per country. In the existing 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. For example, Berger, Grabert, and Kempa (2016) assess the effects of uncertainty using seven variables per country, and Cross, Hou, and Poon (2018) use three variables per economy, pairing one large economy with one small economy. In our larger data set, we have roughly 25 variables for each of the U.S. and E.A. Other work in the uncertainty literature, including Jurado, Ludvigson, and Ng (2015) and Carriero, Clark, and Marcellino (2018), 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 non-fundamentalness of the errors, and it can assess uncertainty's impacts on only a small number of economic indicators.

More specifically, as regards the relationship of our paper to Mumtaz and Theodoridis (2017) and Cuaresma, Huber, and Onorante (2017), we believe our paper provides a more direct assessment of the macroeconomic effects of uncertainty (as typically formulated in the literature, such as in Jurado, Ludvigson, and Ng 2015). The Mumtaz and Theodoridis (2017) model has common factors in macroeconomic data, with stochastic volatility in the factor innovations driven by common factors in volatilities. In their setup, the common volatility factors, which we would view as aggregate uncertainty, are **not** in the conditional mean of the factor model (i.e., the levels of the data). They go on to assess the role of the international volatility factors in fluctuations in **second** moments, but not **first** moments. We instead focus on the typical issue in the single-country uncertainty literature: the effects of volatility factors (uncertainty) on **first** moments. To that end, we include uncertainty in the conditional mean of the model and conduct impulse response analysis not possible in the Mumtaz and Theodoridis (2017) framework. Put another way, our contribution is to answer a question about effects of uncertainty on business cycle (first moment) fluctuations not addressable with the Mumtaz and Theodoridis (2017) model. If the goal were a narrower one of only estimating global economic uncertainty, it would not be essential

to include the first moment link of our model. Unreported comparisons to a version of our model without the first moment effects indicate that, while the first moment link clearly affects and informs the estimate of uncertainty, the restricted estimate of global uncertainty is significantly correlated with our baseline estimate.

Cuaresma, Huber, and Onorante (2017) use a VAR coupled with a factor model of the VAR's innovations. Innovations to the factor have stochastic volatility. However, the time-varying variance does not enter the conditional mean of the VAR. Rather, the factor in the VAR's **first-moment** errors appears to be treated as the measure of risk and uncertainty. By assumption, this shock to first moments is uncorrelated with innovations to second moments (that is, innovations to the volatility process). In this sense, their results may confound first-moment shocks with second-moment changes. In the broader uncertainty literature (e.g., Jurado, Ludvigson, and Ng 2015), it is more common to define an uncertainty shock by a shock to second moments. Our paper follows this tradition, defining uncertainty as a common factor in forecast error variances that can have first-moment effects (i.e., appears in the VAR's conditional mean).

One other difference between our paper and a number of others in the international literature is that we focus on large economies whereas others focus on small advanced or emerging market economies. As examples, Carriere-Swallow and Cespedes (2013) focus on the effects of uncertainty on emerging market economies, and Cross, Hou, and Poon (2018) concentrate on small advanced economies.

While our paper shares with Berger, Grabert, and Kempa (2016) the focus on effects of shocks to macroeconomic uncertainty as most commonly conceived, we believe our approach offers a couple of advantages. One, as noted above, is that we consider a larger dataset (in part of our results; we also consider a GDP-only dataset, as do they). The other is that our approach assesses uncertainty and its effects with an internally-consistent one-step approach, rather than the two-step approach used in Berger, Grabert, and Kempa (2016) and common in other studies in the uncertainty literature. In the two-step approach, 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 (2018), 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 estimate 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. As our results below show, the two-step approach

tends to overestimate the precision of impulse response estimates compared to our preferred one-step approach that accounts for uncertainty around the measure of macroeconomic uncertainty. We acknowledge, however, a tradeoff with respect to potential model misspecification: were our preferred model to sufficiently mis-specify the uncertainty process and its link to economic conditions, it might yield estimates of uncertainty and its effects more biased than could be obtained with a two-step approach.

One final matter is the concept of uncertainty. The uncertainty literature features a range of both concepts and measures, described in Bloom (2014). Some studies (e.g., Basu and Bundick 2017 and Caggiano, Castelnuovo, and Groshenny 2014) use stock volatility-based measures, whereas others (e.g., Baker, Bloom, and Davis 2016 and Caggiano, Castelnuovo, and Figueres 2019) rely on measures uncertainty associated with economic policies, based on newspaper coverage. Jurado, Ludvigson, and Ng (2015) argue for defining and measuring uncertainty with forecast error variances. Rossi, Sekhposyan, and Soupre (2018) provide additional discussion of alternative concepts and measures, including a distinction between ex post and ex ante discussion. The measures of uncertainty we use in this paper are based on the concept of Jurado, Ludvigson, and Ng (2015), and below we will discuss their correlation with some of the alternatives.

3   Data

As indicated above, 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 because it includes relatively large variable sets for each economy.

More specifically, for the GDP growth analysis, we use quarterly data on GDP in 19 industrialized economies, obtained from the OECD's online database (OECD 2017); Table 1 provides the country list. This country set is the same as that in Berger, Grabert, and Kempa (2016), except that we omit New Zealand due to data missing early in our sample. Although we could include more countries in this sample, we don't do so partly out of consideration of model stability. Instabilities seem likely to increase with larger cross-sections of countries, due to differences over time or across countries in economic development.

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 E.A., 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 25 for the E.A.[2] For the U.K., we obtained comparable data on 16 variables from Haver Analytics. Table 2 lists the variables.

This specification reflects some choice as to what constitutes a "macroeconomic" variable for the purpose of measuring uncertainty and its effects. Common large datasets used in factor model or FAVAR analysis include a number of indicators — of stock prices, interest rates, and exchange rates — that may be considered financial indicators. In our model specification, the variables that might be considered more financial than macroeconomic are the bond yields and aggregate stock returns. [Short-term interest rates — the instruments of monetary policy — seem to be appropriately treated as macroeconomic variables.] In our baseline specification, we follow the precedents of Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2019) in including selected bond yields and aggregate stock returns in a macroeconomic model. We have verified that the main results presented below are robust to dropping the bond yields and stock returns from the estimation.

In the applications using both datasets, we follow common practice in the factor model literature and transform each data series for stationarity as needed. With the GDP dataset, we use quarter-on-quarter growth rates computed as log differences. With the 3-economy dataset, we use similar transformations as appropriate; Appendix Table 1 lists any transformations used to achieve stationarity of these data. We also follow common practice in the factor model literature as well as as Jurado, Ludvigson, and Ng (2015) and Carriero, Clark, and Marcellino (2018) by standardizing the data (demean and divide by the simple standard deviation) before estimating the model. Note that, 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.[3] The fact that the models are estimated using some variables differenced for stationarity (e.g., GDP, consumption, and investment) implies that, for some of these variables, the long-run effects of uncertainty shocks on their levels will not entirely die out.

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[2]More specifically, of the variables used by Jarocinski and Mackowiak (2017), we omit: series missing data early in our sample (stock market volatility, bond spreads, and house prices); other private credit-related measures (loans to NFCs, lending rate to NFCs, and mortgage interest rate); narrower measures of the money supply (M1 for the U.S. and M1 and M2 for the E.A.); and some additional variables that rank poorly in their causal priority results (exchange rates and government debt).

[3]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.

The time samples used in estimation reflect data availability, any transformations used for stationarity, and considerations of sample stability. In the baseline estimates with the 19-country GDP dataset, the sample is 1985:Q1-2016:Q3. In this case, although the available data permit a longer sample, we use a 1985 start to reduce the chances that changes in policies or other structural forces of economies more likely over a longer sample induce parameter instabilities (section 6 of the supplemental appendix summarizes a check of robustness in an estimation sample starting in 1960). In estimates with the 3-economy macroeconomic dataset, the sample is 1985:Q4-2013:Q3, reflecting the span of the Jarocinski-Mackowiak dataset.

4   Commonality in International Uncertainty

To assess the global factor structure of macroeconomic uncertainty, we apply to estimates of the stochastic volatilities of BVARs the basic factor model diagnostics surveyed and used in applications by Stock and Watson (2016). The volatility estimates are posterior medians of log stochastic volatilities obtained from conventional BVARs with stochastic volatility (denoted BVAR-SV; due to space restrictions, the by-now familiar model is provided in the appendix's section 3.2 and not the text).[4] We consider the marginal R^2 of volatility factors estimated by principal components and the Ahn and Horenstein (2013) eigenvalue ratio.

For GDP growth in 19 countries, the measures of factor structure suggest one strong factor in the international volatility of the business cycle. The first factor accounts for an average of about 79 percent of the variation in log volatilities (see Appendix Table 2 for detailed estimates). 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 1, 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. In this sense the common volatility factor puts comparable weight on each country's volatility.

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 commonality in volatility.[5] Figure 1 compares volatility estimates across these three economies for a subset of major macroe-

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[4]In this model, the VAR's innovation vector takes the form $v_t = A^{-1}\Lambda_t^{0.5}\epsilon_t$, with the diagonal matrix Λ_t containing the stochastic volatilities, and the reduced-form error variance matrix is $\Sigma_t = A^{-1}\Lambda_t A^{-1\prime}$. 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.

[5]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.

conomic 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. 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.

In the 3-economy macroeconomic dataset, a first factor accounts for an average of about 42 percent of the variation in log volatilities (see Appendix Table 2 for details). 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). For most variables, the estimated loadings on this factor reported in Table 2 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. In this sense the common volatility factor puts comparable (but not equal) weight on the volatility of most variables in the model. Overall, the patterns in the estimated 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 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.

The detected substantial commonality in volatilities is broadly in line with the empirical evidence of Mumtaz and Theodoridis (2017), as well as the prediction of their DSGE model, in which commonality is driven by cross-country risk sharing, globalization, and trade openness.

5   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 — henceforth

referred to as a **BVAR-GFSV** model — we use for that purpose, first for a one-factor model applied to the 19-country GDP dataset and then for a two-factor specification applied to the 3-economy macroeconomic dataset.[6] We then present results for the uncertainty estimates and effects of shocks to uncertainty.

5.1 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. The $n \times 1$ vector of reduced-form shocks to these variables is:

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

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:

$$\ln \lambda_{i,t} = \beta_{m,i} \ln m_t + \ln h_{i,t}, \ i = 1, \ldots, n \tag{2}$$

$$\ln m_t = \sum_{i=1}^{p_m} \delta_{m,i} \ln m_{t-i} + \delta'_{m,y} y_{t-1} + u_{m,t}, \ u_{m,t} \sim iid \ N(0, \phi_m) \tag{3}$$

$$\ln h_{i,t} = \gamma_{i,0} + \gamma_{i,1} \ln h_{i,t-1} + e_{i,t}, \ i = 1, \ldots, n. \tag{4}$$

The volatility factor m_t is our measure of (unobservable) *global* macroeconomic uncertainty. The idiosyncratic component $h_{i,t}$ captures time variation in a country's GDP volatility unique to that country. The uncertainty shock $u_{m,t}$ is independent of the conditional errors ϵ_t and the vector of volatility innovations $\nu_t = (e_{1,t}, \ldots, e_{n,t})'$, which is jointly distributed as iid $N(0, \Phi_\nu)$ with elements independent among themselves, so that $\Phi_\nu = diag(\phi_1, \ldots, \phi_n)$. For identification, we follow common practice in the dynamic factor model literature 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

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[6]In light of space restrictions, we refer the reader to the supplemental appendix's sections 2 and 3.1 and Carriero, Clark, and Marcellino 2018 for details of the Gibbs sampler and priors used to estimate the model. 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.

contained in y_t, contemporaneously and with lags. In particular, y_t is assumed to follow:

$$y_t = \sum_{i=1}^{p} \Pi_i y_{t-i} + \sum_{i=0}^{p_m} \Pi_{m,i} \ln m_{t-i} + v_t, \tag{5}$$

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 (for computational convenience, set to the lag order of the factor process), Π_i is an $n \times n$ matrix, $i = 1, \ldots, p$, and $\Pi_{m,i}$ is an $n \times 1$ vector of coefficients, $i = 0, \ldots, p_m$.

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 $\Pi_{m,i}$, $i = 0, \ldots, p_m$. 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. We return to endogeneity questions after presenting the two-factor model next.)

5.2   Two-Factor BVAR-GFSV Model

With Section 4's principal component-based analysis of volatilities obtained from BVAR-SV estimates pointing to two factors in the 3-economy macroeconomic dataset, we also 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. 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 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.

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 1985, 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:

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

$$v_t = A^{-1} \Lambda_t^{0.5} \epsilon_t, \ \epsilon_t \sim iid \ N(0, I) \tag{7}$$

$$\ln \lambda_{i,t} = \beta_{m,i} \ln m_t + \beta_{f,i} \ln f_t + \ln h_i, \ i = 1, \ldots, n \tag{8}$$

$$\ln m_t = \sum_{i=1}^{p_m} \delta_{m,i} \ln m_{t-i} + \delta'_{m,y} y_{t-1} + u_{m,t}, \ u_{m,t} \sim iid \ N(0, \phi_m) \tag{9}$$

$$\ln f_t = \sum_{i=1}^{p_f} \delta_{f,i} \ln f_{t-i} + \delta'_{f,y} y_{t-1} + u_{f,t}, \ u_{f,t} \sim iid \ N(0, \phi_f). \tag{10}$$

In this case, the log-volatility of each variable i follows a linear factor model with common unobservable 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. The time-invariant idiosyncratic component captures differences in the average level of volatility across economies.

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, $i = 1, \ldots, p$; and $\Pi_{m,i}$ is an $n \times 1$ vector of coefficients, $i = 0, \ldots, p_m$. 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

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$\ln m_t$ 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 $p_f = 2$.

In results omitted in the interest of brevity, we have obtained similar findings with some other modifications of this two-factor model. In one robustness check, we extended the factor process of equations (9) and (10) to allow VAR dynamics rather than AR dynamics in the factors and allow a non-zero correlation between the innovations to the factors. We also considered specifications with up to three factors in volatilities linked to various combinations of the three economies. These estimates continued to point to two common factors, with only one having conditional mean effects — similar to those reported — and with factors similar to those reported. Both the simple factor evidence of section 4 and various specifications of the BVAR-GFSV model point to the data being consistent with just two uncertainty factors.

5.2.1 Rationale for some choices in the baseline model

Before moving on to empirical results, we take up five specific questions related to our choice of a baseline model. First, in light of the specification of Mumtaz and Theodoridis (2017) that features global, regional, and country factors in volatility, why not add such factors to our model? Basically, the data we use — different in coverage from the data of Mumtaz and Theodoridis (2017) that do support more factors — don't seem to warrant it. As the simple factor analysis of section 4 indicates, and as we will discuss with results for our BVAR-GFSV specifications, the evidence points to two factors and not more. For example, once we allow for two factors in the three-economy dataset, there isn't any meaningful time variation in idiosyncratic components (so, as noted above, we modify the model of our previous paper to treat them as constant).

Second, why specify a VAR structure for the levels of data and a factor model in the volatilities of their innovations? Admittedly, along various dimensions, VARs and factor models can both provide effective representations of the data. For variable sets of the size we consider, our estimation method can accommodate a VAR in the levels of the data, and we prefer a VAR over a factor model in order to impose fewer restrictions on dynamics. In the case of the volatilities and uncertainty, given our treatment of macroeconomic uncertainty as aggregate or common uncertainty, it is more natural to measure it as a common factor in volatilities (as others in the literature, such as Jurado, Ludvigson, and Ng 2015, have done). Moreover, the empirical evidence of factor structure is somewhat stronger in volatilities than in the levels of the data. For example, in the 19-country GDP dataset, the first principal component accounts for 30 percent

of variation in GDP growth rates but 79 percent of variation in GDP volatility (as measured in section 4's BVAR-SV results).

Third, why not include idiosyncratic volatility terms in the VAR's conditional mean? One reason is that our analysis (following most of the literature, such as Jurado, Ludvigson, and Ng 2015) focuses on common, aggregate uncertainty. Another, noted above, is that once we allow for two factors, no meaningful variation in idiosyncratic components remains.

Fourth, is the relationship between economic conditions and uncertainty allowed in the model important? Let's start with the response of uncertainty to economic conditions as captured by the coefficient vectors $\delta_{m,y}$ and $\delta_{f,y}$ of the uncertainty factor processes of equations (9) and (10). In additional estimates we produced for 3-economy macroeconomic dataset, when the model is restricted to make $\delta_{m,y}$ and $\delta_{f,y}$ equal 0, the estimates of uncertainty are considerably smoother than in the paper's baseline, the responses of the E.A. and U.K. variables to the uncertainty shock are attenuated, and those of the policy interest rates switch sign. As to the response of economic conditions to uncertainty, captured by the $\Pi_{m,i}$ coefficients in the VAR's conditional mean (equation (6)), these estimates are generally statistically significantly different from zero, in line with the significant impulse responses we will report in the next section. Although the estimates of uncertainty from the restricted model (here, too, we conducted the check with the 3-economy model) are qualitatively similar to those in the unrestricted model of the paper's baseline, the restricted estimate of macroeconomic uncertainty shows less of a rise around the U.S. recessions of the late 1990s and 2001 than does the baseline estimate. Putting these results together, along both of these dimensions of the model's parameterizations, there appears to be substantial evidence of feedback effects between economic conditions and uncertainty.

Finally, why not allow uncertainty to react contemporaneously to economic conditions? As noted above, the BVAR-GFSV model allows macroeconomic uncertainty to respond to economic conditions, but with a lag (y_{t-1} enters the factor processes (9) and (10)). In larger models that have some advantages for the measurement of uncertainty in internally consistent one-step approaches, there does not exist an approach that allows contemporaneous feedback between uncertainty and economic conditions. Carriero, Clark, and Marcellino (2019) and Ludvigson, Ma, and Ng (2019) develop approaches that do allow such feedback, but in smaller models that take the uncertainty measure as given and are not readily extended to large datasets such as the one we use. Importantly, for the U.S., Carriero, Clark, and Marcellino (2019), find little evidence of contemporaneous effects of economic conditions on macroeconomic uncertainty; their results provide support for a specification like this paper's in which the economy responds quickly to macroeconomic uncertainty and uncertainty responds to economic conditions with a delay.

5.3 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 1 and 2. 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, 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 seem 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 measures, 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). In results omitted in the interest of brevity, with the larger variable set 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, including CCM macro and financial uncertainty from Carriero, Clark, and Marcellino (2018); JLN macro and financial uncertainty 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).[7] 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 significantly correlated with the estimate of U.S. macroeconomic uncertainty from Carriero, Clark, and Marcellino (2018) 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. On the other hand, we have noted that most variables have significant loadings on the international uncertainty factors. So by this very simple measure, the uncertainty we capture is global and not specific to the U.S.

To shed further light on the relationship between U.S. and global uncertainty, we have conducted some additional checks. Specifically, we have compared the 3-economy factor estimate of macroeconomic uncertainty m_t from the paper's baseline to country-specific estimates. We obtained the country-specific measures by estimating the one-factor BVAR-GFSV model separately for the U.S., E.A., and U.K. According to these estimates, each of the country-specific factors is significantly correlated with our estimated international factor, with correlations ranging from 0.6 for the U.K. to 0.8 for the U.S. and E.A. We then regress the baseline estimate of m_t on various combinations of the country-specific estimates. In a regression of our baseline estimate on all three economy-specific uncertainty measures, the null that the E.A. and U.K. country-specific factors have zero coefficients is overwhelmingly rejected. These regression results indicate that

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[7]The underlying CCM and JLN estimates are obtained with monthly data and pertain to a one-month ahead horizon. We use quarterly averages of these estimates.

our international factor is not just a U.S. factor.

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.

A related important empirical issue is whether our estimated uncertainty shocks represent an original source of business cycle fluctuations or are simply correlated with traditional macroeconomic shocks. To check, we have computed the correlations of our estimated global macroeconomic uncertainty shocks with some well-known and available macro shocks for the U.S., drawing on comparable exercises in Stock and Watson (2012), Caldara, et al. (2016), and Carriero, Clark, and Marcellino (2018). These estimates, detailed in (supplemental) Appendix Table 3 in the interest of brevity, indicate that 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. While it would be interesting to also assess the correlation of our uncertainty shocks with macroeconomic shocks for other countries or the global economy, we are not aware of standard sources of shocks like those that exist for U.S. data.

5.4 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. Starting with the 19-country results in Figure 4, 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, in line with the association found in Ramey and Ramey (1995).[8] For example,

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[8]Written with the idea that volatility corresponds to uncertainty, Ramey and Ramey (1995) use simple comparisons of cross-country averages and panel regressions to show that countries with higher volatility have lower growth, in both an OECD sample and a large sample of countries. Adding common control variables strengthens the estimated negative relationship.

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 Figueres 2019) 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.

For space savings and readability, Figure 5 covers a subset of variables in providing impulse response estimates for the 3-economy macroeconomic dataset, and it reports posterior medians and 70 percent credible sets for the U.S. responses but just posterior medians for the E.A. and U.K. (Appendix Figure 1 provides complete estimates.) In the estimates for this 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 (see Appendix Figure 1) falls and unemployment rises, 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 some cases — e.g., for GDP — as measured by posterior medians the response of a given variable for the U.S. is larger than the responses for the E.A. and U.K. But this does not apply to all variables — e.g., exports and stock prices.

In general qualitative terms, these results line up with those obtained with monthly data for the U.S. in Carriero, Clark, and Marcellino (2018), 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. For the sake of conciseness, we refer to Carriero, Clark, and Marcellino (2018) for references to economic models that can explain response patterns similar to these. Our empirical results are also in line with those of most of the studies reviewed in Section 2 and based on different methodologies, for example, Fernandez-Villaverde, et al. (2011), Berger, Grabert, and Kempa (2016), or Casarin, et al. (2018). That said, as far as we

are aware, more research is needed to better understand how changes in economic uncertainty affect one major economy more than another.

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 (2018), 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}. The supplemental appendix's section 4 details the basis of the decomposition.

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 growth. 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 somewhat to fluctuations in economic activity, including in GDP, business investment, and housing investment, but not much to inflation or stock prices. Similar patterns 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 (2018) obtain a broadly similar result, as does Benati (2016) with a different approach.

The responses of GDP growth for the U.S., U.K., and some European countries obtained with the GDP-only dataset are larger and more persistent than those resulting from the 3-country multi-variable dataset. Similarly, the contributions of uncertainty shocks to GDP growth are slightly larger with the former dataset than with the latter, in particular during the 2007-2009 recession period. While there is substantial uncertainty about responses and contributions, this result might be due to variable omission (reduced conditioning information) when working with the GDP-only dataset. Results on the effects of uncertainty shocks on the U.S. GDP growth are also different in bivariate and multivariate models in Carriero, Clark, and Marcellino (2019).

To put the importance of uncertainty shocks in broader perspective, it may help to compare their effects to those of U.S. monetary policy shocks, which have been extensively studied. While space constraints preclude a detailed analysis in the paper, we have considered estimates of policy shock effects in the literature and in some checks with our own data. These comparisons indicate that some aspects of the effects of uncertainty shocks resemble those of U.S. policy shocks, in both directions of responses and quantitative importance. For example, a surprise increase in uncertainty significantly reduces economic activity and stock prices. The effects of an uncertainty shock differ from the effects of a policy shock in that the former does not consistently produce a fall in prices (however, recall that a fall in prices results from a policy shock at least partly by definition of a policy shock identified by sign restrictions) or foreign interest rates. As measured by variance contributions, in qualitative terms the importance of an international uncertainty shock resembles that of a monetary policy shock: at medium horizons, the contributions are small (for some economic activity measures, the contributions are modest at short horizons). For example, at an 8-quarter ahead horizon, our estimates put the forecast error variance shares of a shock to global uncertainty at about 5 percent for U.S. GDP, less than 3 percent for E.A. and U.K. GDP, and less than 2 percent for stock prices and short-term interest rates.

6 Robustness

In the first of a few robustness checks, 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).[9] In the first step of the two-step approach, we obtained a measure of uncertainty as the first principal component of log volatilities (posterior medians of $\ln \lambda_{i,t}$) estimated with the BVAR-SV specification. In the second step, we added this uncertainty measure to a 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.[10]

In the supplement, Appendix Figure 2 compares the two-step and BVAR-GFSV estimates. 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 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.

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[9]In light of possible distortions of estimated policy responses stemming from the binding lower bound constraint on short-term interest rates following the most recent global recession, we have also considered a robustness check of replacing the policy rates with historical time series of shadow rates. In particular, we have estimated the 3-economy model with the Wu-Xia shadow rate series replacing the short-term interest rates in the baseline model. The resulting estimates of macroeconomic uncertainty and impulse responses to an uncertainty shock are essentially the same as those reported in the paper.

[10]The supplemental appendix's section 3.3 details the priors for this model. Estimates are based on samples of 5,000 retained draws, obtained by sampling a total of 6,000 draws and discarding the first 1,000.

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 (2018).

We have also used a two-step approach to provide another check on the degree of spillover in uncertainty from one economy to another. As indicated earlier in the paper, our main results yield a strong commonality in uncertainty rather than a leading role for the U.S. as a driver of global uncertainty. As a further check of spillover, we included in a BVAR country-specific measures of uncertainty obtained by estimating the one-factor BVAR-GFSV model detailed in the paper's section 5.1 separately for the U.S., E.A., and U.K. We produced impulse responses to shocks to these uncertainty measures under different orderings. In these estimates, the country-specific uncertainty shocks get transmitted to the other economies and have negative effects qualitatively similar to those of the global uncertainty shocks. This pattern is broadly similar to that of Caggiano, Castelnuovo and, Figueres (2019) and Belke and Osowski (2019) for the case of U.S. economic policy uncertainty shocks. These robustness results are consistent with our main findings of strong commonality in uncertainty that affects all major economies considered.

Finally, we used a two-step approach to verify the distinction of the global uncertainty measure from U.S.-specific uncertainty. We specified a BVAR in the 26 U.S. variables of our 3-economy dataset, the global uncertainty estimate from the 3-economy BVAR-GFSV model, and the U.S.-specific estimate of uncertainty from Carriero, Clark, and Marcellino (2018), with U.S. uncertainty ordered first, global uncertainty second, and the remaining variables following in the sequence of the baseline model. We then estimated impulse responses for a shock to global uncertainty and obtained results very similar to those in the baseline results above, with a shock

to global uncertainty significantly depressing a range of measures of economic activity and stock prices, with responses comparable to those in the paper. These results support the baseline specification, in which uncertainty has a global component distinct from U.S.-specific uncertainty. In these estimates, both global and U.S.-specific uncertainty affect the economy.

7   Conclusions

This paper uses large Bayesian VARs to measure international macroeconomic uncertainty and its effects, using two datasets, one consisting of GDP growth for 19 industrialized economics and the other comprised of 67 variables in quarterly data for the U.S., E.A., 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 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.

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Table 1: 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)

Note: The second column provides loadings on a first common factor estimated as the principal component of log volatilities of a BVAR-SV model. The third column provides estimates of the loadings $\beta_{m,i}$ of equation (2) of the one-factor BVAR-GFSV model.

Table 2: 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)			

Note: The second and fifth columns provide loadings on a first common factor estimated as the principal component of log volatilities of BVAR-SV models estimated for each economy. The third and sixth columns provide estimates of the loadings $\beta_{m,i}$ of equation (9) of the two-factor BVAR-GFSV model.
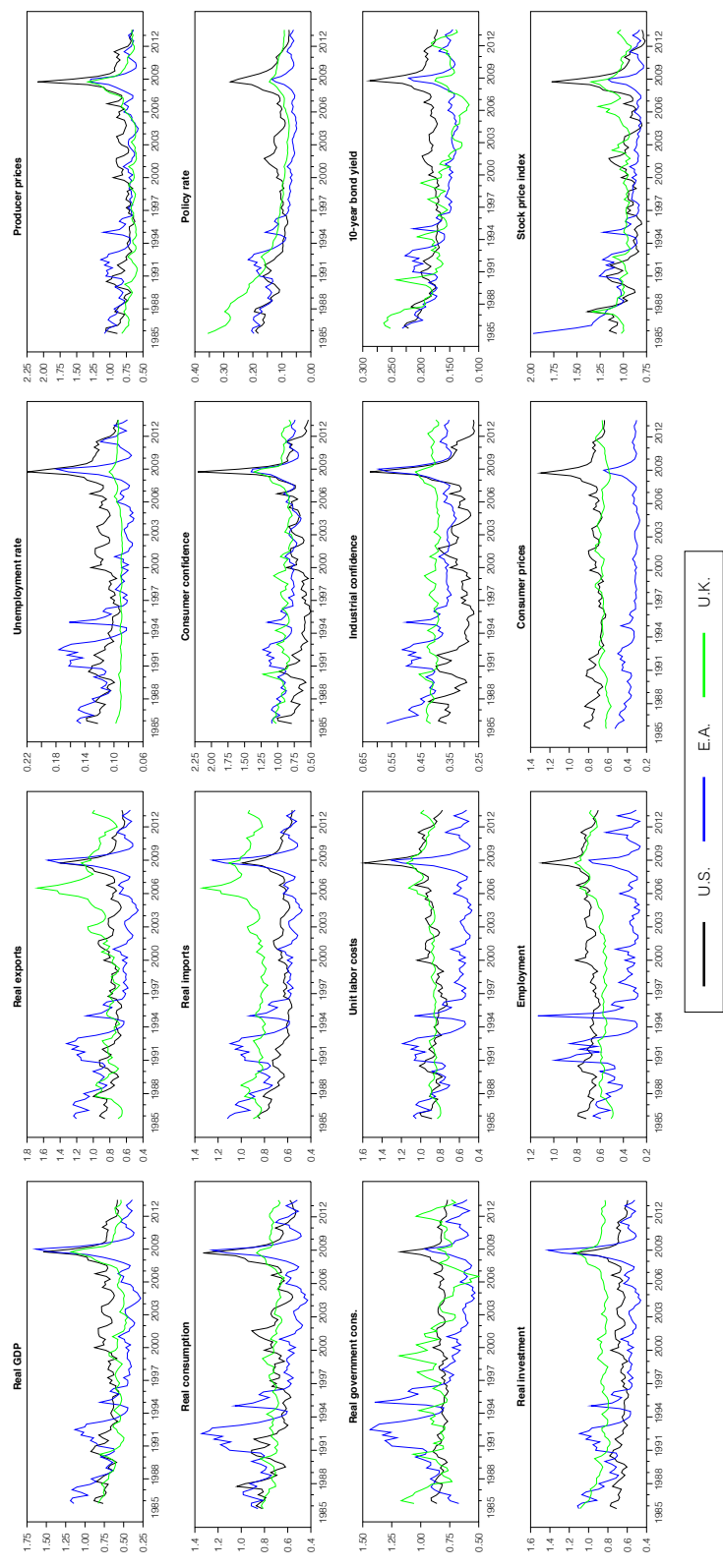
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Figure 1: BVAR-SV estimates of volatilities, selected variables. The reported entries are posterior medians of standard deviations of reduced-form innovations from BVAR-SV models estimated for each economy.
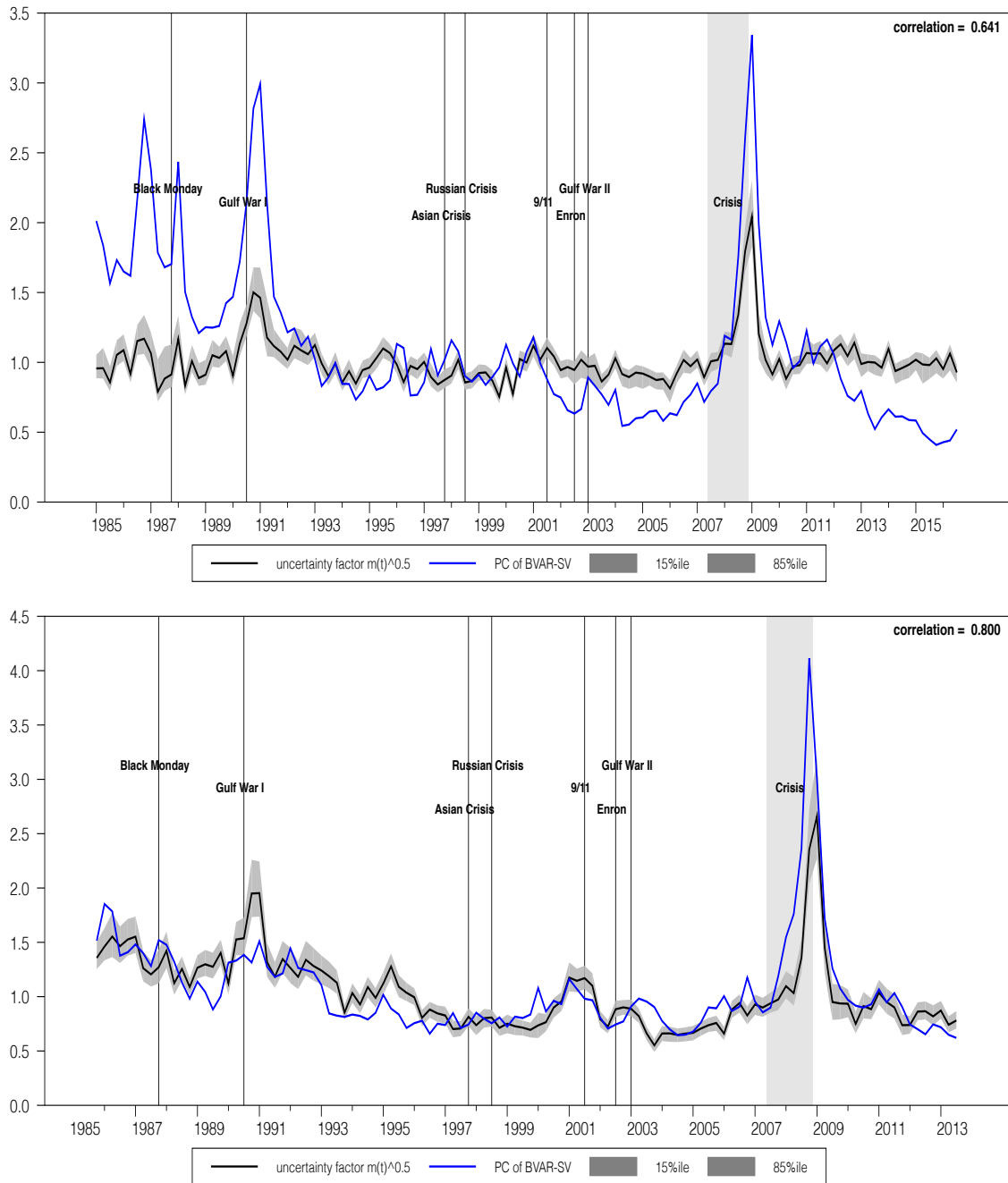
Figure 2: Uncertainty estimates for 19-country GDP dataset in the top panel and for 3-economy macroeconomic dataset in the bottom panel. In each panel, the blue line provides an estimate obtained from the first principal component of the BVAR-SV estimates of log volatility. The solid black line and gray-shaded 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.
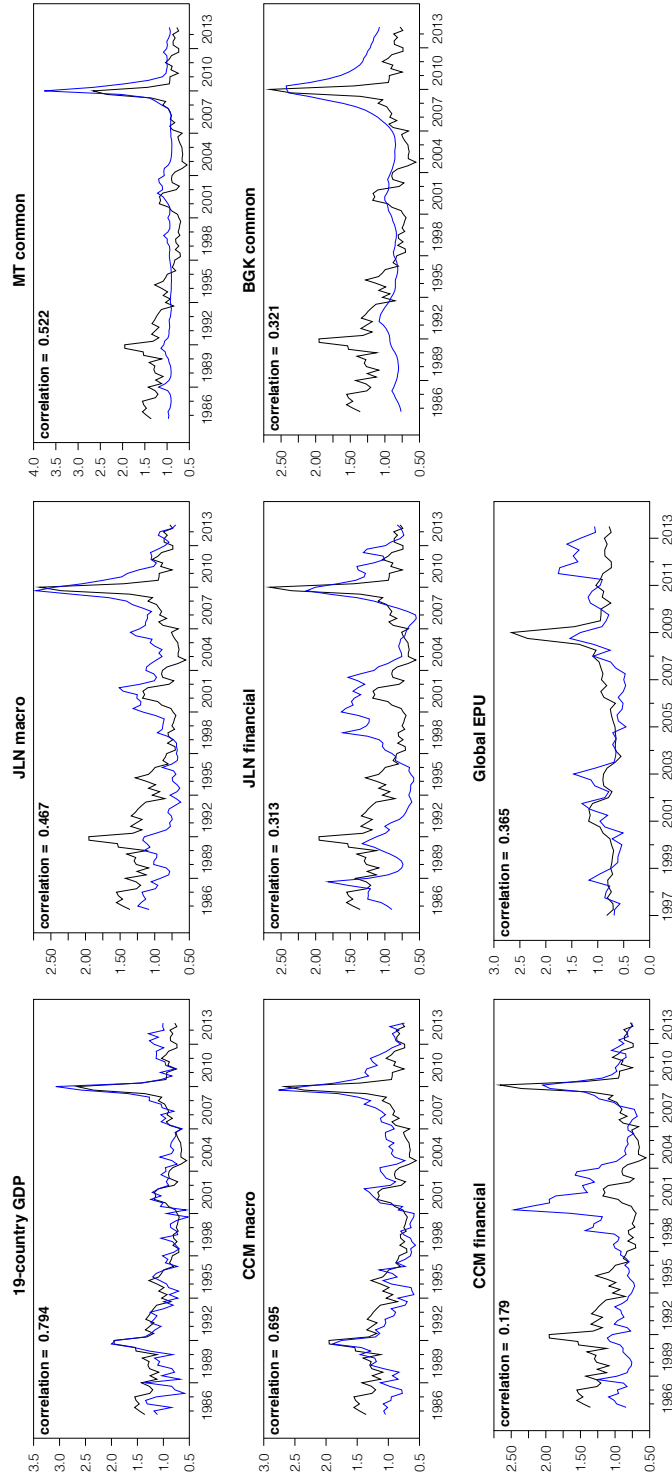
Figure 3: Comparison of uncertainty estimates to others in the literature. The top left panel compares the uncertainty estimate obtained from the 3-economy macroeconomic dataset (black line) to that obtained with the 19-country GDP dataset (blue line). Other panels compare the 3-economy macroeconomic dataset estimate (black line) to a different estimate (blue line) from the literature, normalized to have the same mean and variance as the 3-economy macroeconomic dataset estimate.
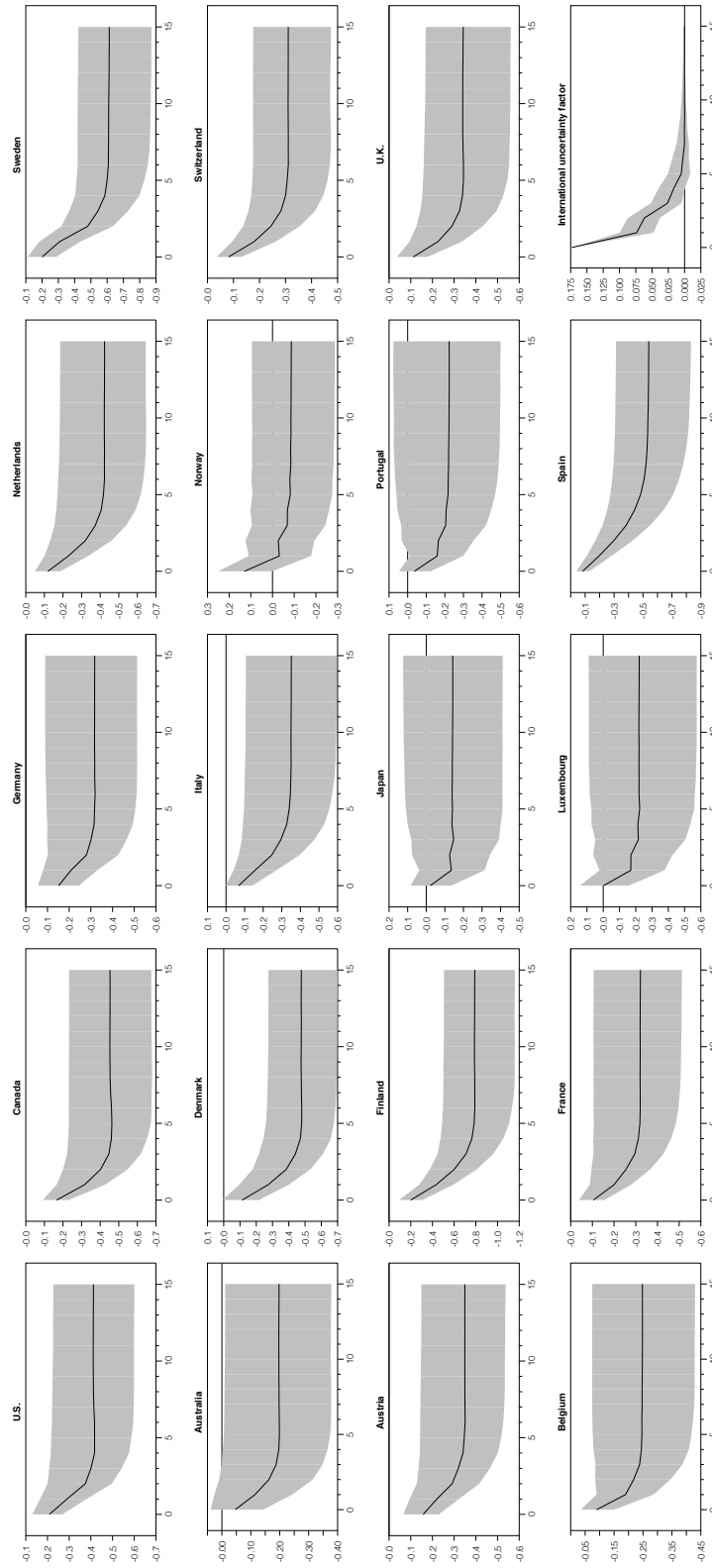
Figure 4: Impulse responses for international uncertainty shock: one-factor BVAR-GFSV estimates for 19-country GDP dataset, posterior median (black line) and 15%/85% quantiles

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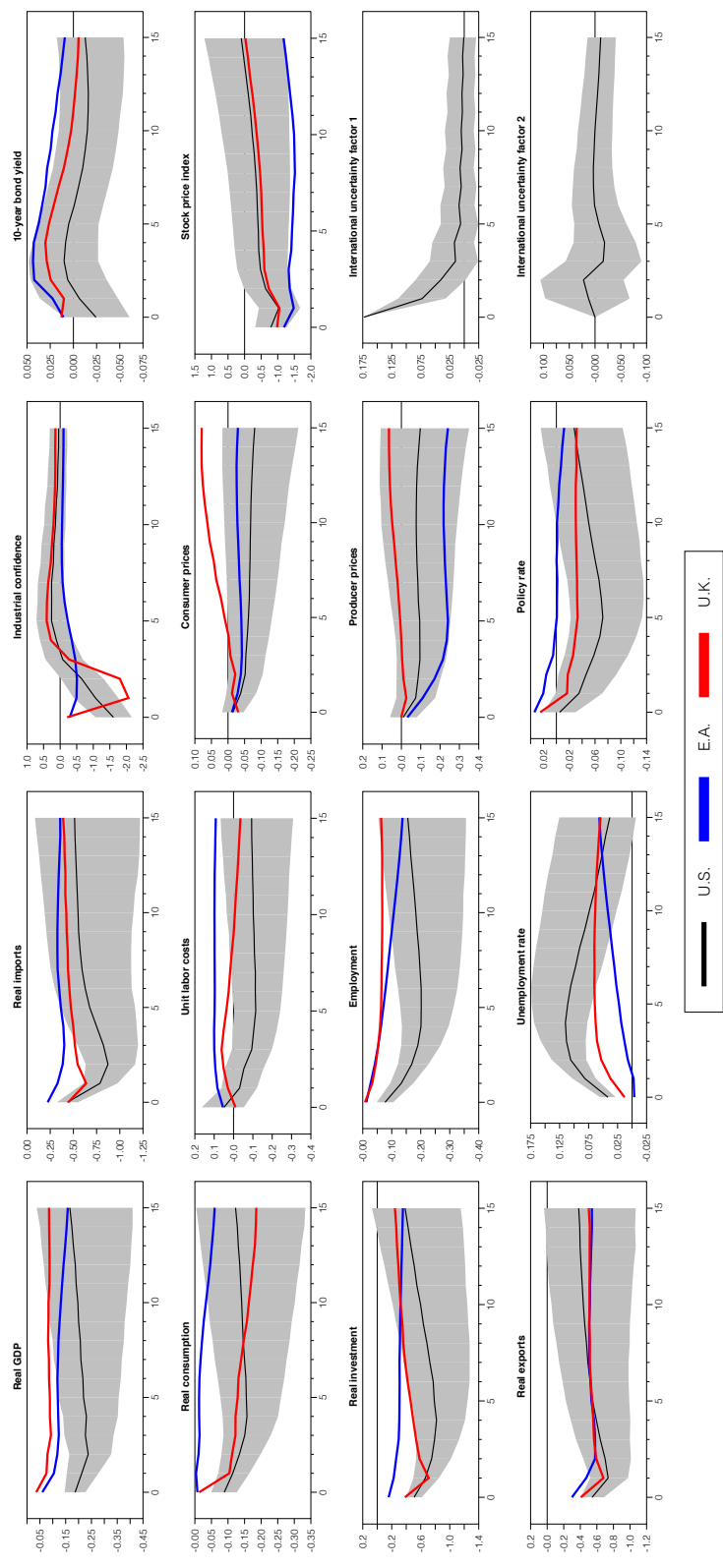
Figure 5: Impulse responses for international uncertainty shock: two-factor BVAR-GFSV estimates for 3-economy macroeconomic dataset, selected variables. The black line and gray shading provide posterior medians and 15%/85% quantiles for the U.S. response. The colored lines provide posterior medians for the E.A. and U.K.
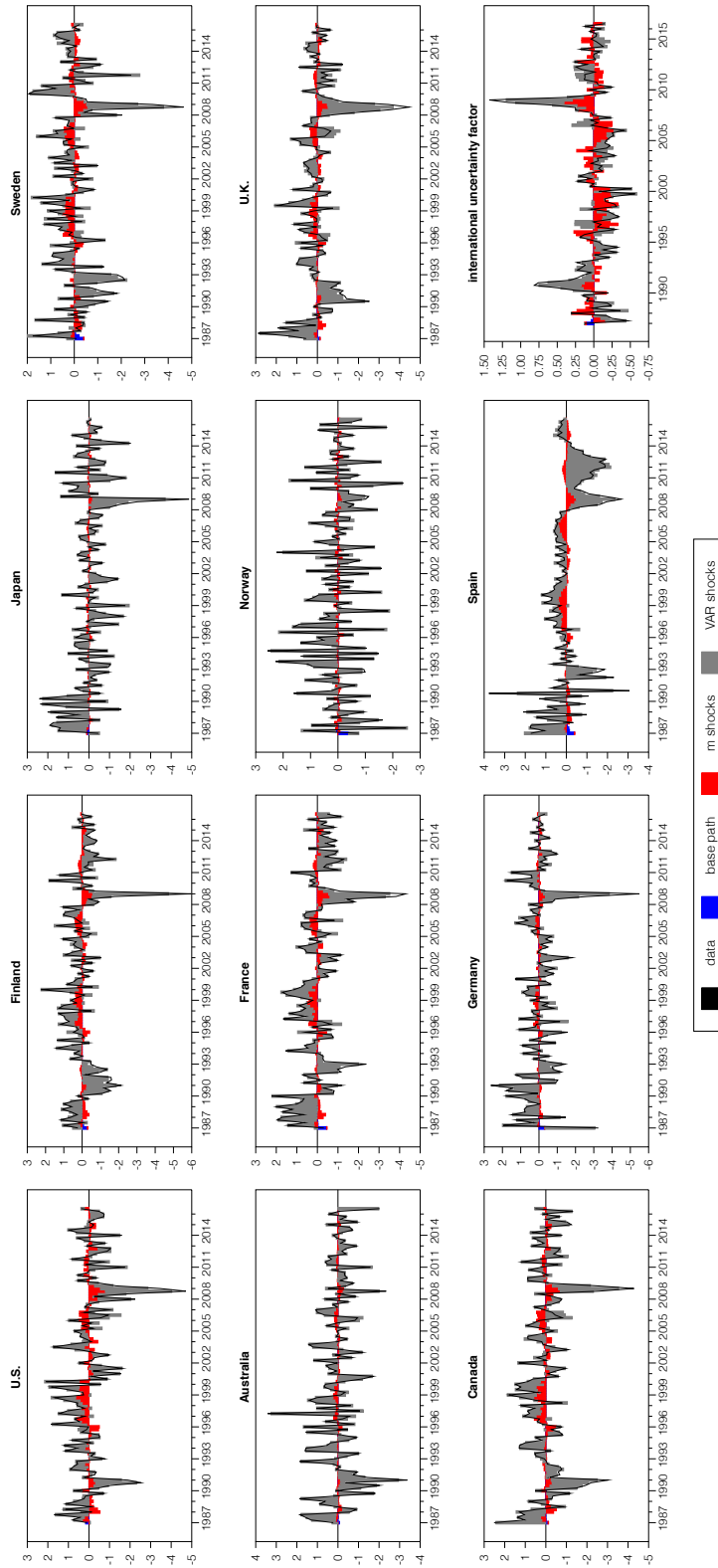
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Figure 6: Historical decompositions: one-factor BVAR-GFSV estimates for 19-country GDP dataset, selected variables, posterior medians

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

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Supplemental Appendix: Assessing International Commonality in Macroeconomic Uncertainty and Its Effects[*]

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1   Introduction

This supplemental appendix provides details and results omitted from the paper for space considerations. Section 2 details the MCMC algorithm for the BVAR-GFSV model used to produce the paper's main results. Section 3 provides priors for this model and spells out the BVAR-SV and BVAR models and priors used in some results in the paper. Section 4 details the historical decomposition used with the BVAR-GFSV estimates. Section 5 summarizes estimates of the correlations of our uncertainty shocks with "known" macroeconomic shocks for the U.S. Section 6 summarizes a robustness check of extending the estimation sample for the GDP-only dataset back in time. The supplement concludes with some additional charts and tables of results mentioned in the paper.

2   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.

For the convenience of self-containment, we begin by repeating the equations of the model:

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

$$\ln \lambda_{i,t} = \beta_{m,i} \ln m_t + \ln h_{i,t}, \ i = 1,\dots,n, \tag{2}$$

$$\ln m_t = \sum_{i=1}^{p_m} \delta_{m,i} \ln m_{t-i} + \delta'_{m,y} y_{t-1} + u_{m,t}, \ u_{m,t} \sim iid \ N(0,\phi_m), \tag{3}$$

$$\ln h_{i,t} = \gamma_{i,0} + \gamma_{i,1} \ln h_{i,t-1} + e_{i,t}, \ i = 1,\dots,n, \tag{4}$$

$$y_t = \sum_{i=1}^{p} \Pi_i y_{t-i} + \sum_{i=0}^{p_m} \Pi_{m,i} \ln m_{t-i} + v_t. \tag{5}$$

Our exposition of priors, posteriors, and estimation makes use of the following additional notation. Let Π denote the collection of the VAR's coefficients. The vector a_j, $j = 2,\dots,n$, contains the jth row of the matrix A (for columns 1 through $j-1$). We define the vector $\gamma = \{\gamma_1,\dots,\gamma_n\}$ 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

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the conditional mean of the transition equation for the states $m_{1:T}$. The coefficient matrices Φ_v and Φ_u 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 (1)-(5), 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 (1), 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):

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{m,j} \ln m_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2, \ \ j = 1, \ldots, n. \tag{6}$$

For the idiosyncratic volatility components, the transition and measurement equations of the state-space system are given by (4) and (6), 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 (16).

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 (6) simplifies to

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{m,j} \ln m_t = \ln h_j + \ln \epsilon_{j,t}^2, \ \ j = 1, \ldots, n, \tag{7}$$

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

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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 (7).

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 (14), (15), (17), (18), and (19). 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).

2.1   Coefficient Priors and Posteriors

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

$$\text{vec}(\Pi) \sim N(\text{vec}(\underline{\mu}_\Pi), \underline{\Omega}_\Pi), \tag{8}$$

$$a_j \sim N(\underline{\mu}_{a,j}, \underline{\Omega}_{a,j}), \ j = 2, \ldots, n, \tag{9}$$

$$\beta_{m,j} \sim N(\underline{\mu}_\beta, \underline{\Omega}_\beta), \ j = 1, \ldots, n, \tag{10}$$

$$\gamma_j \sim N(\underline{\mu}_\gamma, \underline{\Omega}_\gamma), \ j = 1, \ldots, n, \tag{11}$$

$$\delta \sim N(\underline{\mu}_\delta, \underline{\Omega}_\delta), \tag{12}$$

$$\phi_j \sim IG(d_\phi \cdot \underline{\phi}, d_\phi), \ \ j = 1, \ldots, n. \tag{13}$$

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

$$\text{vec}(\Pi) | A, \beta, m_{1:T}, h_{1:T}, y_{1:T} \sim N(\text{vec}(\bar{\mu}_\Pi), \bar{\Omega}_\Pi), \tag{14}$$

$$a_j | \Pi, \beta, m_{1:T}, h_{1:T}, y_{1:T} \sim N(\bar{\mu}_{a,j}, \bar{\Omega}_{a,j}), \ j = 2, \ldots, n, \tag{15}$$

$$\beta_{m,j} | \Pi, A, \gamma, \Phi, m_{1:T}, h_{1:T}, s_{1:T}, y_{1:T} \sim N(\bar{\mu}_\beta, \bar{\Omega}_\beta), \ \ j = 1, \ldots, n, \tag{16}$$

$$\gamma_j | \Pi, A, \beta, \Phi, m_{1:T}, h_{1:T}, y_{1:T} \sim N(\bar{\mu}_\gamma, \bar{\Omega}_\gamma), \ j = 1, \ldots, n, \tag{17}$$

$$\delta | \Pi, A, \gamma, \beta, \Phi, m_{1:T}, h_{1:T}, y_{1:T} \sim N(\bar{\mu}_\delta, \bar{\Omega}_\delta), \tag{18}$$

$$\phi_j | \Pi, A, \beta, \gamma, m_{1:T}, h_{1:T}, y_{1:T} \sim IG\left(d_\phi \cdot \underline{\phi} + \Sigma_{t=1}^T \nu_{jt}^2, \ d_\phi + T\right), \ j = 1, \ldots, n. \tag{19}$$

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:

$$\pi^{(j)} \quad | \quad \pi^{(1:j-1)}, A, \beta, m_{1:T}, h_{1:T}, y_{1:T} \sim N(\bar{\mu}_{\pi^{(j)}}, \overline{\Omega}_{\pi^{(j)}}), \tag{20}$$

$$\bar{\mu}_{\pi^{(j)}} = \overline{\Omega}_{\pi^{(j)}} \left\{ \Sigma_{t=1}^T X_t \lambda_{j,t}^{-1} y_{j,t}^{*\prime} + \underline{\Omega}_{\pi^{(j)}}^{-1} (\underline{\mu}_{\pi^{(j)}}) \right\}, \tag{21}$$

$$\overline{\Omega}_{\pi^{(j)}}^{-1} = \underline{\Omega}_{\pi^{(j)}}^{-1} + \Sigma_{t=1}^T X_t \lambda_{j,t}^{-1} X_t', \tag{22}$$

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 $\underline{\Omega}_\Pi^{-1}$.

2.2 Unobservable States

For the unobserved common volatility states m_t, given the law of motion in (3) 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 $h_{j,t}$, $j = 1, \ldots, n$, given the law of motion for the unobservable states in (4) 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 (7).

2.3   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.

2.4   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.[1] More details can be found in Carriero, Clark, and Marcellino (2016b). With the triangularization, the estimation algorithm will block the conditional posterior distribution 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:

$$\begin{bmatrix} v_{1,t} \\ v_{2,t} \\ \ldots \\ v_{n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \ldots & 0 \\ a_{2,1}^* & 1 & & \ldots \\ \ldots & & 1 & 0 \\ a_{n,1}^* & \ldots & a_{n,n-1}^* & 1 \end{bmatrix} \begin{bmatrix} \lambda_{1,t}^{0.5} & 0 & \ldots & 0 \\ 0 & \lambda_{2,t}^{0.5} & & \ldots \\ \ldots & & \ldots & 0 \\ 0 & \ldots & 0 & \lambda_{n,t}^{0.5} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \ldots \\ \epsilon_{n,t} \end{bmatrix}, \qquad (23)$$

---

[1]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.

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:

$$y_{1,t} = \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{1,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,1}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,1}^{(f)}\ln f_{t-l} + \lambda_{1,t}^{0.5}\epsilon_{1,t}$$

$$y_{2,t} = \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{2,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,2}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,2}^{(f)}\ln f_{t-l} + a_{2,1}^*\lambda_{1,t}^{0.5}\epsilon_{1,t} + \lambda_{2,t}^{0.5}\epsilon_{2,t}$$

$$\cdots$$

$$y_{n,t} = \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{n,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,N}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,N}^{(f)}\ln f_{t-l} + a_{n,1}^*\lambda_{1,t}^{0.5}\epsilon_{1,t} + \cdots$$

$$\cdots + a_{n,n-1}^*\lambda_{n-1,t}^{0.5}\epsilon_{n-1,t} + \lambda_{n,t}^{0.5}\epsilon_{n,t},$$

with the generic equation for variable j:

$$y_{j,t} - (a_{j,1}^*\lambda_{1,t}^{0.5}\epsilon_{1,t} + \cdots + a_{j,j-1}^*\lambda_{j-1,t}^{0.5}\epsilon_{j-1,t})$$

$$= \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{j,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,j}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,j}^{(f)}\ln f_{t-l} + \lambda_{j,t}\epsilon_{j,t}. \tag{24}$$

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 (24) 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:

$$y_{j,t}^* = y_{j,t} - (a_{j,1}^*\lambda_{1,t}^{0.5}\epsilon_{1,t} + \cdots + a_{j,j-1}^*\lambda_{j-1,t}^{0.5}\epsilon_{j-1,t}), \tag{25}$$

and equation (24) becomes a standard generalized linear regression model for the variable in equation (25) 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:

$$\begin{aligned}
p(\Pi|A,\beta,m_{1:T},h_{1:T},y_{1:T}) &= p(\pi^{(n)}|\pi^{(n-1)},\pi^{(n-2)},\ldots,\pi^{(1)},A,\beta,m_{1:T},h_{1:T},y_{1:T}) \\
&\quad \times p(\pi^{(n-1)}|\pi^{(n-2)},\ldots,\pi^{(1)},A,\beta,m_{1:T},h_{1:T},y_{1:T}) \\
&\quad \times \ldots \times p(\pi^{(1)}|A,\beta,m_{1:T},h_{1:T},y_{1:T}), \tag{26}
\end{aligned}$$

where the vector β collects the loadings of the uncertainty factors and $m_{1:T}, h_{1:T} = (h_{1,T},\ldots,h_{n,T})$, and $y_{1:T}$ denote the history of the states and data up to time T.[2] As a result, we are able to

---

[2] 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.

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 (23) 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.[3] 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.

3 Prior settings

3.1 BVAR-GFSV

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

---

[3]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.

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 $\beta_{i,m}$, $i = 1, \ldots, n$, 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 $\beta_{i,f}$, $i = 1, \ldots, n$, 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 (4), 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.

3.2 BVAR-SV

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:

$$
\begin{aligned}
y_t &= \sum_{i=1}^{p} \Pi_i y_{t-i} + v_t, \\
v_t &= A^{-1} \Lambda_t^{0.5} \epsilon_t, \ \epsilon_t \sim N(0, I_n), \ \Lambda_t \equiv \mathrm{diag}(\lambda_{1,t}, \ldots, \lambda_{n,t}), \\
\ln(\lambda_{i,t}) &= \gamma_{0,i} + \gamma_{1,i} \ln(\lambda_{i,t-1}) + \nu_{i,t}, \ i = 1, \ldots, n, \\
\nu_t &\equiv (\nu_{1,t}, \nu_{2,t}, \ldots, \nu_{n,t})' \sim N(0, \Phi),
\end{aligned}
\tag{27}
$$

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. 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.[4]

We set the priors for the BVAR-SV model to generally align with those of the baseline model with factor volatility detailed above. 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 $\theta_2 = 0.5$. Consistent with common settings, the scale parameters σ_i^2 take the values of residual variances from $\text{AR}(p)$ 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 $\text{AR}(p)$ 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.

3.3 BVAR

The homoskedastic BVAR used in the two-step approach to impulse response assessment takes the following form:

$$y_t = \sum_{i=1}^{p} \Pi_i y_{t-i} + v_t, \ v_t \sim i.i.d. \ N(0, \Sigma). \tag{28}$$

---

[4]To speed computation, we estimate the model with the triangularization approach developed in Carriero, Clark, and Marcellino (2016b).

Regarding the priors on the homoskedastic BVAR'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.

4   Historical Decomposition with BVAR-GFSV Model

This section details the computation of the paper's estimated historical decomposition. As a starting point, consider a simple one-factor model with lag orders of 1:

$$\begin{cases} y_t = \Pi y_{t-1} + \Gamma_1 \ln m_t + \Gamma_2 \ln m_{t-1} + v_t \\ \quad \ln m_t = \delta y_{t-1} + \gamma \ln m_{t-1} + u_t \end{cases}, \tag{29}$$

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:

$$y_{t+1} - E_t y_{t+1} = \Gamma_1 u_{t+1} + \hat{\Sigma}_{t+1|t}^{0.5}\epsilon_{t+1} + (\Sigma_{t+1}^{0.5} - \hat{\Sigma}_{t+1|t}^{0.5})\epsilon_{t+1}. \tag{30}$$

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.

5 Correlations of Uncertainty Estimates with Known Macro Shocks

This section reports 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). 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), fiscal policy shocks (Ramey 2011 and Mertens and Ravn 2012), shocks to credit conditions (the excess bond premium of Gilchrist and Zakrajsek 2012), and economic news shocks (Barsky and Sims 2011).[5]

As indicated by the results in Appendix Table 3, 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. While it would be interesting to also assess the correlation of our uncertainty shocks with macroeconomic shocks for other countries or the global economy, we are not aware of standard sources of shocks like those that exist for U.S. data.

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[5]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). We constructed the excess bond premium shock as in the VAR analysis in section IV.B of Gilchrist and Zakrajsek (2012).

6 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 an additional robustness check we have examined the international factor structure of uncertainty and its effects on GDP for a sample of 1960:Q4 through 2016:Q3. 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 BVAR-GFSV estimates over the 1960-2016 sample, the influence of the Great Moderation 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, declining steadily from the early 1960s through the mid-1980s. 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.

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[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.

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Appendix 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.

Appendix 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

Appendix Table 3: 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)
Excess bond premium: Gilchrist and Zakrajsek (2012)	0.059	-0.106
(1985:Q1-2016:Q3, 1985:Q4-2013:Q3)	(0.609)	(0.451)
News: Barsky and Sims (2011)	0.023	0.069
(1985:Q1-2007:Q3, 1985:Q4-2007:Q3)	(0.793)	(0.551)

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).
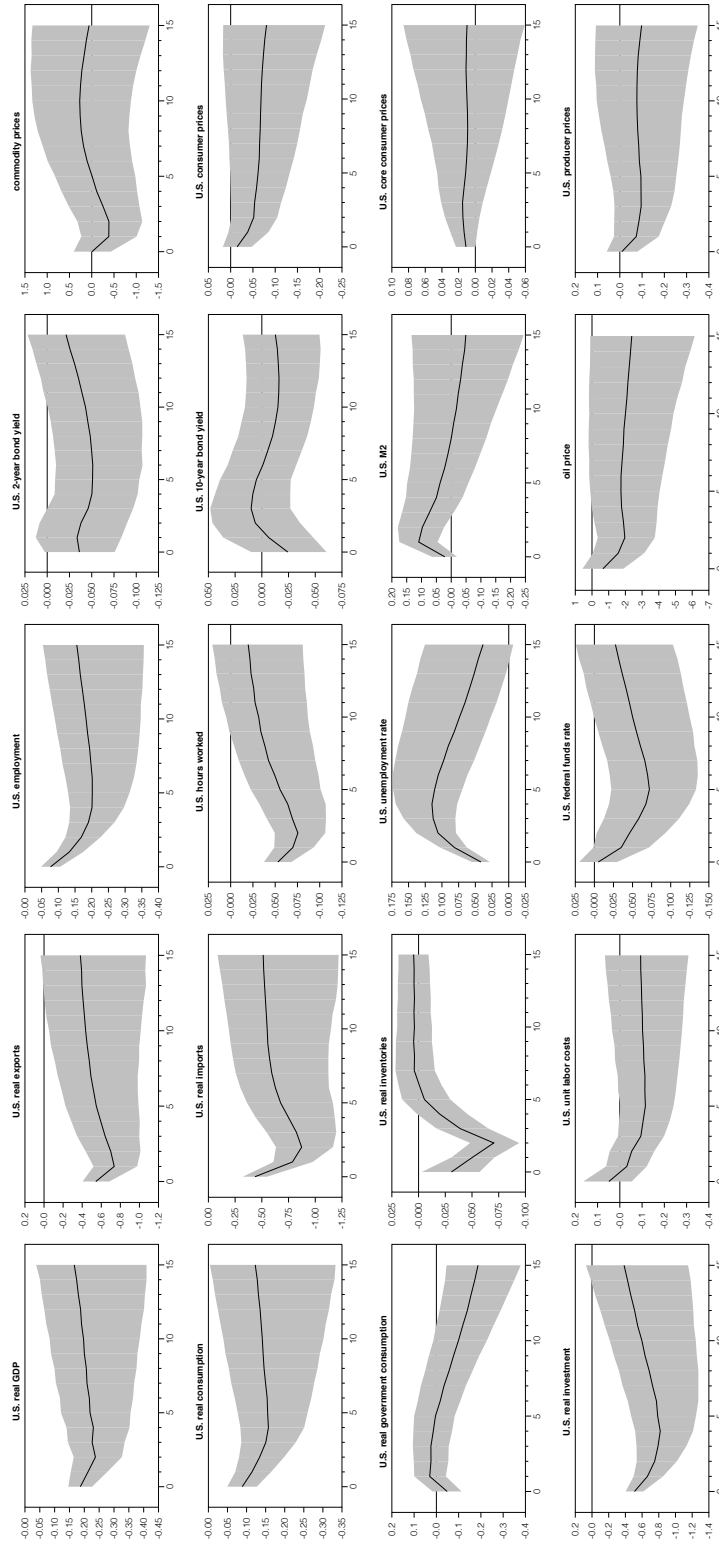
Figure 1: Impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset, posterior median (black line) and 15%/85% quantiles
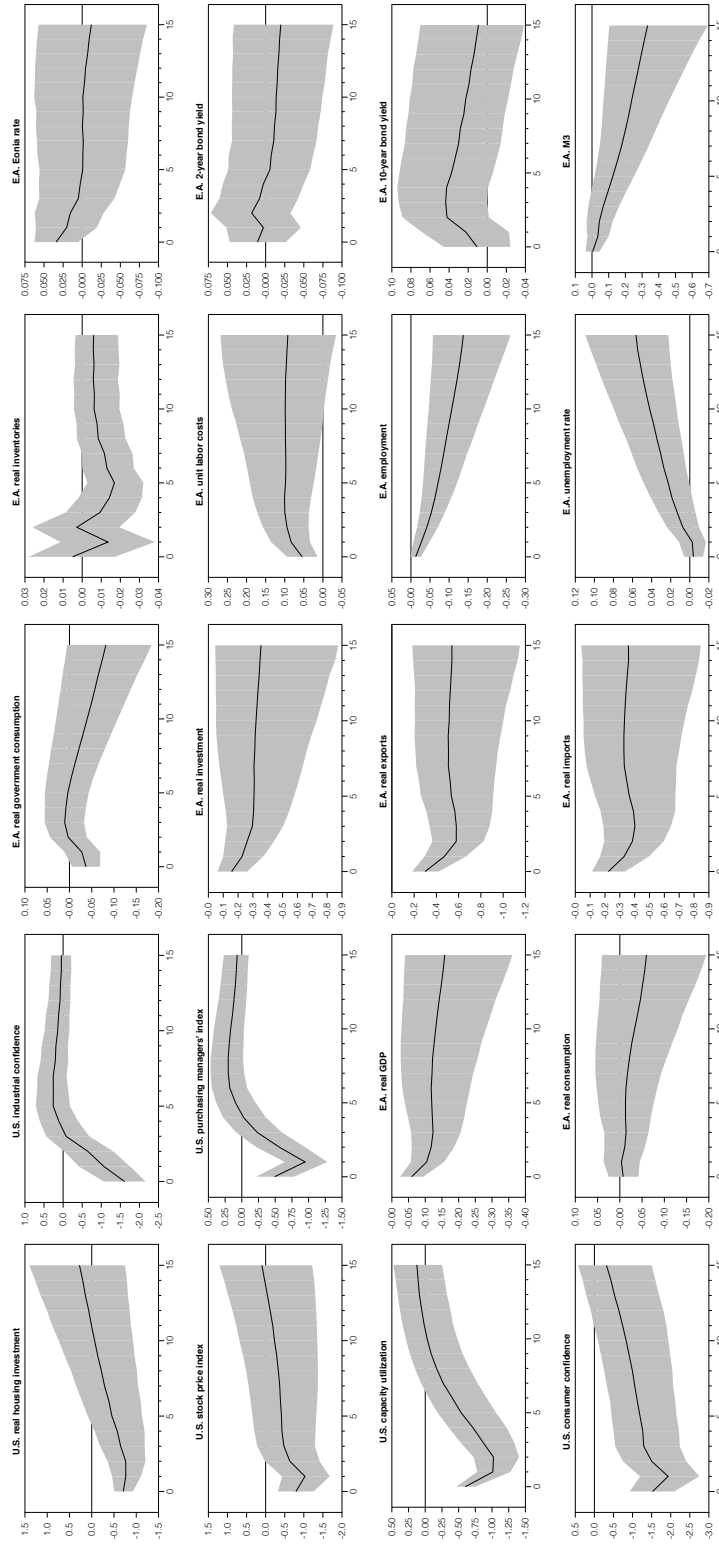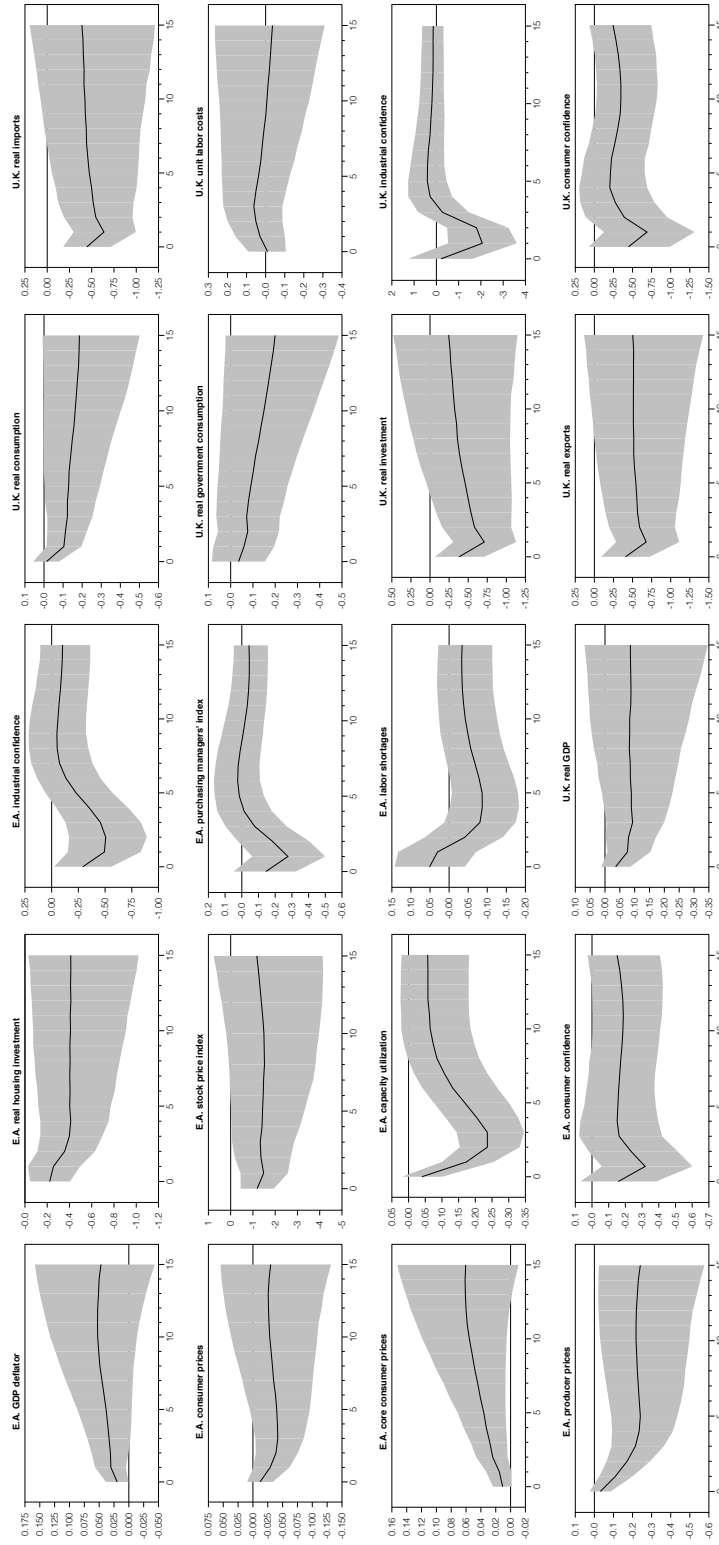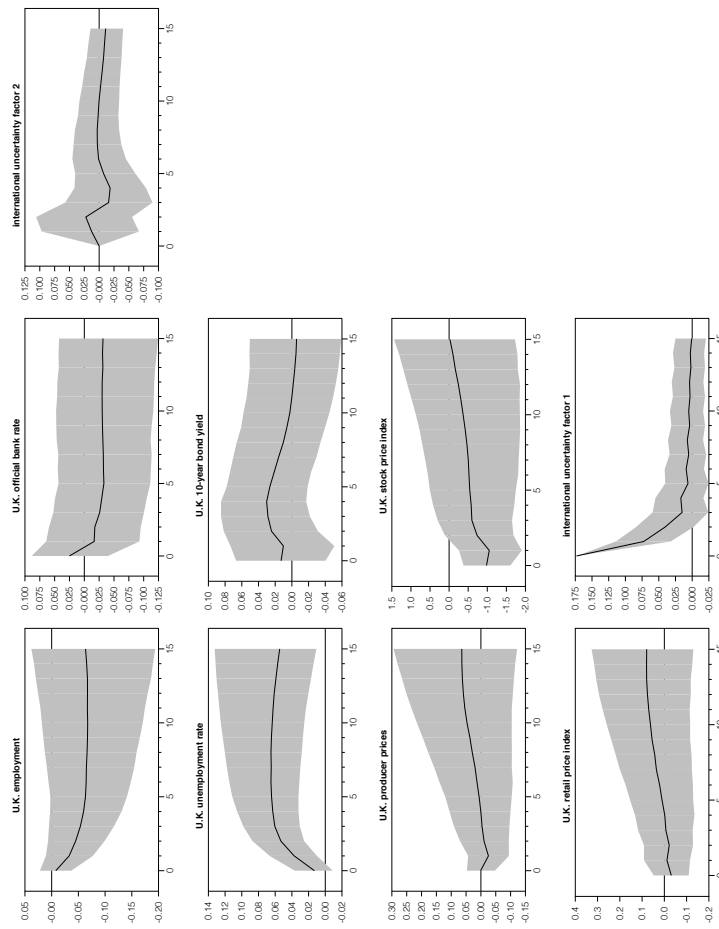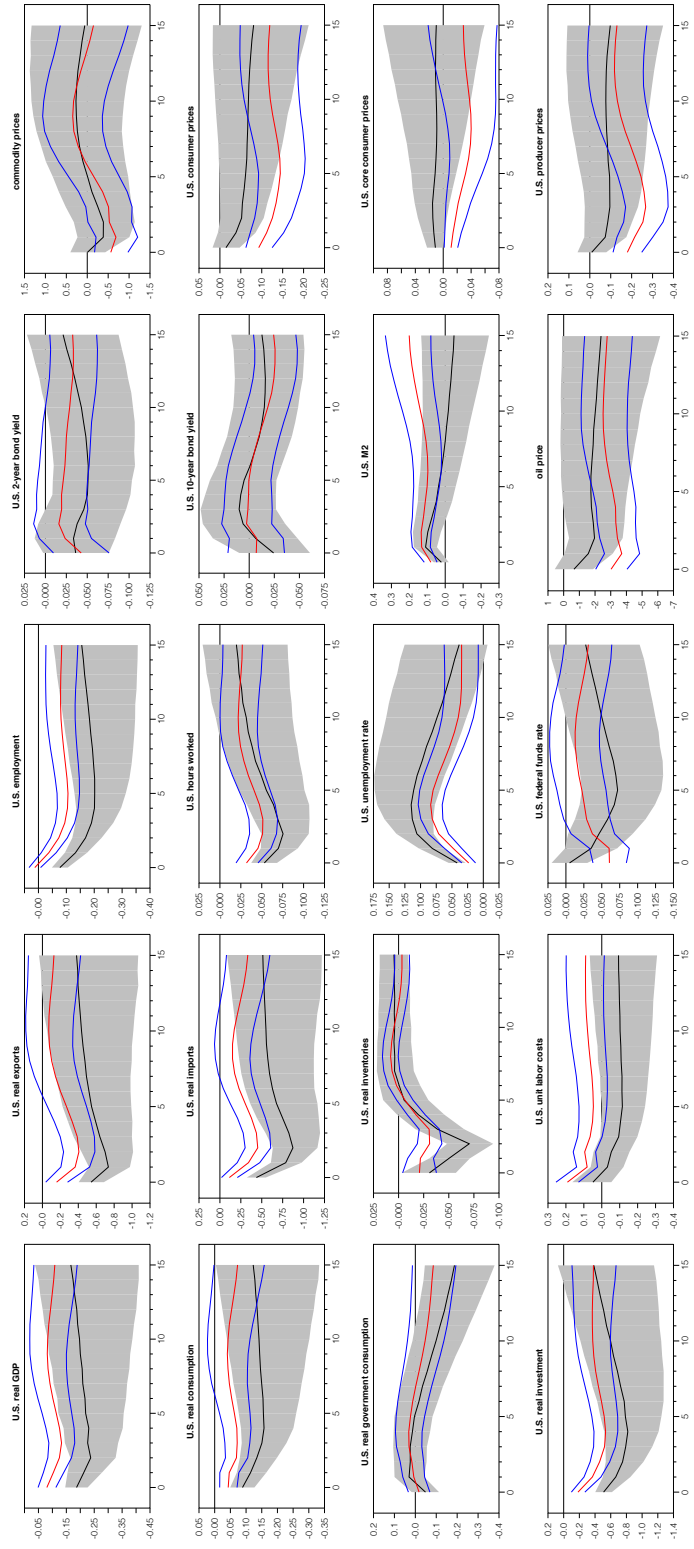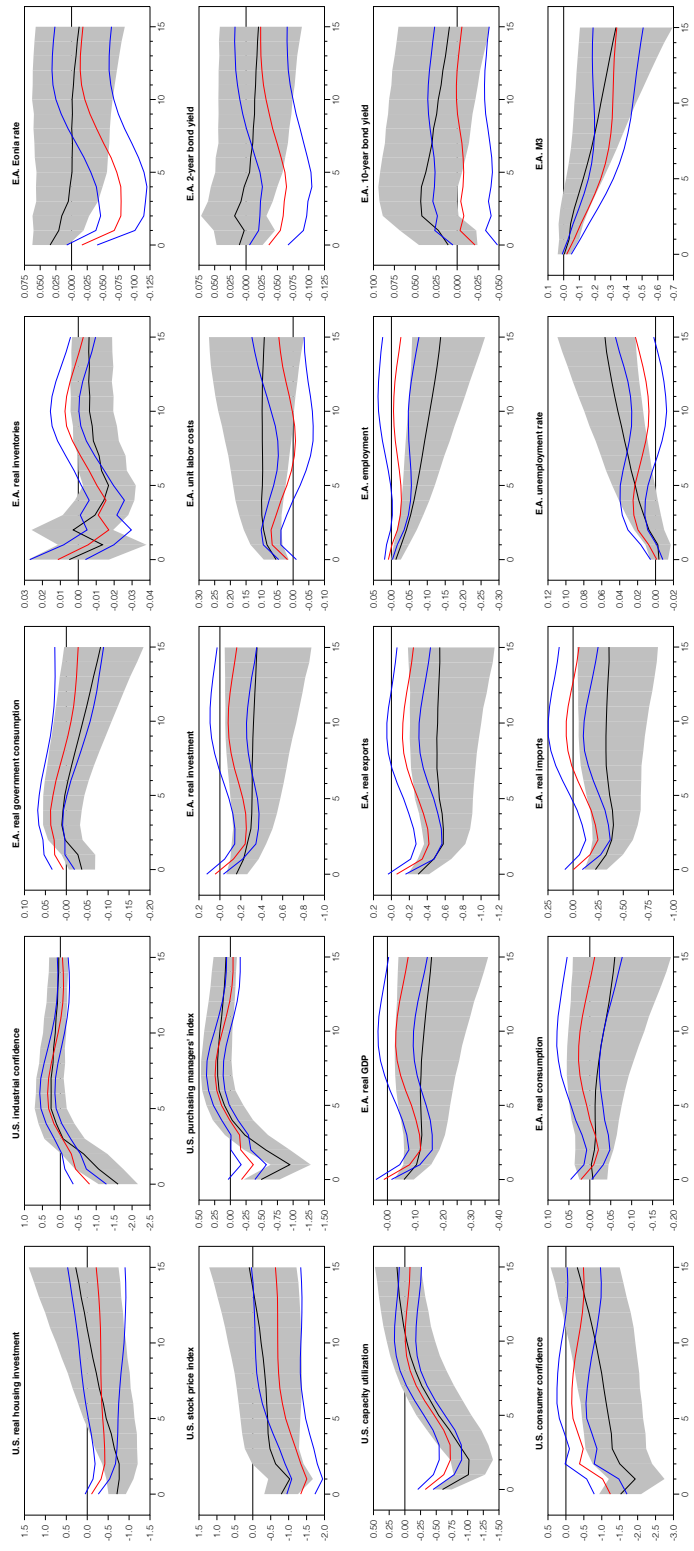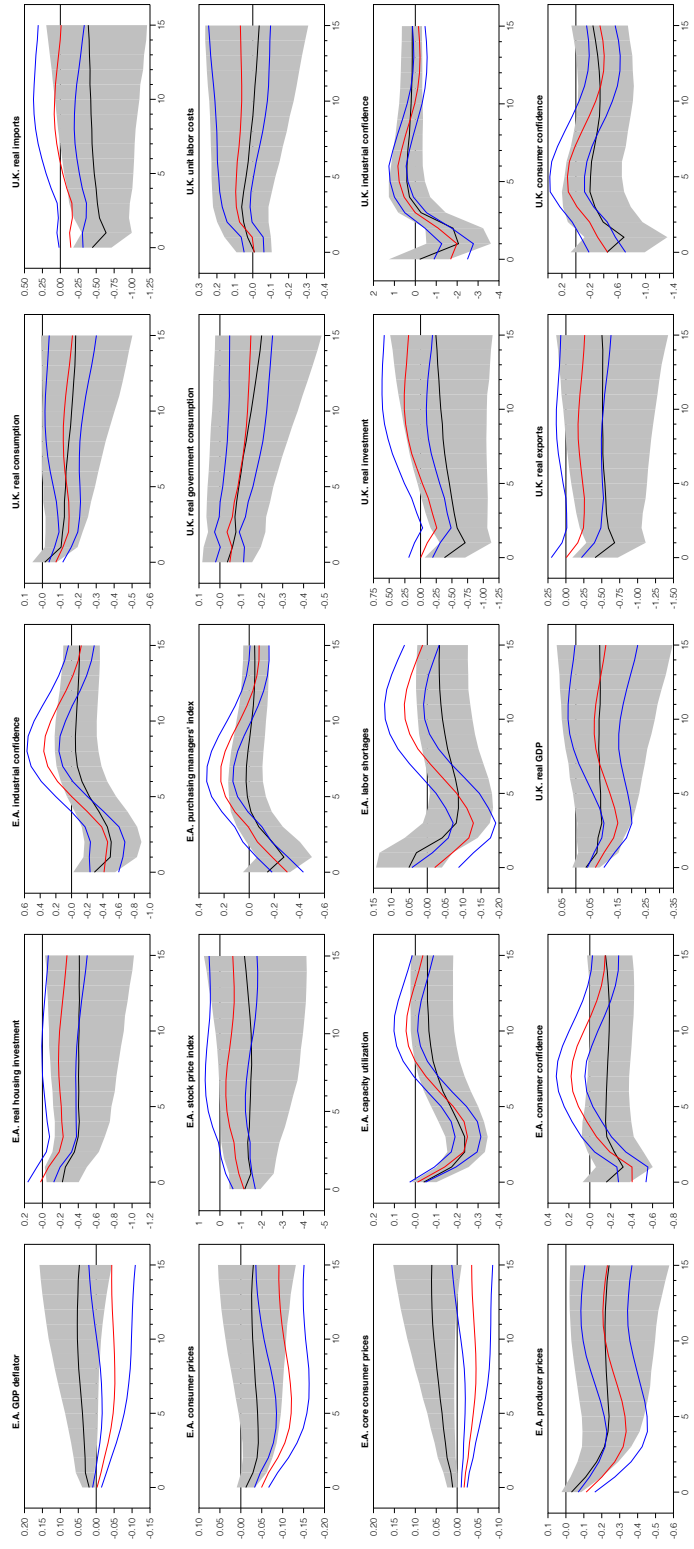
Figure 1: Continued, impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset, posterior median (black line) and 15%/85% quantiles

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Figure 1: Continued, impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset, posterior median (black line) and 15%/85% quantiles

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Figure 1: Continued, impulse responses for international uncertainty shock: BVAR-GFSV estimates for 3-economy macroeconomic dataset, posterior median (black line) and 15%/85% quantiles

Figure 2: Impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates

Figure 2: Continued, impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates

Figure 2: Continued, impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates

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Figure 2: Continued, impulse responses for international uncertainty shock in 3-economy macroeconomic dataset: Comparison of two-step estimates with BVAR-GFSV estimates
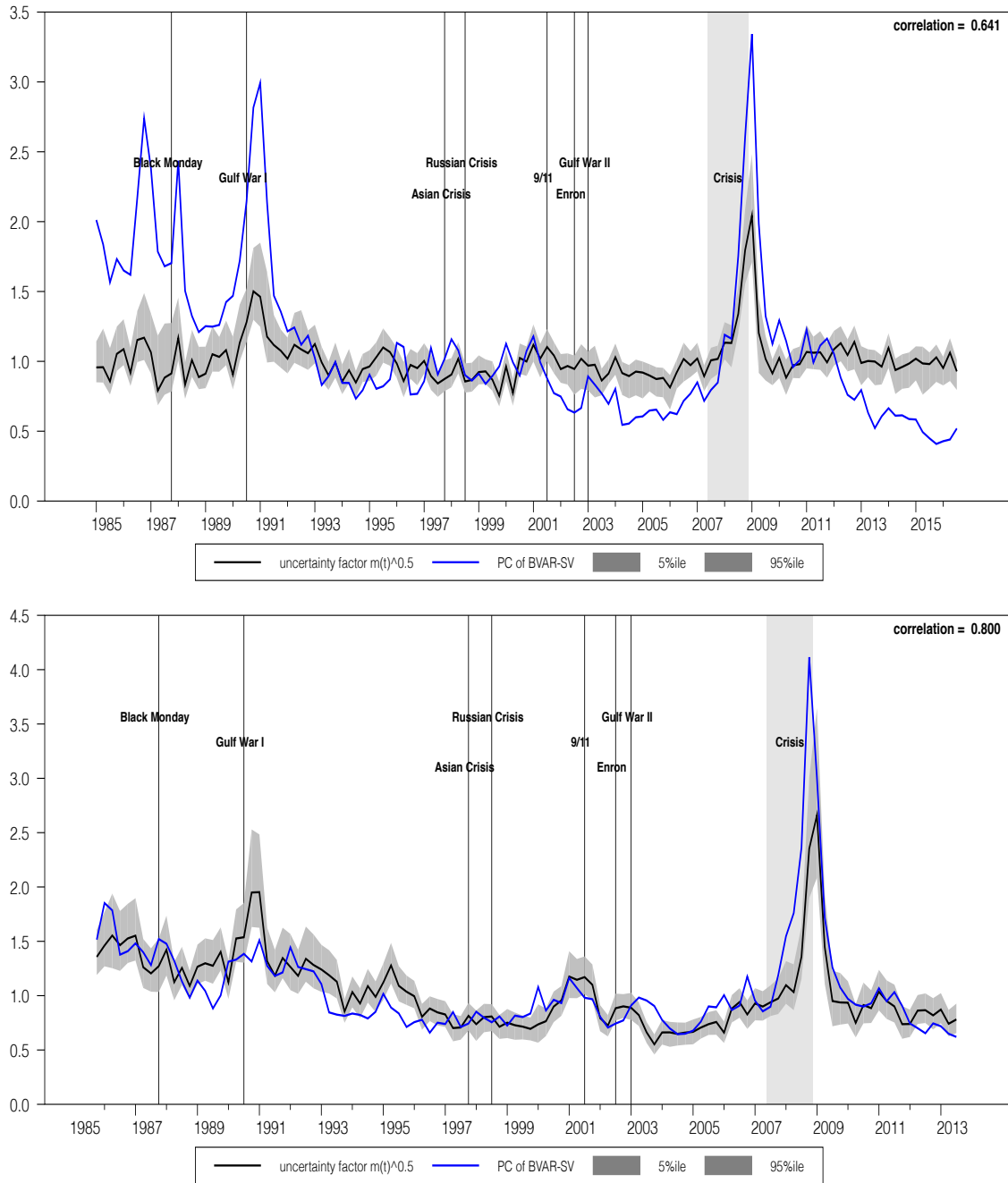
Figure 3: Uncertainty estimates for 19-country GDP dataset in the top panel and for 3-economy macroeconomic dataset in the bottom panel. In each panel, the blue line provides an estimate obtained from the first principal component of the BVAR-SV estimates of log volatility. The solid black line and gray-shaded regions provide the posterior median and 5%/95% 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.