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Measuring Global Macroeconomic Uncertainty and Cross-Country Uncertainty Spillovers

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Abstract: We propose an approach for jointly measuring global macroeconomic uncertainty and bilateral spillovers of uncertainty between countries using a global vector autoregressive (GVAR) model. Over the period 2000Q1–2020Q4, our global index is able to summarize a variety of uncertainty measures, such as financial-market volatility, economic-policy uncertainty, survey-forecast-based measures and econometric measures of macroeconomic uncertainty, showing major peaks during both the global financial crisis and the COVID-19 pandemic. Global spillover effects are quantified through a novel GVAR-based decomposition of country-level uncertainty into the contributions from all countries in the global model. We show that this approach produces estimates of uncertainty spillovers which are strongly related to the structure of the global economy.

Keywords: global uncertainty; uncertainty index; GVAR; spillovers; bootstrap

JEL Classification: C15; C32; D80; E17; F44; G15

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1. Introduction

Uncertainty has been a major concern for economic agents around the world since the global financial crisis of 2007–2009 and is becoming even more important with the ongoing COVID-19 pandemic, the war in Ukraine and the climate transition. It is considered one of the factors that hinder economic activity (e.g., ECB 2009; Stock and Watson 2012; Bloom et al. 2012; Coibion et al. 2021) and its international transmission plays a key role in shaping macroeconomic outlooks (e.g., IMF 2012). Over the years, economists have relied on a variety of methodologies to measure uncertainty and study its effects (see, e.g., the reviews by Bloom 2014 and ECB 2016). Recently, there has been an increasing interest in developing measures of global uncertainty (Ahir et al. 2022; Ozturk and Sheng 2018; Berger et al. 2016 2017; Mumtaz and Theodoridis 2017; Mumtaz and Musso 2019; Caggiano and Castelnuovo 2021) and assessing international spillovers from uncertainty to economic and financial indicators (e.g., Bhattarai et al. 2020; Londono et al. 2021; Caggiano et al. 2020; Carrière-Swallow and Céspedes 2013; Colombo 2013). Still, assessing how uncertainty originating in one country or region influences uncertainty in the rest of the world, i.e., the global propagation of uncertainty, remains, to a large extent, an open issue. The available econometric approaches for measuring global uncertainty (Berger et al. 2017; Mumtaz and Theodoridis 2017; Mumtaz and Musso 2019; Carriero et al. 2020; Crespo Cuaresma et al. 2019; Cesa-Bianchi et al. 2020; Caggiano and Castelnuovo 2021) are generally designed to estimate a common component of uncertainty across countries, but not also bilateral spillovers between country-specific uncertainties. On the other hand, some estimates of bilateral spillovers have been proposed in the literature (Klößner and Sekkel 2014; Rossi and Sekhposyan 2017; Angelini et al. 2018; Bacchiocchi and Dragomirescu-Gaina 2022), but (i) they are generally obtained for advanced economies only and (ii) the methodologies used to measure spillovers between uncertainty indices differ from the ones used to measure the uncertainty indices themselves, so that the two types of measure may not be fully consistent with each other. In other words, the quantification of uncertainty spillovers currently relies on a two-step, two-methodology approach: in the first step, uncertainty indices are constructed for some countries using a specific methodology, e.g., newspaper word counts as in Baker et al. (2016); in the second step, a different methodology is used to estimate spillovers between country-specific indices, e.g., the methodology by Diebold and Yilmaz (2009) based on forecast error variance decomposition in structural vector autoregressive (SVAR) models.[1] Klößner and Sekkel (2014) estimate bilateral spillovers of policy uncertainty among six developed countries by applying the Diebold and Yilmaz (2009) methodology to the economic policy uncertainty (EPU) indices constructed by Baker et al. (2016). Rossi and Sekhposyan (2017) estimate spillovers in the Euro area using the Diebold and Yilmaz (2009) approach and measures of uncertainty derived from survey forecasts using the Rossi and Sekhposyan (2015) methodology. Angelini et al. (2018) investigate uncertainty spillovers between four Eurozone countries by estimating an SVAR model on the uncertainty measures constructed by Meinen and Roehe (2017) for these countries using the methodology by Jurado et al. (2015). Bacchiocchi and Dragomirescu-Gaina (2022) measure spillovers of uncertainty across Euro-area countries, using the European Central Bank's Composite Indicator for Systemic Stress (CISS) (Kremer et al. 2012) as a measure of financial uncertainty and the EPU index as a measure of policy uncertainty, and estimating a global vector autoregression (Pesaran et al. 2004) on these variables.

This paper proposes a single econometric approach for jointly measuring global macroeconomic uncertainty and global bilateral spillovers of uncertainty between countries using a global vector autoregressive (GVAR) model (Pesaran et al. 2004; Dées et al. 2007a). The GVAR is one of the most popular frameworks for analyzing macroeconomic and financial interconnections between countries at the global level and is widely used in forecasting (see Chudik and Pesaran 2016 for a review of the numerous applications of the GVAR in the literature). We construct an index of global macroeconomic uncertainty (GMU) based on the dispersion of forecasts resulting from parameter uncertainty in the GVAR model. Thus, our index explicitly takes into account network interactions between a large number of countries, both advanced and emerging, using both real and financial variables. Specifically, we track uncertainty over time by means of a bootstrap procedure iterated over recursive and rolling sample windows. In each window, we (i) estimate the distribution of GVAR parameters by a non-parametric bootstrap, following Dées et al. (2007a, 2007b); (ii) generate the distribution of out-of-sample forecasts resulting from parameter uncertainty; and (iii) measure the standard deviations of forecasts for all the variables in the global economy and aggregate them. Importantly, our econometric approach allows, at the same time, to estimate spillovers from uncertainty in one country to uncertainty in all other countries in the global economy. We estimate spillovers by decomposing country-level uncertainties into the contributions from all countries. To do so, we perform bootstrap simulations in which parameter uncertainty is selectively "switched on" or "switched off" for one country-specific model at a time within the GVAR.

We find that our GMU index combines features of different uncertainty measures, such as indicators of financial-market volatility and economic-policy uncertainty. Overall, it turns out to be very similar to a common factor (first principal component) extracted from a number of existing indices of uncertainty. The GMU index captures large increases in uncertainty during both the global financial crisis and the COVID-19 pandemic (a result which is not obtained by some widely used measures of global uncertainty, such as the Global Economic Policy Uncertainty Index by Davis 2016 and Baker et al. 2016 and the World Uncertainty Index by Ahir et al. 2022). We also show that the GMU index is broadly consistent with an uncertainty measure obtained by applying the methodology by Jurado et al. (2015) (arguably the most influential econometric approach for measuring uncertainty) to all the variables included in the GVAR model. However, unlike the Jurado et al. (2015) approach and similar factor model-based approaches, our GVAR-based approach also allows for a direct quantification of bilateral spillovers of uncertainty. In addition, compared to conventional two-step approaches using SVAR models in the second step to measure uncertainty spillovers, this approach produces spillover estimates which are more directly related to economic linkages between countries. We show this by comparing our measures of spillovers with alternative measures constructed using the Diebold and Yilmaz (2009) methodology and the country-specific uncertainty indices by Ozturk and Sheng (2018), which are available for almost all countries considered in this paper.

The paper relates to the thriving literature on uncertainty measures. Some of the proxies proposed by previous research are derived from observables, such as indices of option-implied stock-market volatility (Bloom 2009), distributions of survey forecasts and forecast errors (Lahiri and Sheng 2010; Bachmann et al. 2013; Rossi and Sekhposyan 2015 2017; Scotti 2016) or the frequency of newspaper articles containing specific keywords (Baker et al. 2016). Ozturk and Sheng (2018) develop an index of global uncertainty using survey forecast data. Ahir et al. (2022) construct an index of uncertainty for 143 individual countries using the frequency of the word "uncertainty" in the quarterly Economist Intelligence Unit country reports, and obtain their World Uncertainty Index by averaging the country-specific indices. Other uncertainty measures are based on econometric models, typically factor models with stochastic volatility. In their seminal paper, Jurado et al. (2015) measure uncertainty in the United States through a factor-augmented vector autoregression, using a large dataset of monthly macro and financial indicators. They introduce a measure of uncertainty based on the average conditional volatility of unforecastable errors across a large number of series. Berger et al. (2016 2017), Mumtaz and Theodoridis (2017) and Mumtaz and Musso (2019) use multi-country factor models with stochastic volatility to decompose uncertainty in OECD countries into common and country-specific components. Based on U.S. data, Carriero et al. (2017) jointly estimate uncertainty and its impact on the economy through a large VAR in which stochastic volatility is driven by common factors. Carriero et al. (2020), Crespo Cuaresma et al. (2019) and Pfarrhofer (2022) use large Bayesian VARs with common factors of volatility to measure uncertainty and its effects in advanced economies. Benati (2008) measures macroeconomic uncertainty in the U.K. by simulating a Bayesian time-varying parameter VAR with stochastic volatility. Caggiano and Castelnuovo (2021) estimate global financial uncertainty as the global component across a large set of financial-market realized volatilities, using a dynamic factor model with global, regional, and country-specific factors. Cesa-Bianchi et al. (2020) employ a multi-country panel VAR model to identify global factors and study the two-way relationship between realized equity price volatility and GDP growth.

This paper focuses on parameter uncertainty as "core" uncertainty. Since parameter uncertainty undermines individuals' confidence in the estimated probability distributions of economic outcomes, our measure is conceptually closer to Knightian or radical uncertainty than to risk (see, e.g., Rossi et al. 2018; Epstein and Wang 1994; Drechsler 2013). Conversely, most of the existing econometric measures of uncertainty are based on the estimated volatility of shocks, implicitly treating probability distributions as certain and, thus, pertaining more to the concept of risk (see, however, Carriero et al. 2017; Orlik and Veldkamp 2014; Benati 2008 for other approaches accounting for parameter uncertainty). The economic literature has emphasized the key role of parameter uncertainty in several contexts. In a seminal paper, Brainard (1967) showed that parameter uncertainty affects policymakers' optimal choices, while error volatility can be ignored when setting policy variables under standard quadratic objective functions. The subsequent literature has expanded on the importance of parameter uncertainty for monetary policy (e.g., Wieland 2000; Söderström 2002; Orphanides and Williams 2007). Theoretical models with parameter uncertainty and learning have proven effective in explaining key macro puzzles, such as the equity premium puzzle (Hansen 2007; Collin-Dufresne et al. 2016; Weitzman 2007), thus improving on rational expectations models. In finance, parameter uncertainty also crucially affects the relationship between the investment horizon and the optimal portfolio allocation (e.g., Xia 2001).

As parameter uncertainty depends on the size of errors or shocks, our measure of global uncertainty is consistent with theoretical models in which high macroeconomic uncertainty is driven by large first-moment shocks to macroeconomic variables, determining large forecast errors. Van Nieuwerburgh and Veldkamp (2006) develop a general equilibrium model in which asymmetric business-cycle phases (fast downturns and slow recoveries) are determined by procyclical learning about technology and, thus, countercyclical uncertainty, and uncertainty is proxied by a representative agent's forecast error (to calibrate the model, the authors measure uncertainty using the median forecast errors across a panel of forecasters). Decker et al. (2016) propose a model in which firm-level risk depends on first-moment shocks to total factor productivity (TFP) and is negatively correlated with the business cycle: positive TFP shocks enable firms to expand into more markets, reducing risk through a standard diversification mechanism, while negative TFP shocks increase risk. Firm-level risk is proxied by the square of the prediction error, i.e., the purely unpredictable component, of firms' sales growth. In line with these theoretical frameworks and with a well-known stylized fact of uncertainty (see Bloom 2014), our GMU index is strongly countercyclical. Other theoretical models in which high uncertainty reflects large (negative) shocks are surveyed by Bachmann et al. (2013). From an empirical perspective, several measures of uncertainty proposed in the literature are based on realized forecast errors. The index by Scotti (2016) is based on the difference between actual releases of macroeconomic variables and Bloomberg survey expectations, i.e., the forecast error or "news surprise". The index by Rossi and Sekhposyan (2015) is based on the quantile associated with the actual realized value of the forecast error in the unconditional distribution of observed forecast errors. Bachmann et al. (2013) use ex-ante disagreement in survey forecasts and the dispersion of ex-post forecast errors to measure uncertainty, and find that both measures are positively and strongly correlated with the average size of forecast errors. The uncertainty measure by Jurado et al. (2015) also depends on realized forecast errors, to the extent that they affect estimates of error volatility.

We measure time-varying uncertainty using recursive and rolling sample windows rather than full-sample estimation of a model with time-varying volatility, as in the Jurado et al. (2015) approach. While the results suggest that this is not crucial for determining the main qualitative characteristics of our uncertainty measure, it allows us to construct our index at any point in time without using data on subsequent periods (thus, the index is not revised when new observations become available, except for mere standardization). Accordingly, this approach can be used to capture real-time uncertainty about the state of the economy, which is arguably the type of uncertainty on which economic agents base their decisions. At the same time, recursive and rolling windows allow us to accommodate temporal instability in all parameters of the model. Jurado et al. (2015) develop their measure of uncertainty assuming that all coefficients other than volatility are time-invariant, building on the result that dynamic factor models are more robust against parameter instabilities than small models, as instabilities tend to "average out" in the construction of common factors (similar considerations apply to the GVAR model, see Dées et al. 2007a). However, in their robustness checks, Jurado et al. (2015) also use recursive windows to allow for time-varying parameters. Moreover, in the case of the GVAR model, using recursive and rolling windows to measure time-varying uncertainty offers another advantage: it avoids the difficulty of estimating long-run (cointegration) relationships, which are a central element of the GVAR framework as developed by Pesaran et al. (2004), in the case of country-specific VARX* models with stochastic volatility. While the Bayesian GVAR variant with stochastic volatility proposed by Huber (2016) rules out cointegration, a proper econometric analysis of cointegrated GVAR models with stochastic volatility has not yet been carried out.

The remainder of the paper is organized as follows. Section 2 presents the methodology used to measure uncertainty and its spillovers. Section 3 presents the empirical implementation and the results. Section 4 concludes.

2. The Econometric Framework

2.1. The GVAR Model

The GVAR model (Pesaran et al. 2004) results from the aggregation of country-specific VARX* models, in which domestic macroeconomic variables are related to their foreign counterparts. To reduce the dimensionality of the parameter space, the foreign variables are built as cross-country weighted averages, using weights based on international trade flows. These foreign aggregates are treated as weakly exogenous in each VARX*, which implies that the estimation is performed at the country level. Our GVAR model is estimated on quarterly data.

Let $\mathbf{x}_{it}$ denote the $k_i \times 1$ vector of domestic macroeconomic variables of a generic country i at time t, with $i = 1, ..., N$, where N is the total number of countries. Let $\mathbf{x}^*_{it}$ denote the $k^*_i \times 1$ vector of foreign variables. The VARX* model for country i can be written as:

$$\mathbf{x}_{it} = \mathbf{a_0}_i + \mathbf{a_1}_i t + \sum_{j=1}^{p_i} \mathbf{\Phi}_{ji}\mathbf{x}_{i,t-j} + \sum_{l=0}^{q_i} \mathbf{\Lambda}_{li}\mathbf{x}^*_{i,t-l} + \boldsymbol{\nu}_{it} \tag{1}$$

where $\mathbf{a_0}_i$ and $\mathbf{a_1}_i$ are $k_i \times 1$ vectors of constants and trend coefficients, respectively; $\mathbf{\Phi}_{ji}$, for $j = 1, \ldots, p_i$, and $\mathbf{\Lambda}_{li}$, for $l = 0, 1, \ldots, q_i$, are $k_i \times k_i$ and $k_i \times k^*_i$ matrices of parameters, respectively; and $\boldsymbol{\nu}_{it} \sim iid(\mathbf{0}, \mathbf{\Sigma}_i)$ is the vector of errors. In the GVAR literature, quarterly VARX* models typically include one or two lags of the domestic and foreign variables (e.g., Pesaran et al. 2004; Dées et al. 2007a). We include two lags for all variables and all countries, i.e., $p_i = q_i = 2$ for every i. As shown by Dées et al. (2007a), country-specific foreign variables serve as a proxy for global common unobserved factors.

Let k be the total number of endogenous variables in the global economy, i.e., $k = \sum_i^N k_i$. Domestic and foreign variables can be expressed in terms of the $k \times 1$ stacked vector of global endogenous variables $\mathbf{x}_t$:

$$\begin{pmatrix} \mathbf{x}_{it} \\ \mathbf{x}^*_{it} \end{pmatrix} = \mathbf{W}_i \begin{bmatrix} \mathbf{x}_{1t} \\ \mathbf{x}_{2t} \\ \vdots \\ \mathbf{x}_{Nt} \end{bmatrix} = \mathbf{W}_i \mathbf{x}_t \tag{2}$$

where $\mathbf{W}_i$ is the $(k_i + k^*_i) \times k$ matrix of country-specific trade-based weights.

The error correction representation of the country-specific model, or VECX*, distinguishes long-run (cointegrating) relationships between variables and short-run dynamics. Defining $\mathbf{z}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it})'$, it can be written as:

$$\Delta\mathbf{x}_{it} = \bar{\mathbf{a}}_{\mathbf{0}i} - \mathbf{\Pi}_i[\mathbf{z}_{i,t-1} - \gamma_i(t-1)] - \mathbf{\Phi}_{2i}\Delta\mathbf{x}_{i,t-1} + \mathbf{\Lambda}_{0i}\Delta\mathbf{x}^*_{it} - \mathbf{\Lambda}_{2i}\Delta\mathbf{x}^*_{i,t-1} + \boldsymbol{\nu}_{it} \tag{3}$$

where $\mathbf{\Pi}_i$ is a $k_i \times (k_i + k^*_i)$ matrix of parameters, $\bar{\mathbf{a}}_{\mathbf{0}i}$ is a $k_i \times 1$ vector of constants and γ_i is a $(k_i + k^*_i) \times 1$ vector of trend coefficients. Given (1), $\mathbf{a_0}_i = \bar{\mathbf{a}}_{\mathbf{0}i} - \mathbf{\Pi}_i\gamma_i$ and $\mathbf{a_1}_i = \mathbf{\Pi}_i\gamma_i$. The rank r_i of matrix $\mathbf{\Pi}_i$ represents the number of long-run relationships between the variables in $\mathbf{z}_{it}$. In particular, $\mathbf{\Pi}_i = \boldsymbol{\alpha}_i\boldsymbol{\beta}'_i$, where $\boldsymbol{\alpha}_i$ is the $k_i \times r_i$ matrix of loadings and $\boldsymbol{\beta}_i$ is the $(k_i + k^*_i) \times r_i$ matrix of cointegrating vectors (see Johansen 1995). In addition, given (1), it is readily seen that $\mathbf{\Pi}_i = \left(\mathbf{I}_{k_i} - \sum_{j=1}^{2} \mathbf{\Phi}_{ji}, -\sum_{l=0}^{2} \mathbf{\Lambda}_{li}\right)$, where $\mathbf{I}_{k_i}$ is the $k_i \times k_i$ identity matrix.

Stacking all country-specific VARX* models provides a vector autoregressive representation of the global economy:

$$\mathbf{G}\mathbf{x}_t = \mathbf{a_0} + \mathbf{a_1}t + \mathbf{H}_1\mathbf{x}_{t-1} + \mathbf{H}_2\mathbf{x}_{t-2} + \boldsymbol{\nu}_t \tag{4}$$

where $\mathbf{a_0} = \left(\mathbf{a_0}_1', \mathbf{a_0}_2', \cdots, \mathbf{a_0}_N'\right)'$ and $\mathbf{a_1} = \left(\mathbf{a_1}_1', \mathbf{a_1}_2', \cdots, \mathbf{a_1}_N'\right)'$ are the $k \times 1$ vectors of stacked global constants and trends, respectively; $\boldsymbol{\nu}_t = \left(\boldsymbol{\nu}_{1t}', \boldsymbol{\nu}_{2t}', \cdots, \boldsymbol{\nu}_{Nt}'\right)'$ is the $k \times 1$ vector of stacked errors and:

$$\mathbf{G} = \begin{pmatrix} \left(\mathbf{I}_{k_1}, -\boldsymbol{\Lambda}_{01}\right)\mathbf{W}_1 \\ \left(\mathbf{I}_{k_2}, -\boldsymbol{\Lambda}_{02}\right)\mathbf{W}_2 \\ \vdots \\ \left(\mathbf{I}_{k_N}, -\boldsymbol{\Lambda}_{0N}\right)\mathbf{W}_N \end{pmatrix}, \quad \mathbf{H}_1 = \begin{pmatrix} \left(\boldsymbol{\Phi}_{11}, \boldsymbol{\Lambda}_{11}\right)\mathbf{W}_1 \\ \left(\boldsymbol{\Phi}_{12}, \boldsymbol{\Lambda}_{12}\right)\mathbf{W}_2 \\ \vdots \\ \left(\boldsymbol{\Phi}_{1N}, \boldsymbol{\Lambda}_{1N}\right)\mathbf{W}_N \end{pmatrix}, \quad \mathbf{H}_2 = \begin{pmatrix} \left(\boldsymbol{\Phi}_{21}, \boldsymbol{\Lambda}_{21}\right)\mathbf{W}_1 \\ \left(\boldsymbol{\Phi}_{22}, \boldsymbol{\Lambda}_{22}\right)\mathbf{W}_2 \\ \vdots \\ \left(\boldsymbol{\Phi}_{2N}, \boldsymbol{\Lambda}_{2N}\right)\mathbf{W}_N \end{pmatrix} \tag{5}$$

The reduced form of the global model can be written as:

$$\mathbf{x}_t = \mathbf{c_0} + \mathbf{c_1}t + \mathbf{F}_1\mathbf{x}_{t-1} + \mathbf{F}_2\mathbf{x}_{t-2} + \boldsymbol{\varepsilon}_t \tag{6}$$

where:

$$\begin{aligned} \mathbf{c_0} &= \mathbf{G}^{-1}\mathbf{a_0}, & \mathbf{c_1} &= \mathbf{G}^{-1}\mathbf{a_1}, \\ \mathbf{F}_1 &= \mathbf{G}^{-1}\mathbf{H}_1, & \mathbf{F}_2 &= \mathbf{G}^{-1}\mathbf{H}_2 \end{aligned} \tag{7}$$

and $\boldsymbol{\varepsilon}_t = \mathbf{G}^{-1}\boldsymbol{\nu}_t$ is the vector of reduced-form global errors.

Finally, it is useful to express the model in companion form:

$$\begin{bmatrix} \mathbf{x}_t \\ \mathbf{x}_{t-1} \end{bmatrix} = \begin{bmatrix} \mathbf{c}_0 \\ \mathbf{0} \end{bmatrix} + \begin{bmatrix} \mathbf{c}_1 \\ \mathbf{0} \end{bmatrix} t + \begin{bmatrix} \mathbf{F}_1 & \mathbf{F}_2 \\ \mathbf{I}_k & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{x}_{t-1} \\ \mathbf{x}_{t-2} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \mathbf{0} \end{bmatrix} \tag{8}$$

In what follows, the companion form will be denoted as:

$$\tilde{\mathbf{x}}_t = \tilde{\mathbf{c}}_\mathbf{0} + \tilde{\mathbf{c}}_\mathbf{1}t + \tilde{\mathbf{F}}\tilde{\mathbf{x}}_{t-1} + \tilde{\boldsymbol{\varepsilon}}_t \tag{9}$$

2.2. Time-Varying Uncertainty

To derive time profiles of uncertainty from the GVAR model, we employ a non-parametric bootstrap procedure, consisting of the following steps:

(i) The GVAR is repeatedly estimated over recursive and rolling sample windows. We first consider the recursive scheme, in which the shortest window goes from time 1 to time T_0, then the sample is extended by one-quarter increments up to $[1, T_{max}]$, where T_{max} identifies the last observation in the dataset. To estimate the country-specific VECX* models on each window, window-specific foreign variables are constructed using trade data that were available in the final quarter of the window under consideration (Section 3 provides more details). In a generic window w ending in period T_w, the maximum-likelihood estimate of the GVAR obtained using actual data is expressed as:

$$\mathbf{x}_t = \widehat{\mathbf{c}}_\mathbf{0}^{(w)} + \widehat{\mathbf{c}}_\mathbf{1}^{(w)}t + \widehat{\mathbf{F}}_1^{(w)}\mathbf{x}_{t-1} + \widehat{\mathbf{F}}_2^{(w)}\mathbf{x}_{t-2} + \widehat{\boldsymbol{\varepsilon}}_t^{(w)} \tag{10}$$

where the $\widehat{}$ symbol denotes estimates and $t = 1, 2, \ldots, T_w$.

(ii) In each window, we perform a non-parametric bootstrap of the estimates, following the approach by Dées et al. (2007ab). First, we simulate alternative historical paths for all the variables in the global model within the sample window, using the maximum-likelihood GVAR (10) and the empirical distribution of residuals. Then, we re-estimate the model on the simulated time series.

More specifically, in window w:

(a) The window-specific maximum-likelihood GVAR estimate (10) produces a $k \times T_w$ matrix of global residuals $\widehat{\boldsymbol{\mathcal{E}}}^{(w)} = \left(\widehat{\boldsymbol{\varepsilon}}_1^{(w)}, \widehat{\boldsymbol{\varepsilon}}_2^{(w)}, \ldots, \widehat{\boldsymbol{\varepsilon}}_{T_w}^{(w)}\right)$.

(b) In the generic b-th bootstrap iteration, with $b = 1, \ldots, B$, the T_w columns of matrix $\widehat{\boldsymbol{\mathcal{E}}}^{(w)}$ are resampled. Then, we simulate time series for all the variables using model (10) and adding the resampled residuals as shocks.

Denoting iteration b in window w with the superscript (w, b), let $\boldsymbol{\varepsilon}_t^{(w,b)}$ be the bootstrap shocks, generated by randomly drawing columns from $\widehat{\boldsymbol{\mathcal{E}}}^{(w)}$ (thereby preserving the cross-sectional covariances) with replacement. The simulated time series are given by:

$$\mathbf{x}_t^{(w,b)} = \widehat{\mathbf{c}}_\mathbf{0}^{(w)} + \widehat{\mathbf{c}}_\mathbf{1}^{(w)} t + \widehat{\mathbf{F}}_1^{(w)} \mathbf{x}_{t-1}^{(w,b)} + \widehat{\mathbf{F}}_2^{(w)} \mathbf{x}_{t-2}^{(w,b)} + \boldsymbol{\varepsilon}_t^{(w,b)} \tag{11}$$

with $\mathbf{x}_0^{(w,b)} = \mathbf{x}_0$ and $\mathbf{x}_{-1}^{(w,b)} = \mathbf{x}_{-1}$.

Iteration-specific foreign variables $\mathbf{x}_{it}^{*(w,b)}$ are then constructed using the window-specific trade weight matrix $\mathbf{W}_i^{(w)}$ for every i.

(c) In each bootstrap iteration, all the VECX* models are re-estimated on the simulated data. Following Dées et al. (2007ab), we estimate:

$$\begin{aligned}\Delta \mathbf{x}_{it}^{(w,b)} = \widehat{\mathbf{a}}_{\mathbf{0}i}^{(w,b)} - \widehat{\boldsymbol{\alpha}}_i^{(w,b)} \widehat{EC}_{i,t-1}^{(w,b)} - \widehat{\boldsymbol{\Phi}}_{2i}^{(w,b)} \Delta \mathbf{x}_{i,t-1}^{(w,b)} + \widehat{\boldsymbol{\Lambda}}_{0i}^{(w,b)} \Delta \mathbf{x}_{it}^{*(w,b)} + \\ - \widehat{\boldsymbol{\Lambda}}_{2i}^{(w,b)} \Delta \mathbf{x}_{i,t-1}^{*(w,b)} + \widehat{\boldsymbol{\nu}}_{it}^{(w,b)}\end{aligned} \tag{12}$$

where $\widehat{EC}_{i,t-1}^{(w,b)} = \widehat{\boldsymbol{\beta}}_i^{(w)\prime} \left[\mathbf{z}_{i,t-1}^{(w,b)} - \widehat{\boldsymbol{\gamma}}_i^{(w)} (t-1) \right]$ is the vector of estimated error correction terms corresponding to the $\widehat{r}_i^{(w)}$ cointegrating relations found on actual data in window w.

As a result, we obtain B different estimates of the GVAR model for each quarter from T_0 to T_{max}, denoted as:

$$\mathbf{x}_t^{(w,b)} = \widehat{\mathbf{c}}_\mathbf{0}^{(w,b)} + \widehat{\mathbf{c}}_\mathbf{1}^{(w,b)} t + \widehat{\mathbf{F}}_1^{(w,b)} \mathbf{x}_{t-1}^{(w,b)} + \widehat{\mathbf{F}}_2^{(w,b)} \mathbf{x}_{t-2}^{(w,b)} + \widehat{\boldsymbol{\varepsilon}}_t^{(w,b)} \tag{13}$$

(iii) Each of the B window-specific GVAR estimates is used to produce pseudo-out-of-sample forecasts for all the variables in the global economy (taking as starting values for each variable the last two actual values within the sample window). Let $\mathbf{x}_{T_w+h}^{(f)(b)}$ denote the h-step-ahead forecasts of the model estimated on window w in iteration b.

The outcome of the procedure is a sequence of multivariate distributions of global forecasts from T_0 to T_{max}. In each quarter, we measure variable-specific uncertainty as the standard deviation of four-quarter-ahead forecasts. Denoting with $x_{v,t}$ the generic v-th variable in the global vector $\mathbf{x}_t$ and with $u_{v,t}$ the corresponding uncertainty measure, we have:

$$u_{v,t} = \sqrt{\frac{1}{B-1} \sum_{b=1}^{B} \left(x_{v,t+4}^{(f)(b)} - \frac{1}{B} \sum_{b=1}^{B} x_{v,t+4}^{(f)(b)} \right)^2} \tag{14}$$

Each time series of uncertainty is then standardized by subtracting its mean and dividing by its standard deviation. We compute aggregate measures of uncertainty for each country by averaging the standardized $u_{v,t}$ across the respective domestic variables. Like in Jurado et al. (2015), we assign equal weights to the variables. However, using the first principal component yields very similar results, confirming that the driving factor of variable-specific uncertainties is their cross-sectional average. Global uncertainty is calculated as the weighted average of country-specific uncertainties, where the weights are given by annual GDP levels in purchasing-power parity (PPP) terms (in each quarter, we consider the previous year's GDP to ensure that the approach only uses data that were actually available in that quarter).[2]

Then, we repeat the procedure using rolling windows of length T_0 and we take the average between the uncertainty values produced by the recursive and rolling schemes. In this way, we make our index more robust to structural breaks, striking a balance between the higher efficiency achieved by the recursive scheme in the case of time-invariant parameters (which captures processes of "learning" on the part of economic agents) and the higher flexibility of the rolling scheme in the case of structural breaks. Clark and McCracken (2009) show that averaging recursive and rolling windows tends to improve forecast accuracy compared to either scheme, in the presence of structural breaks. Pesaran et al. (2009) argue for averaging GVAR forecasts across alternative estimation windows.

Our main results do not hinge on the forecast horizon considered. Very similar measures of uncertainty are obtained in standardized terms when a different forecast horizon is selected.

2.3. Spillovers of Uncertainty

Our GVAR-based approach allows to quantify global bilateral spillovers of uncertainty. The spillover from country i to country j is measured as the contribution of country i to uncertainty in country j, i.e., the component of forecast variance in country j that depends on parameter uncertainty in the country-specific model for i. This contribution can be decomposed into two terms.[3]

The first term is the effect of the variance–covariance matrix of parameters in the VARX* model for country i. Such an effect can be estimated by running a bootstrap simulation in which only the parameters of the VARX* for country i (i.e., the uncertainty-exporting country) are bootstrapped, while the other country-specific models are fixed at their point estimates. In particular, in step (2c) of the bootstrap procedure in Section 2.2, only the i-th VARX* is re-estimated on simulated data. All the other steps remain the same. As a result, in each iteration, the GVAR model is built by combining the bootstrapped estimates for country i with the maximum-likelihood estimates for the other countries, and forecasts are produced accordingly. We use $\bar{u}^2_{v_j,t,(i)}$ to denote the forecast variance of variable v_j in country j that results from this simulation at time t.

The second term is the effect of the covariances between the parameters of the VARX* model for country i and the parameters of the VARX* models for the other countries. This can be derived by running a bootstrap simulation in which all country-specific models are bootstrapped *except* the one for country i. More specifically, using $\bar{u}^2_{v_j,t,(-i)}$ to denote the forecast variance of variable v_j that results from this simulation (i.e., the forecast variance conditional on country i's parameters) and $u^2_{v_j,t}$ to denote the total forecast variance based on (14) (i.e., the forecast variance obtained when all country-specific models are bootstrapped at the same time), the difference $u^2_{v_j,t} - \bar{u}^2_{v_j,t,(-i)}$ captures the combined effect of country i's variance–covariance matrix (i.e., $\bar{u}^2_{v_j,t,(i)}$) and 2 times its covariances with all the other countries. Hence, the effect of the cross-country covariances can be derived as $\frac{1}{2}\left(u^2_{v_j,t} - \bar{u}^2_{v_j,t,(-i)} - \bar{u}^2_{v_j,t,(i)}\right)$.

The total contribution of country i to uncertainty in variable v_j is given by the sum of the two terms:

$$\bar{u}^2_{v_j,t,(i)} + \frac{1}{2}\left(u^2_{v_j,t} - \bar{u}^2_{v_j,t,(-i)} - \bar{u}^2_{v_j,t,(i)}\right) = \frac{1}{2}\left(\bar{u}^2_{v_j,t,(i)} + u^2_{v_j,t} - \bar{u}^2_{v_j,t,(-i)}\right) \tag{15}$$

Finally, this contribution is expressed as a fraction of the total forecast variance $u^2_{v_j,t}$. The ratios thus derived are averaged across domestic variables for country j and the average is taken as an aggregate measure of the spillover from i to j. Thus, the spillover from country i to country j at time t can be written as:

$$spillover_{j,i,t} = \frac{1}{k_j} \sum_{v_j=1}^{k_j} \frac{\frac{1}{2}\left(\bar{u}^2_{v_j,t,(i)} + u^2_{v_j,t} - \bar{u}^2_{v_j,t,(-i)}\right)}{u^2_{v_j,t}} \tag{16}$$

where k_j, as before, is the number of domestic variables in country j.

Importantly, by construction, these spillover measures do not rely on any particular ordering of countries. This is a difference compared to measures obtained from SVAR models using the Cholesky decomposition, as in the methodology by Diebold and Yilmaz (2009). In that case, different orderings may result in significantly different estimates of spillovers. Thus, to obtain measures that are invariant to the ordering of countries, spillovers have to be calculated across all possible permutations of the ordering and then averaged (see Klößner and Sekkel 2014).[4]

3. The Empirical Implementation

3.1. Data

The approach described in Section 2 is implemented for the 33 countries considered in Cesa-Bianchi, Pesaran, and Rebucci (2014) using quarterly data for the period 1979Q1–2020Q4. Sixteen countries are aggregated into three areas; hence, 20 economies are included in the GVAR: Australia (AUS), Brazil (BRA), Canada (CAN), China (CHN), the Euro area (EUR), India (IND), Japan (JAP), an aggregation of other Latin American economies (LAM), Mexico (MEX), New Zealand (NZL), Norway (NOR), Saudi Arabia (SAU), South Africa (ZAF), South-East Asia (SEA), South Korea (KOR), Sweden (SWE), Switzerland (CHE), Turkey (TUR), the United Kingdom (GBR) and the United States (USA). The composition of the three areas is the following: the Euro area includes Austria, Belgium, Finland, France, Germany, Italy, the Netherlands and Spain; the Latin American area includes Argentina, Chile and Peru; South-East Asia is composed of Indonesia, Malaysia, Philippines, Thailand and Singapore.

The variables included in the GVAR are real GDP levels, CPI quarterly inflation rates, short-term interest rates, exchange rates with respect to the USD and equity price indices. Exchange rates and equity indices are deflated using the consumer price index.[5] Domestic and foreign GDP, inflation and exchange rates are included in all the VARX* models (except for the domestic exchange rate in the U.S. model, since the USD is the numeraire currency). Domestic short-term interest rates are included as endogenous in all VARX* models except for Saudi Arabia (unavailable data) and for countries that experienced skyrocketing interest rates (higher than 100% on an annual basis) during major crises in the 80s and 90s (Brazil, Mexico, other Latin American countries and Turkey). Stock-market indices are included for the major financial economies, i.e., the United States, the Euro area, the United Kingdom and Japan. As is common in the GVAR literature, the U.S. model has fewer weakly exogenous variables than the others, given the special status of the United States in the global economy: in particular, the foreign interest rate and equity index are excluded, as they are more likely to be affected by the U.S. domestic counterparts, while foreign GDP, inflation and exchange rate are included. Foreign interest rates are included in all other country models, while foreign equity indices are included for the other major financial economies.

For any pair of countries i and j, the weight assigned to j in the construction of i's foreign variables is based on the average of i's exports to j and i's imports from j. In particular, to calculate window-specific foreign variables, we use the average trade weights observed in the 3 years prior to the final year of the window. The weights used to aggregate countries into areas are based on annual GDP levels in PPP. In each quarter, the aggregation weights are computed as the GDP shares in the previous year.

Unlike financial data, GDP and inflation data are typically revised, which raises the question of whether the accuracy of uncertainty measures can be improved by using real-time vintage data (see, e.g., Clements 2017). On the other hand, Jurado et al. (2015) claim that the use of real-time data may actually lead to biased estimates of uncertainty, since a substantial amount of information on macro variables becomes available to economic agents and forecasters well before official data releases. This paper does not use an exhaustive set of real-time GVAR vintages, which has not been compiled by previous research and may be considered for future extensions. However, the uncertainty measures are constructed using three available vintages of the GVAR dataset: the 2013 vintage by Cesa-Bianchi et al.

(2014), which is used to estimate uncertainty up to 2013Q1; the 2016 vintage prepared by Mohaddes and Raissi (2018), which is used to estimate uncertainty from 2013Q2 to 2016Q4; and the 2019 vintage prepared by Mohaddes and Raissi (2020), from 2017Q1 to 2019Q4. Finally, the observations for 2020Q1–2020Q4 are obtained by extrapolating forward the GVAR 2019 vintage, using data on growth rates (for real GDP, CPI indices, equity indices and exchange rates) and quarterly changes (for short-term interest rates). The data sources used for these quarters are reported in Appendix A. In any case, the approach proposed in the paper allows for full-fledged real-time measurement of uncertainty.

3.2. *Results*

3.2.1. *Global Macroeconomic Uncertainty (GMU) Index*

This section presents the uncertainty measure constructed using the approach described in Section 2.[6] As explained above, we estimate the GVAR on both recursive and rolling windows and we average the values of uncertainty obtained using the two schemes, in order to make our indicator robust to structural breaks while exploiting all available data. In the first case, the shortest window spans the period 1979Q4–2000Q1, then the sample is extended by one-quarter increments up to 1979Q4–2020Q4. In the second, we take 1979Q4–2000Q1 as the initial window, we fix the window length and we repeatedly move the sample forward, up to 2000Q3–2020Q4.[7] Figure 1 plots our global macroeconomic uncertainty (GMU) index, constructed from 2000Q1 to 2020Q4. The index exhibits large increases during the global financial crisis (GFC) and, in particular, the COVID-19 crisis. It shows a local peak (at 2.4 standard deviations above the mean) in 2008Q4, around the Lehman Brothers collapse, then goes back to normal levels in the second half of 2009. It reaches its global peak in 2020Q2 (5.2 standard deviations, approximately), then decreases but remains at high levels in 2020Q3 (2.7 standard deviations) and 2020Q4 (0.6).

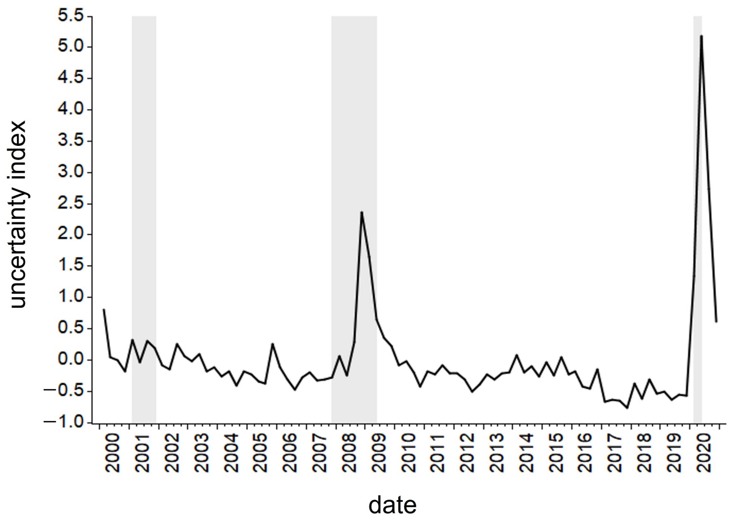

Figure 1. Global macroeconomic uncertainty (GMU) index. *Notes:* The index is calculated as the PPP GDP-weighted average of country-level uncertainties and is expressed in standardized units. Each country-level index is calculated as the average uncertainty across the domestic variables included in the GVAR model. The data are quarterly and span the period 2000Q1–2020Q4. Shaded areas indicate NBER recession periods.

Next, we compare the GMU index with a variety of other measures of uncertainty. Figure 2 provides pairwise comparisons of GMU with seven alternative measures: the VIX, i.e., the index of option-implied volatility in the S&P 500; the U.S. macro uncertainty index by Jurado et al. (2015) (JLN henceforth); the World Uncertainty Index (WUI) by Ahir et al. (2022); the Global Economic Policy Uncertainty (GEPU) index by Baker, Bloom and Davis (Baker et al. 2016; Davis 2016); the global uncertainty measure by Ozturk and Sheng (2018) (OS); the PPP GDP-weighted average of the uncertainty measures by Scotti (2016) (constructed for USA, EU, UK, Canada and Japan); and the PPP GDP-weighted average of the uncertainty measures for Euro area countries (Germany, France, Italy and Spain) by Meinen and Roehe (2017) (MR), based on the Jurado et al. (2015) approach. At the time of writing, the VIX, JLN, WUI and GEPU indices are available over the entire period 2000Q1–2020Q4, the OS index up to 2020Q3, the Scotti index from 2003Q2 to 2020Q4 and the MR index from 2000Q1 to 2015Q4. In Figure 2, all indices are standardized over the period 2000Q1–2020Q4 or the shorter period for which they are available (with the exception of GMU when compared to MR, in which case both are standardized over 2000Q1–2015Q4). In the last (bottom-right) panel of the figure, we compare GMU with the first principal component (PC) of all the other uncertainty measures, excluding MR because of its short time span. As the figure shows, the time profile of GMU is very similar to that of the common factor (PC) of the other uncertainty measures, and GMU shares important characteristics with all types of different measures. First of all, it is broadly consistent with the VIX, JLN and OS. Like GMU, these indices experience large increases during both the GFC period and the COVID-19 crisis. The VIX spikes in the same quarters as GMU, 2008Q4 and 2020Q2, and the levels of the peaks in JLN and OS are very similar to those of GMU. Excluding crisis periods, these indices also share a similar downward trend between 2000 and 2019. However, there are also some remarkable differences. The peak in financial-market volatility during the COVID-19 crisis (1.8 standard deviations above the mean) is much lower than during the GFC (almost 5 standard deviations), whereas global macroeconomic uncertainty increases more during the COVID-19 pandemic. More generally, the average level of the VIX during the COVID-19 crisis is not especially high: for instance, similar levels were observed in 2002, following the dot-com bubble. These differences between GMU and VIX do not simply reflect the fact that the VIX is a U.S.-based measure while GMU is global. The global financial uncertainty (GFU) index recently proposed by Caggiano and Castelnuovo (2021) behaves very similarly to the VIX (over the period 2000Q1–2020Q2, the correlation between the two is 0.92). Unlike GMU, which decreases in the last part of 2020, the JLN index continues to increase over the entirity of 2020, reaching 4.3 standard deviations above the mean in the last quarter.

Compared to the WUI, the GMU index tends to associate global uncertainty increases with major crises. Conversely, the WUI does not show any remarkable increase during the GFC. Also, it rises quite dramatically in 2018–2019 and peaks in 2020Q1, at the beginning of the COVID-19 epidemic, then goes rapidly down to pre-COVID levels in 2020Q2. The GEPU index is similar to the WUI, except that it remains at very high levels in 2020Q2–2020Q4. Like GMU, policy uncertainty has a global peak in 2020Q2. Overall, GMU appears less noisy than WUI and GEPU.

The GMU index is broadly consistent with the Scotti index, especially during the COVID-19 period, but is substantially higher during the GFC period. The paths of GMU and MR are also quite similar, especially from 2000 to 2009. In the period 2010–2012, MR is a bit higher, which reflects the larger weight of countries hit by the debt crisis (Italy and Spain) in its construction, while after 2012, GMU is slightly higher.

Table 1 shows the correlations between the different uncertainty measures considered. The correlations are computed over different samples, depending on the availability of the series (the correlations between GMU, VIX, JLN, WUI and GEPU are computed over the period 2000Q1–2020Q4, the correlations with OS over 2000Q1–2020Q3, with Scotti over 2003Q2–2020Q4, and with MR over 2000Q1–2015Q4). As already suggested by Figure 2, GMU is especially correlated with the survey-forecast-based indices of Scotti (correlation of 0.87) and OS (0.75), as well as with JLN (0.74), but is also highly correlated with the VIX (0.64). The correlation of GMU with the first principal component of the other uncertainty measures is 0.89. Importantly, GMU appears to reconcile different uncertainty measures: the average correlation between GMU and all other indices in Table 1 is 0.58 (0.57 excluding the shorter MR series), which is greater than the average correlation between the other indices, 0.41 (0.39). No other uncertainty index shows a greater average correlation with different measures. Thus, for instance, GMU reconciles financial-market uncertainty and economic-policy uncertainty (on the decoupling of the two in the past, see ECB 2017): the correlation between GMU and VIX (0.64) and the correlation between GMU and GEPU (0.39) are both greater than the correlation between VIX and GEPU (0.19). Still, the results indicate that macroeconomic uncertainty has been more strongly associated with financial uncertainty than with policy uncertainty, in recent decades. At the same time, GMU appears to summarize the information provided by survey-forecast-based measures of uncertainty: the OS index (which is based on survey data from the *Consensus Forecasts*, published by Consensus Economics) and the Scotti index (which is constructed using the forecast errors associated with the median of Bloomberg survey forecasts) are both more strongly correlated with GMU (0.81, on average) than with each other (0.56). The remaining measure of global uncertainty, the WUI, is highly correlated with GEPU (0.67) but almost uncorrelated with all other indices.

Table 1. Correlations between uncertainty measures.

	VIX	JLN	WUI	GEPU	OS	Scotti	MR	GMU
VIX	1.00							
JLN	0.62	1.00						
WUI	0.01	−0.02	1.00					
GEPU	0.19	0.33	0.67	1.00				
OS	0.67	0.89	0.14	0.35	1.00			
Scotti	0.34	0.61	0.05	0.49	0.56	1.00		
MR	0.83	0.65	0.01	0.32	0.75	0.22	1.00	
GMU	0.64	0.74	0.06	0.39	0.75	0.87	0.62	1.00

Notes: In this table, GMU is the global macroeconomic uncertainty index; VIX is the volatility index by the Chicago Board Options Exchange; JLN is the U.S. macro uncertainty index by Jurado et al. (2015); WUI is the World Uncertainty Index by Ahir et al. (2022); GEPU is the global index of economic policy uncertainty by Baker, Bloom and Davis (Baker et al. 2016; Davis 2016); OS is the global uncertainty index by Ozturk and Sheng (2018); Scotti is the (PPP) GDP-weighted average of the country-specific uncertainty indices by Scotti (2016); and MR is the (PPP) GDP-weighted average of the uncertainty measures for Euro area countries by Meinen and Roehe (2017). Correlations between GMU, VIX, JLN, WUI and GEPU are computed over the period 2000Q1–2020Q4. Due to data availability issues, correlations with the other three measures are computed over shorter periods: 2000Q1–2020Q3 for OS, 2003Q2–2020Q4 for Scotti and 2000Q1–2015Q4 for MR.

Next, we construct an alternative measure of global uncertainty by applying the Jurado et al. (2015) methodology, based on a factor-augmented VAR with stochastic volatility, to all the endogenous variables included in the GVAR (78 variables),[8] and we compare GMU with this alternative measure, which we label as Global JLN, in Figure 3. As the figure shows, the two measures are quite similar (the correlation coefficient is 0.77). The main differences are that Global JLN predicts roughly equal levels of uncertainty during the GFC and the COVID-19 periods, lower uncertainty in 2013–14 compared to GMU and higher uncertainty in 2007 and early 2008. It should be reiterated, however, that Global JLN, like the original U.S. JLN shown in Figure 2 and unlike GMU, is an ex-post measure of uncertainty, resulting from full-sample (1979Q2–2020Q4) estimation of the model.

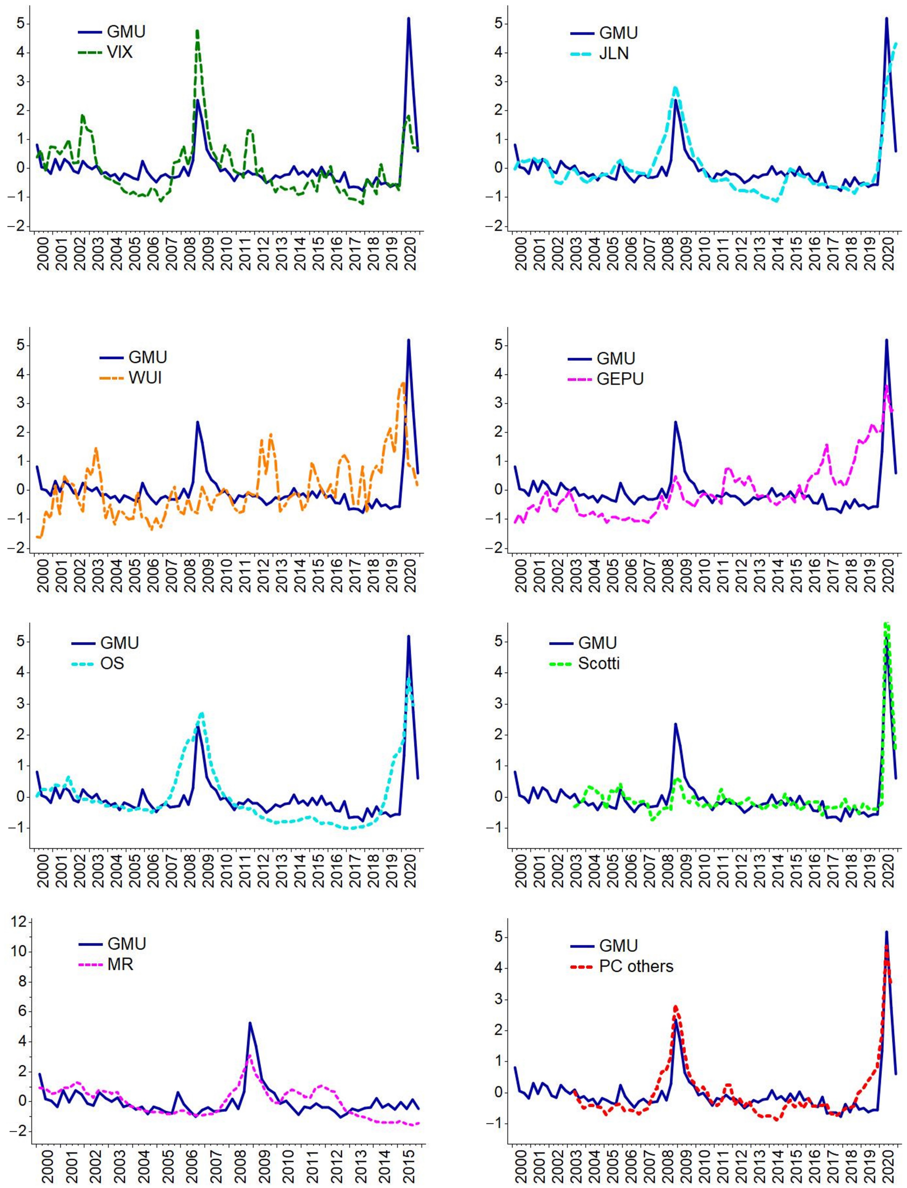

Figure 2. GMU compared to other uncertainty measures. *Notes:* In this figure, GMU is the global uncertainty index from Figure 1; VIX is the U.S. stock market volatility index by the Chicago Board Options Exchange; JLN is the updated version (as of July 2021) of the 12-month-ahead macro uncertainty index by Jurado et al. (2015); WUI is the World Uncertainty Index by Ahir et al. (2022); GEPU is the global index of economic policy uncertainty by Baker, Bloom and Davis (Baker et al. 2016; Davis 2016); OS is the global uncertainty index by Ozturk and Sheng (2018); Scotti is the (PPP) GDP-weighted average of the country-specific uncertainty indices by Scotti (2016); MR is the (PPP) GDP-weighted average of the uncertainty measures for Euro-area countries by Meinen and Roehe (2017); and PC others is the first principal component of all uncertainty measures other than GMU (excluding MR because of the shorter sample). All indices are reported at the quarterly frequency; those available at higher frequencies are averaged within each quarter. All indices are standardized over the period 2000Q1–2020Q4 or the shorter period for which they are available.

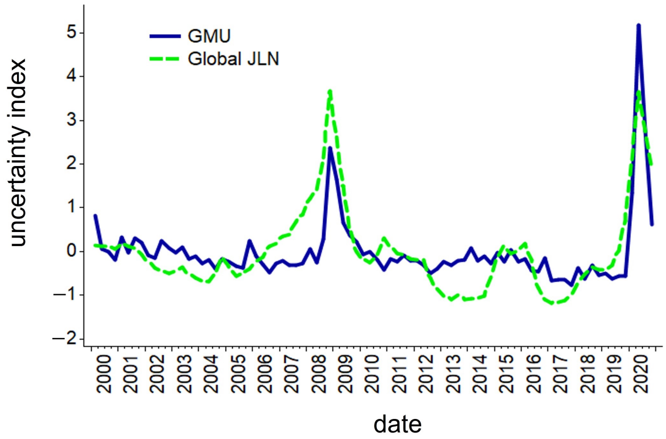

Figure 3. GMU and Global JLN uncertainty measures. *Notes:* The figure shows the GMU index along with an alternative measure of global uncertainty obtained by applying the methodology by Jurado et al. (2015) to the variables considered in the GVAR model (Global JLN).

Figure 4 plots our country-level measures of macroeconomic uncertainty and variable-specific uncertainties for a selection of economies: U.S., Euro area, U.K., China and India. The uncertainty measures are highly correlated across countries (the average correlation in the GVAR is 0.94 over the entire sample, 0.86 excluding 2020). Their dynamics, thus, reflect a global common component of uncertainty. Such co-movement results from global uncertainty shocks (captured by the international correlations of country-specific shocks in the GVAR) and from the dynamic propagation of country-specific shocks to other countries. Dées et al. (2007a) first showed that the GVAR approximates a global factor model, by including cross-country averages in country-specific models. At the same time, it allows to track the international transmission of country-specific shocks, a feature that we further exploit to calculate global spillovers of uncertainty in Section 3.2.2. Figure 4 also shows that, while the dynamics of macroeconomic uncertainty are largely shared across countries, the level of uncertainty differs remarkably. For instance, GDP and inflation uncertainties tend to be higher in China and India than in the U.S., Euro area and U.K.

Thus, our GVAR-based approach appears to capture a common component of uncertainty, reflecting strong economic interactions between countries as well as macroeconomic and financial linkages within countries. To shed more light on the long-run relationships between variables at the global level, we consider the cointegration equations estimated in country-specific VECX* models, linking domestic and foreign variables. As explained in Section 2.2, the estimates of cointegrating vectors and cointegration ranks are updated in every sample window used to construct our uncertainty measure. To comment on the long-run properties of the GVAR model, we focus on the estimates of the cointegration parameters ($\boldsymbol{\beta}_i$ from Section 2.1) and the associated adjustment coefficients ($\boldsymbol{\alpha}_i$) obtained using the full sample 1979Q2–2020Q4. We report these estimates for all VECX* models in Appendix B.

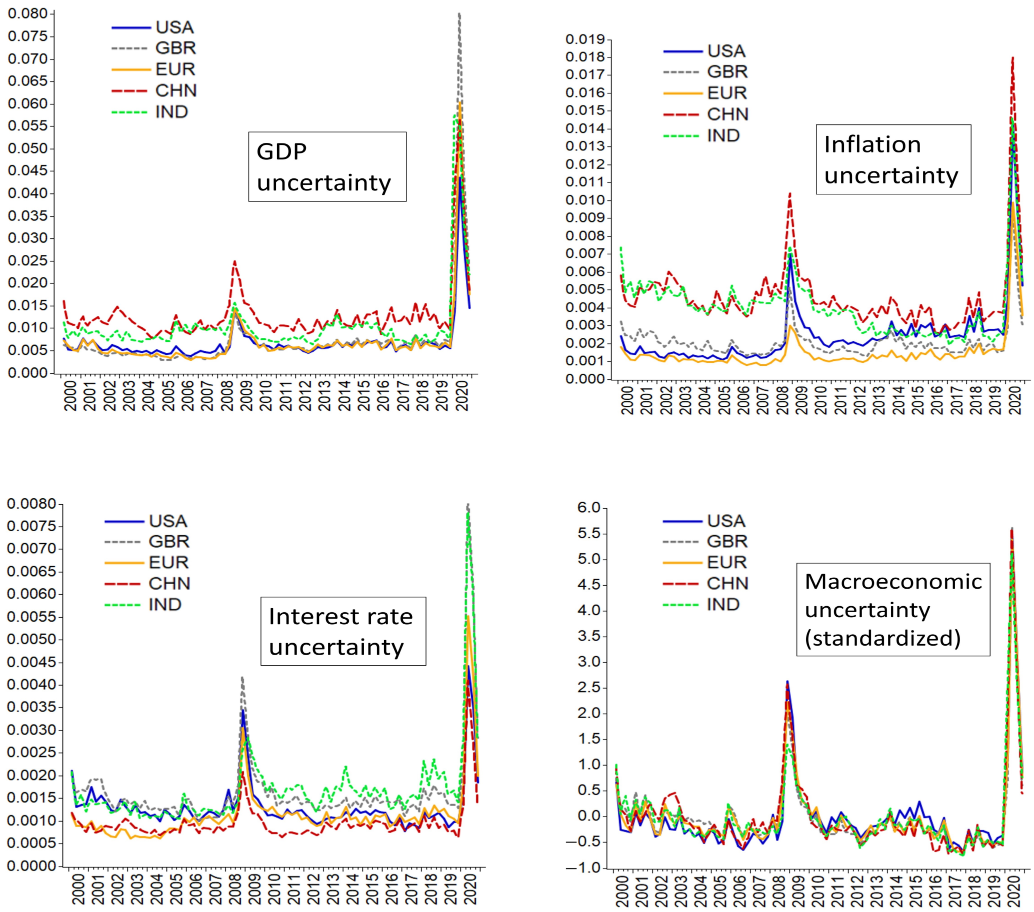

Figure 4. Macroeconomic uncertainty and variable-specific uncertainties in the U.S., Euro area, U.K., China and India. *Notes:* Each index in the bottom-right panel is calculated as the average uncertainty across the respective domestic variables and is expressed in standardized units. The other panels show non-standardized variable-specific uncertainties: the vertical axis measures the forecast standard deviation of the corresponding variable. The data are quarterly and span the period 2000Q1–2020Q4.

Overall, cointegration analysis provides several results (in line with the findings of previous GVAR literature, see, e.g., Pesaran et al. 2004) that help account for the strong international transmission of shocks, and, thus, the substantial commonality between uncertainty measures across countries and variables. First, the global economy is strongly interconnected in the long run: at least one foreign variable is significant in the cointegration equations of every country-specific VECX* model, except for the United States, which is unsurprisingly less affected by the rest of the world. For instance, the levels of domestic GDP and foreign GDP are positively and significantly linked in the long run (i.e., foreign GDP is associated with a negative and significant coefficient in the cointegrating vector normalized to 1 for domestic GDP) in half of the country-specific models (EUR, GBR, AUS, CAN, CHN, IND, KOR, NOR, SEA, ZAF). Second, the estimates indicate substantial long-run linkages between real and financial variables. For instance, higher output is significantly associated in the long run (all else being equal) with higher short-term interest rates in all four "financial economies" (USA, EUR, JAP, GBR) and with exchange-rate appreciation (specifically, a positive coefficient on the domestic exchange rate, measured in units of domestic currency per USD, and a negative coefficient on the foreign exchange rate in cointegrating vectors $\boldsymbol{\beta}_i$) in the majority of economies (EUR, GBR, JAP, AUS, CAN, CHE, CHN, IND, NZL, SEA, SWE, MEX, SAU). Third, the global economy tends to adjust towards its long-run equilibrium, i.e., the adjustment coefficients (α_i) tend to be well-behaved. More specifically, about two thirds of the adjustment coefficients have opposite sign compared to the cointegrating coefficients on the same variables, indicating a reduction in the short-run disequilibrium.

3.2.2. *Global Spillovers of Uncertainty*

We then quantify global cross-country spillovers of macroeconomic uncertainty, applying the GVAR-based decomposition described in Section 2.3.[9] Table 2 reports all bilateral spillovers measured in 2019Q4 using the GVAR estimates obtained on the sample 1979Q4–2019Q4, so that the results are not driven by the exceptional period of the COVID-19 pandemic.

Each number in the table represents the contribution of the country in the column to the domestic uncertainty of the country in the row, in percentage. The *From* column reports the total contribution of foreign countries to the uncertainty of the country in the row, and the row *To* reports the average contribution from the country in the column to all other countries, weighted by the PPP GDP levels of the destination countries. On average, spillovers from foreign countries account for approximately 40% of domestic uncertainty.

The single largest source of uncertainty at the end of 2019 is China. The average spillover from China, weighted by the PPP GDP of the destination countries, is 9.1%, approximately. Large spillovers are also generated by the Unites States (average spillover: 5.7%) and the Euro area (4.0%). Brazil is another country which produces sizeable spillover effects (5.4%, although this result appears largely driven by the huge fluctuations in Brazilian inflation in the period up to the mid 1990s, and is downsized to about 1% if we exclude that period). The largest spillovers from the U.S. are observed in Canada (24%), the Euro area (15%), and the U.K. (15%). Spillovers from the Euro area are especially high in Sweden (20%), Norway (19%), Turkey (17%), U.K. (15%), and Switzerland (14%). Spillovers from Brazil are highest in the Latin-American area (19%). China, Brazil and South-East Asia are also the economies where domestic sources of uncertainty play the largest role (total foreign contributions account for 15%, 19% and 22%, respectively). At the other extreme, the countries that receive the largest spillovers from the rest of world are Canada (where the total foreign contribution amounts to 74% of uncertainty), Sweden (73%), the U.K. (59%) and Switzerland (58%).

Interestingly, our estimate of the average spillover effect lies in between those found by Klößner and Sekkel (2014), on the one hand, and Rossi and Sekhposyan (2017), on the other, both estimating spillovers between advanced economies using the network approach by Diebold and Yilmaz (2009). Klößner and Sekkel (2014) investigate spillovers of the EPU index between Canada, France, Germany, Italy, the U.K. and the U.S. between 1997 and 2013. According to their estimates, the overall spillovers among these countries account for approximately one quarter of total uncertainty. Rossi and Sekhposyan (2017) study the spillover effects of output growth and inflation uncertainty within the Euro area. They find that overall spillovers amount to about 74% of output growth uncertainty and 78% of inflation uncertainty. Other papers only estimate aggregate foreign contributions to domestic uncertainty. Cesa-Bianchi et al. (2020) find that more than half of the total variance of realized country-specific financial volatility is explained by common (global) financial shocks. Mumtaz (2018) estimates that the contribution of foreign uncertainty to U.K. macroeconomic uncertainty was, on average, between 40% and 45% after the 1970s. All these papers measure spillovers using forecast error variance decomposition. Angelini et al. (2018) and Bacchiocchi and Dragomirescu-Gaina (2022) assess spillover effects in the Euro area in a different but related way, i.e., using impulse response functions (IRFs). As explained below, we consider IRFs in Appendix C.

As already stressed, this paper provides value added by developing a single econometric framework for measuring both global uncertainty and bilateral spillovers, thus avoiding the dual-methodology approach adopted so far in the literature and ensuring coherence in the measurement of uncertainty and spillovers. To conclude our analysis, we compare our results with an alternative measure of global spillovers obtained in a two-step way. In particular, we take the country-specific uncertainty indices constructed by Ozturk and Sheng (2018) and apply the Diebold and Yilmaz (2009) methodology to measure spillovers. Thus, we estimate an SVAR model on the uncertainty indices and perform forecast error variance decomposition to estimate spillovers. We label these spillover measures as OS-DY spillovers. We use the uncertainty measures by Ozturk and Sheng (2018) as they are available for almost all countries considered in this paper, unlike other indicators. In addition, as shown in Figure 2 and Table 1, GMU and the global uncertainty index by Ozturk and Sheng (2018) are highly consistent with each other. We estimate a quarterly SVAR from 2001Q3 to 2019Q4 (including only one lag, given the relatively short time span). The start date of the sample is dictated by data availability issues (in particular, the indices for Argentina, Brazil, Chile, Mexico, and Peru are only available from 2001Q2), while the end date is chosen to allow for a direct comparison with the results reported in Table 2. The uncertainty measures by Ozturk and Sheng (2018) are available for all countries considered in this paper except Saudi Arabia and South Africa. We also exclude Turkey from the SVAR and Philippines from the construction of the South-East Asia aggregate because the uncertainty indices for these countries are only available for short periods (from 2007Q2 and 2009Q3, respectively). Thus, we include 17 variables in the SVAR. Ozturk and Sheng (2018) provide an aggregate uncertainty index for the Eurozone from 2003Q1, for previous quarters we use the PPP GDP-weighted average of the indices for France, Germany, Italy, Netherlands and Spain. To be consistent with the forecast horizon used to construct our uncertainty measure, we estimate OS-DY spillovers by considering forecast error variance decomposition over a horizon of four quarters after the shocks (hence five quarters including the period in which the shocks occur). As mentioned in Section 2.3, unlike the spillover measures proposed in this paper, SVAR-based measures are not invariant to the ordering of countries. Thus, we need to consider all possible permutations of the Cholesky ordering (in this case, $!17 = 3.56 \times 10^{14}$) and then average the estimates across different permutations.[10]

Table 3 presents the results. Compared to our GVAR-based measures of global spillovers, OS-DY spillovers show some remarkable differences. First, foreign sources of uncertainty appear to play a much larger role in Table 3. On average, 80% of country-level uncertainty is estimated to be imported from the rest of the world (the corresponding estimate from Table 2 is about 40%). Even for the United States, around 76% of macroeconomic uncertainty is accounted for by foreign factors, a result which appears hard to rationalize based on economic considerations, given the prominent role of the U.S. in the global economy and its low trade-to-GDP ratio (23% in 2020, according to World Bank data). Second, unlike in Table 2, China is estimated to generate small spillover effects. The largest global OS-DY spillovers are generated by Australia (the average spillover weighted by the PPP GDP of the destination countries is 13%), the Euro area (13%), Switzerland (10%) and the U.S. (8%). Looking at similarities between the two tables, in both cases, Canada and Sweden are among the countries that receive the largest spillovers from abroad, while the Euro area and the U.S. are among the largest sources of spillovers.

Table 2. Global spillovers of macroeconomic uncertainty.

	AUS	BRA	CAN	CHE	CHN	EUR	GBR	IND	JAP	KOR	LAM	MEX	NOR	NZL	SAU	SEA	SWE	TUR	USA	ZAF	*From*
AUS	66.9	2.6	0.1	−0.1	14.2	1.8	0.5	0.8	3.1	1.3	1.0	0.5	0.2	0.6	0.8	3.6	−0.4	0.1	2.4	0.3	33.1
BRA	0.4	80.8	−0.2	−0.3	5.7	3.0	0.1	0.4	1.9	0.8	2.4	1.0	−0.1	0.1	0.1	1.0	−0.5	0.2	3.0	0.1	19.2
CAN	1.5	6.0	25.8	0.2	14.9	7.1	2.1	1.5	4.1	1.8	0.8	4.8	0.1	0.3	1.4	3.2	0.0	0.2	23.7	0.5	74.2
CHE	0.9	12.2	0.1	41.7	10.7	13.6	3.6	0.6	3.3	0.3	0.9	1.8	0.0	0.2	0.8	1.0	−0.5	0.3	8.2	0.3	58.3
CHN	0.0	6.7	0.0	−0.1	84.7	1.4	0.8	0.0	2.0	0.3	0.3	0.1	0.0	0.0	0.4	2.8	−0.3	0.0	0.8	−0.1	15.3
EUR	0.9	9.7	0.1	0.2	11.8	46.8	3.7	0.9	3.1	1.3	1.1	2.2	0.1	0.2	1.0	2.2	−0.5	0.6	14.8	0.0	53.2
GBR	0.7	6.0	0.0	0.2	10.3	14.8	41.1	1.0	2.5	1.3	1.0	2.0	0.0	0.2	1.2	2.1	−0.2	0.5	15.3	−0.1	58.9
IND	1.4	5.2	0.3	0.5	10.7	4.9	2.5	58.1	3.5	1.5	1.3	1.4	0.0	0.1	2.3	0.0	−0.2	0.7	5.5	0.3	41.9
JAP	1.2	2.3	0.3	−0.2	8.1	4.3	1.4	0.5	69.0	1.1	0.6	1.3	-0.1	0.1	0.4	3.1	−0.2	0.0	6.8	0.1	31.0
KOR	0.7	2.4	0.3	0.5	8.3	2.8	1.7	1.1	3.0	66.3	1.3	1.5	0.0	0.1	0.9	6.1	0.2	0.6	2.3	0.0	33.7
LAM	−0.1	18.9	−0.1	−0.4	4.4	1.4	−0.3	0.6	0.1	−0.2	73.0	0.1	0.0	0.2	0.2	−0.4	−0.2	−0.5	3.0	0.1	27.0
MEX	0.7	5.7	0.2	0.4	4.7	1.1	1.1	0.9	0.7	1.2	0.4	75.0	0.1	0.1	0.6	−0.8	0.1	−0.1	7.9	−0.1	25.0
NOR	0.5	3.5	0.0	0.5	6.6	19.3	2.9	0.6	2.4	0.1	0.9	0.7	56.2	0.1	0.1	1.7	0.4	0.4	3.1	0.1	43.8
NZL	4.2	2.9	0.5	0.0	10.2	3.0	1.1	0.5	2.3	0.8	1.2	1.3	0.2	62.7	0.4	6.7	−0.1	0.2	1.6	0.2	37.3
SAU	0.3	3.5	0.6	0.5	10.0	3.6	1.4	1.1	5.1	1.0	0.8	0.4	0.1	0.0	69.8	−2.0	−0.2	1.1	2.8	0.1	30.2
SEA	0.1	1.9	1.1	−0.3	4.9	2.2	1.2	0.2	2.8	3.1	1.4	0.9	0.1	0.1	0.3	77.9	−0.1	0.7	1.4	0.0	22.1
SWE	0.9	13.0	0.4	0.3	11.9	19.6	4.6	0.9	3.9	1.0	1.3	2.6	0.6	0.3	1.2	2.5	27.6	0.6	6.7	0.2	72.4
TUR	0.2	4.2	−0.1	0.6	8.1	17.1	2.2	1.5	2.9	0.6	0.3	1.2	−0.1	0.1	1.4	0.2	0.0	56.1	3.1	0.5	43.9
USA	1.4	2.1	0.9	0.1	8.9	4.2	1.7	1.3	1.5	1.9	0.9	6.2	0.1	0.3	0.9	3.0	0.0	0.2	64.3	0.1	35.7
ZAF	0.6	2.7	0.1	0.2	8.6	1.9	1.3	0.6	4.2	0.1	1.0	0.6	0.0	0.1	0.8	4.9	−0.1	0.0	2.3	70.0	30.0
To	0.7	5.4	0.3	0.1	9.1	4.0	1.7	0.7	2.4	1.2	0.9	2.1	0.0	0.1	0.8	2.2	−0.2	0.3	5.7	0.1	39.3

Notes: The table shows the cross-country spillovers of macroeconomic uncertainty measured in 2019Q4 using the parameter estimates obtained on the sample 1979Q4–2019Q4. Each number represents the contribution of the country in the column to the domestic uncertainty of the country in the row, in percentage. The column *From* reports the total contribution from other countries to the uncertainty of the country in the row. The row *To* reports the average contribution from the country in the column to all other countries, weighted by the PPP GDP levels of the destination countries. Please refer to Section 2 in the paper for details on how spillovers are calculated. Countries are identified by ISO codes (see Section 3.1). The codes for the aggregate areas are: EUR = Euro area, LAM = Latin-American area and SEA = South-East Asia.

Table 3. Spillovers of Ozturk and Sheng (2018) uncertainty measures estimated using the Diebold and Yilmaz (2009) approach.

	AUS	BRA	CAN	CHE	CHN	EUR	GBR	IND	JAP	KOR	LAM	MEX	NOR	NZL	SEA	SWE	USA	*From*
AUS	16.5	6.6	5.2	10.3	2.8	15.7	4.6	2.6	1.4	4.4	1.2	2.0	3.2	7.2	1.9	3.5	11.1	83.5
BRA	7.3	22.4	3.5	4.5	8.3	12.8	5.3	5.9	1.8	4.0	2.8	2.6	0.9	2.8	3.5	2.5	9.0	77.6
CAN	14.3	4.3	9.8	5.4	7.1	18.2	5.4	3.6	0.9	2.6	3.1	3.5	1.6	3.0	4.0	1.7	11.5	90.2
CHE	18.7	3.6	6.2	19.8	3.5	13.6	2.7	5.6	1.3	1.0	1.3	1.1	3.9	3.7	2.5	1.5	9.9	80.2
CHN	15.1	5.7	3.4	16.6	17.5	10.3	3.0	2.1	1.7	3.3	1.4	2.3	2.3	2.4	2.9	2.6	7.7	82.5
EUR	14.4	4.9	4.7	6.8	3.0	33.4	2.7	2.8	1.0	3.0	2.1	0.9	3.0	3.6	1.6	4.9	7.3	66.6
GBR	9.6	3.6	7.7	5.4	4.0	21.6	14.4	2.2	1.6	1.7	1.1	1.2	1.3	6.5	3.0	2.1	13.0	85.6
IND	7.5	8.6	2.7	11.2	4.0	6.5	2.0	37.5	3.8	2.9	0.6	0.7	1.8	1.9	2.9	2.6	2.9	62.5
JAP	5.1	6.5	2.9	9.3	2.3	10.8	2.3	5.3	18.4	3.9	0.9	1.8	3.3	3.2	2.5	2.1	19.5	81.6
KOR	9.4	3.9	2.6	15.0	3.5	8.1	2.4	3.1	6.0	14.0	0.6	2.2	2.5	6.8	2.2	5.2	12.3	85.9
LAM	10.5	10.9	1.3	1.5	1.4	9.8	2.0	1.3	1.0	1.2	32.2	9.2	4.5	0.9	1.4	1.3	9.6	67.8
MEX	8.4	4.1	3.3	5.2	9.5	19.8	3.3	4.8	2.6	3.1	5.8	13.4	1.3	2.2	2.9	2.0	8.3	86.6
NOR	5.7	4.3	1.7	16.0	1.4	7.6	4.5	7.4	4.5	1.3	1.4	1.4	28.2	3.6	1.0	7.7	2.4	71.8
NZL	8.7	2.1	7.6	8.8	2.6	11.1	5.0	6.0	5.0	4.6	0.7	1.6	2.0	13.9	2.6	2.4	15.1	86.1
SEA	11.1	6.0	7.1	8.9	6.0	18.2	3.1	3.7	1.4	5.0	1.8	2.5	1.8	3.0	10.2	2.3	7.8	89.8
SWE	7.2	1.4	2.9	18.2	0.9	14.5	2.1	7.3	5.2	1.4	1.2	3.0	5.6	8.5	3.1	13.9	3.6	86.1
USA	18.3	3.9	4.1	5.6	1.1	16.1	3.0	3.5	3.6	1.1	1.0	2.0	1.3	4.4	5.4	2.0	23.8	76.2
To	13.1	5.5	4.0	9.8	3.4	12.9	2.9	3.2	2.3	2.8	1.5	2.0	2.1	3.3	3.2	2.7	8.4	80.0

Notes: The table shows spillovers of country-specific uncertainty measures by Ozturk and Sheng (2018), estimated using the Diebold and Yilmaz (2009) methodology. Spillovers are estimated over the sample 2001Q3–2019Q4 using an SVAR model with the uncertainty measures as endogenous variables (see Section 3.2.2 for more details). Each number represents the contribution of the country in the column to the domestic uncertainty of the country in the row, in percentage. The column *From* reports the total contribution from other countries to the uncertainty of the country in the row. The row *To* reports the average contribution from the country in the column to all other countries, weighted by the PPP GDP levels of the destination countries. Countries are identified by ISO codes (see Section 3.1). The codes for the aggregate areas are: EUR = Euro area, LAM = Latin-American area and SEA = South-East Asia.

Overall, these results reflect an important difference between the approach proposed in this paper and the alternative approach now considered. The GVAR-based approach allows to impose more economic structure on the estimated spillovers of uncertainty, since economic and financial interactions between countries are explicitly modeled in the GVAR and taken into account in the decomposition of uncertainty. Conversely, the two-step SVAR-based approach provides a statistical decomposition of uncertainty that does not exploit information on cross-country economic linkages. For instance, our approach allows to obtain estimates of international spillovers of macroeconomic uncertainty that are much more consistent with the relative size of different economies and with international trade patterns. The total global spillovers generated by individual countries (the row *To* in Tables 2 and 3) are more highly correlated with their GDP levels in the case of our GMU spillovers (which show a correlation of 0.8 with PPP GDP levels, averaged over the period 2000–2019) than in the case of OS-DY spillovers (the correlation is 0.3). The estimated average contribution to uncertainty from foreign economies in Table 2, roughly 40%, is closer to the trade-to-GDP ratio at the world level (about 56% on average over the period 2000–2019, according to World Bank data), compared to the 80% value from Table 3. In addition, cross-border spillovers from Table 2 (i.e., the off-diagonal elements) are more highly correlated with international trade flows (the correlation with trade weights as of 2019 is 0.7, approximately), than the OS-DY spillovers (the correlation is 0.3, approximately). Overall, GMU spillovers appear to more strongly reflect the roles played by different countries in the global economy.

As an extension of our spillover analysis, in Appendix C we consider dynamic spillover effects as measured by the impulse response functions (IRFs) of an SVAR model, estimated using, alternatively, our GVAR-based uncertainty measures and the country-specific uncertainty measures by Ozturk and Sheng (2018).

4. Conclusions

Economic uncertainty is a global phenomenon in two ways: on the one hand, global uncertainty shocks (e.g., generated by the COVID-19 pandemic) hit different countries at the same time; on the other, country-specific shocks spread across borders through international economic and financial linkages, increasing uncertainty on a global scale. The main contribution of this paper is to provide a unified econometric framework, based on the GVAR model, for simultaneously measuring global uncertainty and global bilateral spillovers between country-level uncertainties, in a mutually coherent way. The available econometric approaches for measuring global uncertainty do not directly quantify bilateral spillovers, which are currently measured (only for advanced economies) in a two-step way, using one methodology to measure uncertainty and a different methodology to measure uncertainty spillovers.

We show that our index of global macroeconomic uncertainty (GMU) is able to reconcile a variety of different measures, including financial-market volatility, economic-policy uncertainty, survey-forecast-based measures and uncertainty measures *à la* Jurado et al. (2015). Moreover, since economic and financial relationships between countries are explicitly modeled in the GVAR and taken into account when measuring uncertainty spillovers, the approach proposed in the paper produces spillover estimates that are directly related to the structure of the global economy, e.g., they are strongly correlated with the relative size of different economies and with international trade patterns. We show that this is an important difference compared to a conventional two-step approach using an SVAR-based statistical decomposition of uncertainty to estimate spillovers.

Empirically, we find that about 40% of country-level uncertainty, on average, is accounted for by spillovers from the rest of the world. As of 2019, China, the United States and the Euro area generate comparatively large spillovers, while Canada, Sweden, the U.K. and Switzerland are the countries that receive the largest spillovers from the rest of world.

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Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found here: vintages of the GVAR dataset at sites.google.com/site/gvarmodelling/data and www.mohaddes.org/gvar; the IMF's International Financial Statistics and Direction of Trade Statistics at data.imf.org; data from the OECD at data.oecd.org; the World Bank at data.worldbank.org; the Department of Statistics Malaysia at dosm.gov.my; the Central Reserve Bank of Peru at www.bcrp.gob.pe; the Philippine Statistics Authority at psa.gov.ph; the U.K. Office for National Statistics at ons.gov.uk; the Reserve Bank of India at dbie.rbi.org.in; the Central Bank of Malaysia at bnm.gov.my. Other data were obtained from Refinitiv Datastream (www.refinitiv.com/en/products/datastream-macroeconomic-analysis). Restrictions apply to the availability of these data.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Data Sources for 2020Q1–2020Q4

The observations for quarters 2020Q1–2020Q4 in our dataset are obtained by extrapolating forward the 2019 GVAR vintage by Mohaddes and Raissi (2020) using year-on-year growth rates for real GDP and CPI indices, quarter-on-quarter growth rates for exchange rates and equity indices, and quarterly changes for short-term interest rates.

For real GDP growth rates, the data source is the IMF's International Financial Statistics (IFS) for all countries except China (data from the National Bureau of Statistics of China/Thomson Reuters), Singapore (Department of Statistics of Singapore), Malaysia (Department of Statistics Malaysia), Peru (Central Reserve Bank of Peru), Philippines (Philippine Statistics Authority), India only for 2020Q4 (OECD) and the U.K. only for 2020Q4 (Office for National Statistics). All data are seasonally adjusted except for India, Malaysia, Peru and Philippines.

For quarterly inflation rates, we use the percentage change in the IFS Consumer Price Index (item: "Consumer Prices, All items", not seasonally adjusted). For Argentina, we use the annual inflation rate by the OECD, assuming constant quarterly inflation within the year.

For short-term interest rates, following Cesa-Bianchi et al. (2014), we use IFS data for China (item: "Deposit Rate"); New Zealand (item: "Discount Rate"); Philippines, South Africa, U.S. (item: "Treasury Bill Rate"); South Korea, Singapore, Spain and Thailand (item: "Money Market Rate"). For Austria, Belgium, Finland, France, Germany, Italy and the Netherlands we use the 3-month Euribor rate. For India, we use the 3-month Treasury bill yield provided by the Reserve Bank of India (available for 2020Q1–2020Q2) and the short-term interest rate by the OECD (2020Q3–2020Q4). For Australia, Canada, Indonesia, Japan, Norway, Sweden, Switzerland and the U.K., we use the OECD short-term interest rate data. For Malaysia, we use the 3-month money-market rate published by the Central Bank of Malaysia.

For exchange rates and equity prices, we use Refinitiv data and Datastream Market indices, respectively.

Data on imports (c.i.f.) and exports are from the IMF's Direction of Trade Statistics. Annual GDP levels in purchasing-power parity terms (current international USD) are from the World Bank's World Development Indicators.

Appendix B. Cointegration Relationships in the GVAR

Tables A1 and A2 report the estimates of cointegrating vectors and the associated adjustment coefficients for the country-specific models in the GVAR, estimated over the full sample 1979Q2–2020Q4.[11] The variables included in the models are: real GDP (*rgdp*), CPI inflation (*infl*), real equity prices (*eq*), exchange rates (units of domestic currency per USD) deflated using the consumer price index (*fx*) and short-term interest rates (*rshort*). The symbol * indicates foreign variables. See Section 3.1 for more details on the data.

Cointegrating vectors are identified by normalizing with respect to the first variables, in the order presented in the table. The upper part of the tables reports the vectors of cointegrating coefficients ($\boldsymbol{\beta}$) associated with the variables in the second column. The bottom part of the tables reports the adjustment coefficients ($\boldsymbol{\alpha}$), i.e., the coefficients on error-correction terms (cointegration residuals) in the short-run equations for the variables in the second column. See Section 3.2 for comments.

Table A1. Estimated cointegration relationships (1979Q2–2020Q4).

Coeff.	Variable	EUR	GBR		JAP		USA
$\boldsymbol{\beta}$	rgdp	1.00	1.00	0.00	1.00	0.00	1.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	infl	6.37	0.00	1.00	0.00	1.00	16.2
		(5.08)	(0.00)	(0.00)	(0.00)	(0.00)	(1.56)
	eq	0.41	−0.07	0.02	−0.07	0.00	−0.09
		(0.10)	(0.06)	(0.01)	(0.03)	(0.00)	(0.03)
	fx	0.84	0.10	−0.01	0.22	−0.00	
		(0.16)	(0.05)	(0.01)	(0.05)	(0.00)	
	rshort	−47.8	−10.5	−0.11	−14.1	−0.77	−5.23
		(5.82)	(1.58)	(0.22)	(3.18)	(0.13)	(1.79)
	rgdp *	−1.65	−1.07	−0.07	−0.22	−0.01	-0.47
		(0.62)	(0.23)	(0.03)	(0.32)	(0.01)	(0.28)
	infl *	8.80	−0.91	−0.25	4.689	−0.01	0.91
		(2.01)	(1.37)	(0.19)	(2.16)	(0.09)	(0.80)
	eq *	−0.44	0.10	−0.00	0.08	−0.01	
		(0.12)	(0.05)	(0.01)	(0.05)	(0.00)	
	fx *	−1.43	−0.11	0.00	−0.36	0.01	0.03
		(0.310)	(0.05)	(0.01)	(0.11)	(0.00)	(0.09)
	rshort *	50.8	12.2	0.01	−10.4	−0.15	
		(6.52)	(2.22)	(0.31)	(3.78)	(0.16)	
$\boldsymbol{\alpha}$	rgdp	0.04	−0.01	−0.14	−0.09	0.43	−0.03
		(0.00)	(0.04)	(0.19)	(0.01)	(0.29)	(0.01)
	infl	0.00	0.01	−0.48	0.03	−1.06	−0.04
		(0.00)	(0.01)	(0.07)	(0.01)	(0.12)	(0.00)
	eq	0.02	0.11	0.64	0.03	0.39	−0.15
		(0.04)	(0.16)	(0.81)	(0.11)	(2.26)	(0.08)
	fx	0.01	0.05	−1.71	0.06	2.40	
		(0.02)	(0.12)	(0.60)	(0.07)	(1.57)	
	rshort	0.00	0.03	0.07	0.00	0.06	0.00
		(0.00)	(0.01)	(0.03)	(0.00)	(0.03)	(0.00)

Notes: The table shows the estimates of the cointegrating vectors ($\boldsymbol{\beta}$) and the associated adjustment coefficients ($\boldsymbol{\alpha}$), with standard errors in parentheses, of the VECX* models for the Euro area (EUR), United Kingdom (GBR), Japan (JAP) and the United States (USA). The variables included in the models are: real GDP (*rgdp*), CPI inflation (*infl*), real equity prices (*eq*), exchange rates (units of domestic currency per USD) deflated using the consumer price index (*fx*) and short-term interest rates (*rshort*). The symbol * indicates foreign variables. See Section 3.1 for more details on the data.

Table A2. Estimated cointegration relationships (1979Q2–2020Q4).

Coeff.	Variable	AUS	CAN	CHE	CHN		IND		KOR		NOR	NZL		SEA		SWE			ZAF		LAM		MEX	SAU		TUR	
$\boldsymbol{\beta}$	rgdp	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00	1.00	1.00	0.00	1.00	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	infl	−11.5	−7.92	−50.1	0.00	1.00	0.00	1.00	0.00	1.00	4.75	0.00	1.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	−6.93	0.00	1.00	0.00	1.00
		(1.13)	(0.77)	(6.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.85)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.94)	(0.00)	(0.00)	(0.00)	(0.00)
	fx	0.35	0.12	1.10	2.17	−0.043	0.27	0.00	−2.62	0.12	−0.27	0.21	−0.01	0.356	−0.00	0.00	0.00	1.00	−1.48	−0.10	−0.20	−0.05	1.31	1.85	0.00	−0.04	−0.25
		(0.07)	(0.03)	(0.33)	(0.30)	(0.01)	(0.03)	(0.01)	(0.82)	(0.04)	(0.10)	(0.09)	(0.01)	(0.09)	(0.01)	(0.00)	(0.00)	(0.00)	(1.00)	(0.05)	(0.05)	(0.01)	(0.24)	(0.32)	(0.00)	(0.05)	(0.04)
	rshort	7.31	2.46	10.8	−86.5	−0.11	−1.11	0.37	−129	4.43	4.29	−9.41	−1.12	−17.6	−0.68	165	15.0	190	116	5.92							
		(1.15)	(1.45)	(5.28)	(12.8)	(0.49)	(1.21)	(0.30)	(15.9)	(0.81)	(1.30)	(1.29)	(0.14)	(2.28)	(0.13)	(25.3)	(2.28)	(28.5)	(20.6)	(1.04)							
	rgdp *	−0.48	−1.02	0.14	−6.12	0.11	−0.65	−0.01	−8.57	0.25	−1.00	0.68	0.04	−1.67	−0.03	0.99	0.12	1.48	−8.65	−0.50	1.26	0.25	1.78	−1.24	0.01	0.62	−1.06
		(0.19)	(0.08)	(0.66)	(1.40)	(0.05)	(0.18)	(0.05)	(2.78)	(0.14)	(0.18)	(0.35)	(0.04)	(0.60)	(0.03)	(2.32)	(0.21)	(2.61)	(3.88)	(0.19)	(0.64)	(0.13)	(0.81)	(0.81)	(0.01)	(0.31)	(0.25)
	infl *	2.67	0.79	8.26	−0.26	−0.022	−0.56	−0.08	−3.26	0.13	5.87	2.47	−0.11	−1.30	−0.03	−17.9	−2.48	−17.3	−35.0	−2.15	−0.85	−0.41	3.39	−2.42	0.07	4.65	1.40
		(1.24)	(0.94)	(6.33)	(5.08)	(0.19)	(0.87)	(0.22)	(16.2)	(0.83)	(1.35)	(2.62)	(0.28)	(4.50)	(0.26)	(28.7)	(2.59)	(32.2)	(35.7)	(1.81)	(0.76)	(0.16)	(6.13)	(3.70)	(0.06)	(2.35)	(1.86)
	fx *	−0.62	−0.26	−0.90	−2.72	0.05	−0.11	0.03	−2.07	0.06	0.20	−0.04	0.04	−0.8!	0.02	−0.24	−0.02	−1.29	−1.52	−0.06	0.88	−0.02	−0.60	−0.86	0.00	0.27	0.32
		(0.10)	(0.04)	(0.39)	(0.45)	(0.02)	(0.05)	(0.01)	(0.72)	(0.04)	(0.12)	(0.10)	(0.01)	(0.26)	(0.02)	(0.59)	(0.05)	(0.67)	(1.23)	(0.06)	(0.21)	(0.04)	(0.27)	(0.30)	(0.00)	(0.10)	(0.08)
	rshort *	−6.01	1.17	16.8	6.27	1.02	−9.48	−0.81	138	−5.13	−0.96	9.88	0.93	30.4	0.65	−169	−15.8	−211	−115	−6.68	−22.0	−8.00	−2.97	12.6	0.00	−8.61	−0.20
		(2.23)	(1.71)	(11.8)	(14.37)	(0.55)	(1.79)	(0.45)	(43.5)	(2.23)	(2.37)	(3.86)	(0.4!)	(10.5)	(0.61)	(49.0)	(4.42)	(55.2)	(51.2)	(2.60)	(11.6)	(2.37)	(9.07)	(7.81)	(0.13)	(4.35)	(3.43)
$\boldsymbol{\alpha}$	rgdp	0.00	−0.04	0.00	0.018	−0.24	−0.51	−0.43	−0.00	−0.30	−0.13	0.06	−0.22	0.03	−0.06	−0.05	−0.12	0.05	0.02	−0.55	−0.02	0.08	0.03	−0.01	0.28	−0.23	−0.04
		(0.01)	(0.02)	(0.00)	(0.00)	(0.14)	(0.07)	(0.30)	(0.01)	(0.12)	(0.02)	(0.02)	(0.16)	(0.01)	(0.12)	(0.02)	(0.21)	(0.01)	(0.01)	(0.16)	(0.01)	(0.04)	(0.01)	(0.01)	(0.55)	(0.04)	(0.05)
	infl	0.09	0.10	0.01	0.00	−0.22	−0.00	−0.80	−0.00	−0.11	−0.06	0.06	−0.59	0.02	−0.61	0.05	−0.78	0.02	0.04	−0.76	−0.12	−0.47	0.06	0.04	−0.84	0.11	−0.25
		(0.01)	(0.01)	(0.00)	(0.00)	(0.08)	(0.02)	(0.10)	(0.00)	(0.08)	(0.01)	(0.01)	(0.10)	(0.00)	(0.08)	(0.01)	(0.11)	(0.00)	(0.00)	(0.10)	(0.03)	(0.10)	(0.01)	(0.01)	(0.30)	(0.05)	(0.07)
	fx	−0.19	0.03	−0.02	−0.05	−0.85	−0.02	0.10	0.02	0.48	0.10	0.06	−0.96	0.02	−4.52	0.16	−0.82	−0.08	0.04	−0.87	0.23	−0.52	−0.04	−0.04	0.21	0.22	0.45
		(0.07)	(0.09)	(0.02)	(0.01)	(0.34)	(0.07)	(0.31)	(0.02)	(0.38)	(0.05)	(0.06)	(0.54)	(0.05)	(0.95)	(0.06)	(0.65)	(0.03)	(0.04)	(0.78)	(0.04)	(0.14)	(0.02)	(0.01)	(0.32)	(0.10)	(0.13)
	rshort	−0.00	−0.00	−0.00	0.00	0.06	−0.01	0.00	0.01	0.14	−0.01	0.01	0.12	0.01	−0.02	0.00	−0.01	−0.00	0.00	−0.02							
		(0.00)	(0.00)	(0.00)	(0.0)	(0.01)	(0.00)	(0.02)	(0.00)	(0.02)	(0.01)	(0.00)	(0.03)	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)	(0.00)	(0.03)							

Notes: The table shows the estimates of the cointegrating vectors ($\boldsymbol{\beta}$) and the associated adjustment coefficients ($\boldsymbol{\alpha}$), with standard errors in parentheses, of the VECX* models for the countries listed in the first row. Countries are identified by ISO codes. The codes for aggregate areas are: LAM = Latin-American area and SEA = South-East Asia. The variables included in the models are: real GDP (*rgdp*), CPI inflation (*infl*), exchange rates (units of domestic currency per USD) deflated using the consumer price index (*fx*) and short-term interest rates (*rshort*). The symbol * indicates foreign variables. See Section 3.1 for more details on the data.

Appendix C. SVAR Impulse Response Functions

In this appendix, we extend our spillover analysis by considering dynamic responses to country-specific uncertainty shocks. Specifically, we report impulse response functions (IRFs) from an SVAR model estimated using, alternatively, our GVAR-based macroeconomic uncertainty measures and the uncertainty measures by Ozturk and Sheng (2018) (OS) as endogenous variables. We include all 20 economies in the case of GVAR-based measures (see Section 3.1) and 17 economies in the case of OS measures, as explained in Section 3.2.2 of the paper. As in Section 3.2.2, we exclude the COVID-19 period (2020Q1–2020Q4) from the sample to avoid spillover estimates simply capturing outliers. The sample is 2000Q1–2019Q4 for GVAR-based uncertainty measures and 2001Q3–2019Q4 for OS measures (see Section 3.2.2 for details on data availability issues). We estimate the SVAR with a lag order of 1. To generate the IRFs, we identify shocks using a Cholesky ordering based on countries' levels of real GDP (in PPP terms), averaged over the period 2000–2019. This amounts to assuming that uncertainty in any given economy responds to shocks in larger economies contemporaneously and responds with a lag to shocks in smaller economies.[12]

In Figures A1 and A2, we report the estimated IRFs along with 95% confidence intervals. In the interest of space, we focus on the subset of five economies already considered in Figure 4 of Section 4: USA, China, Euro area, India and UK. We consider a horizon of 12 quarters (including the period when the shock occurs). Figure A1 reports the IRFs of our GVAR-based uncertainty measures. As the figure shows, all five countries generate positive and significant dynamic spillovers of uncertainty except India. The results suggest that these dynamic spillovers generally become non-significant within one year (approximately) after the uncertainty shock. This is broadly consistent with the results provided by Angelini et al. (2018) and Bacchiocchi and Dragomirescu-Gaina (2022) for Eurozone countries. A similar result is also obtained in Figure A2, using Ozturk and Sheng (2018) measures. In this case, however, only the U.S. and the Euro area are found to generate significant dynamic spillovers to other countries (with only slightly longer effects compared to Figure A1). China only generates a small significant effect on impact on UK uncertainty. Thus, in line with the analysis of Section 3.2.2, our approach tends to assign a larger role to China as a source of international uncertainty spillovers.

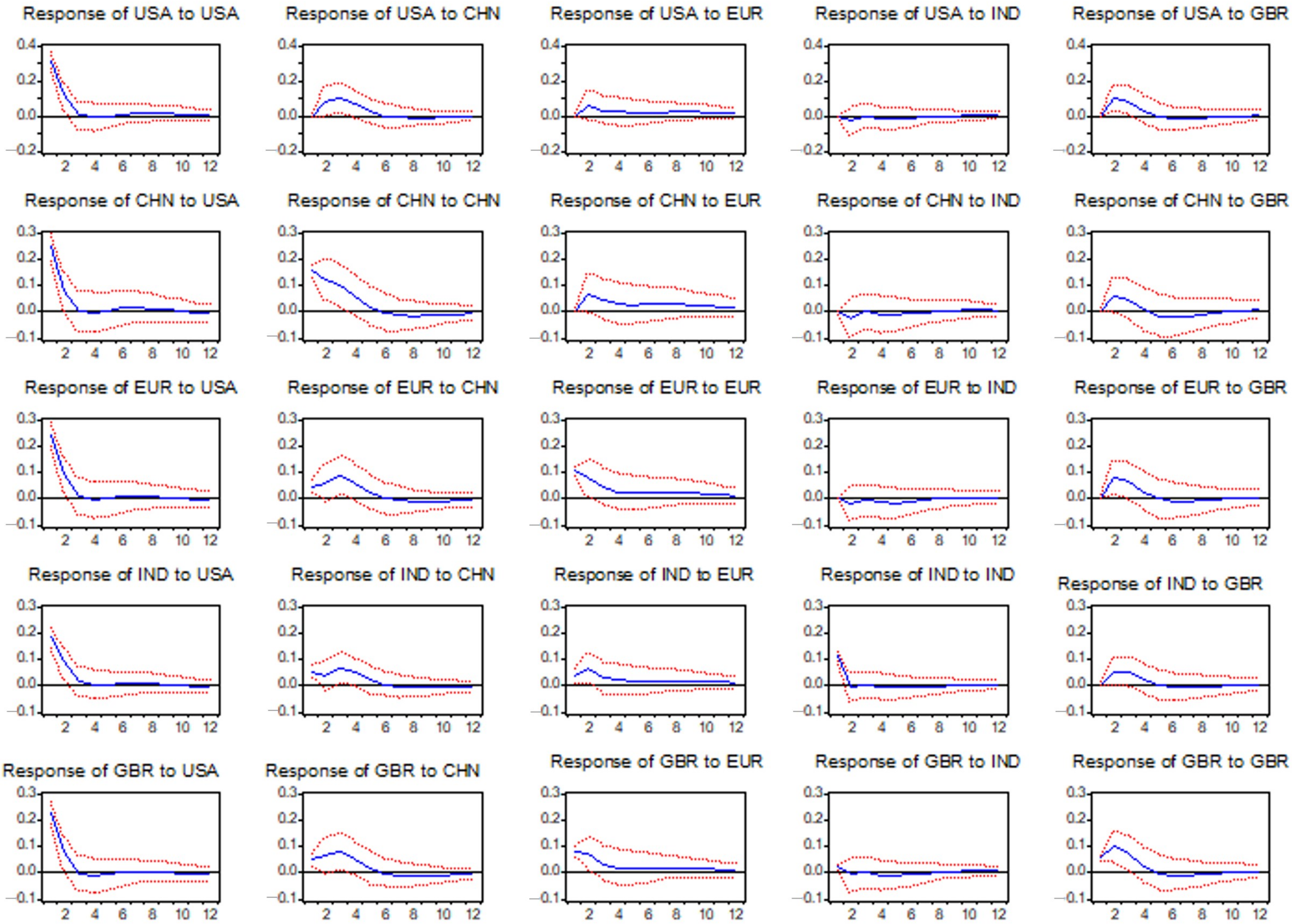

Figure A1. Impulse response functions of GVAR-based macroeconomic uncertainty measures. *Notes:* The figure shows impulse response functions (with 95% confidence intervals) from an SVAR model estimated on our GVAR-based uncertainty measures for the 20 economies considered in the paper (listed in Section 3.1). The figure reports IRFs for USA, China, Euro Area, India and UK.

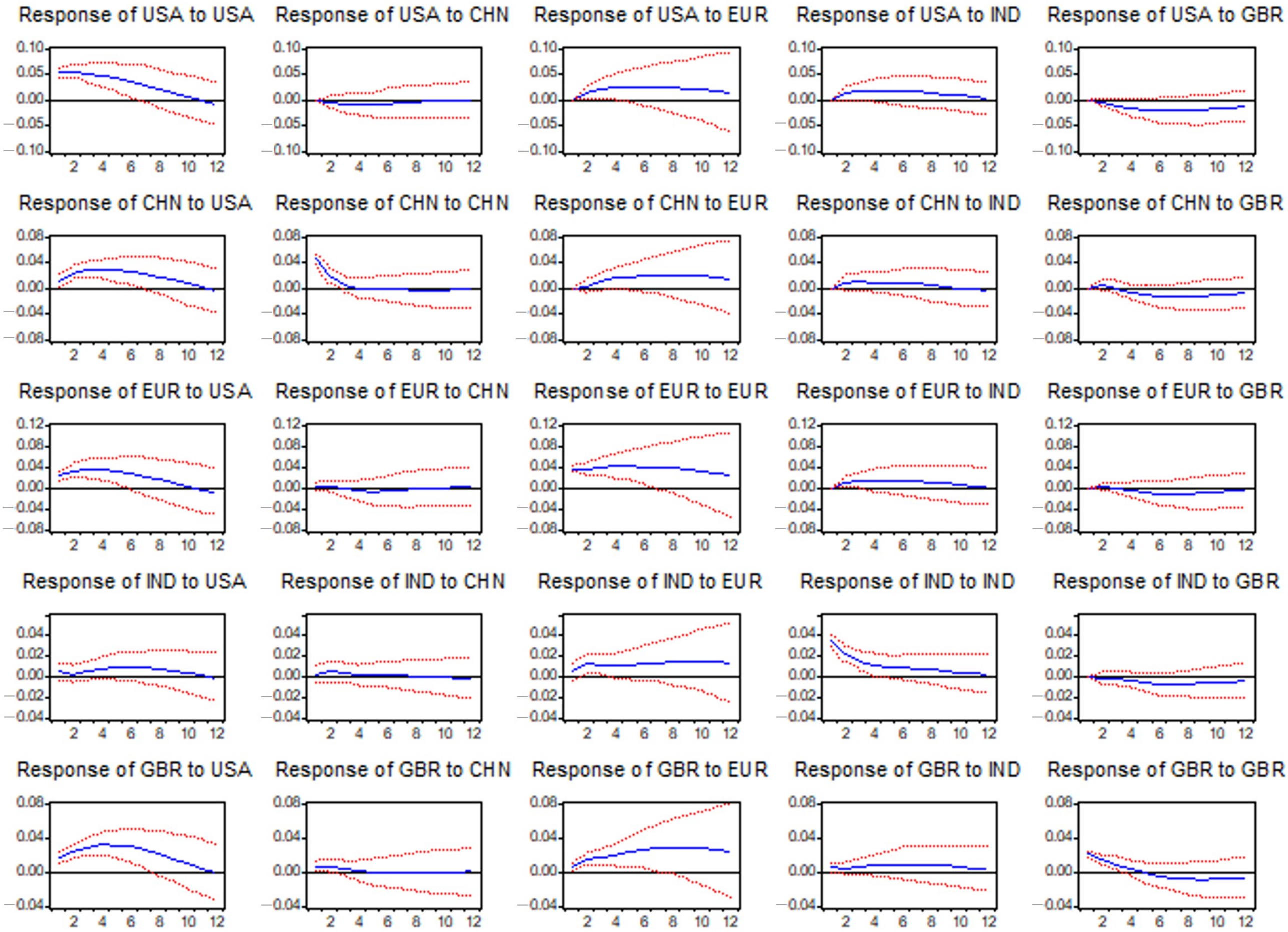

Figure A2. Impulse response functions of Ozturk and Sheng (2018) uncertainty measures. *Notes:* The figure shows impulse response functions (with 95% confidence intervals) from an SVAR model estimated on the country-specific uncertainty measures by Ozturk and Sheng (2018) for 17 economies (see Section 3.2.2 for details). The figure reports IRFs for USA, China, Euro area, India and UK.

Notes

1. Moreover, as mentioned by Bhattarai et al. (2020), this kind of two-step estimation procedure is generally subject to the so-called generated regressor problem (Pagan 1984).
2. The estimates of uncertainty may be inflated by explosive roots in (13). For this reason, in each iteration we check whether the estimated models are dynamically stable, i.e., whether all the eigenvalues of the companion matrices are less than or equal to 1 in modulus. The stability check is performed both on the country-specific models and on the resulting global model. Unstable models are discarded, so that uncertainty is measured using stable models only. At the country level, each cointegration rank $\hat{r}_i^{(w)}$ is determined by the Johansen trace test (at the 5% significance level), unless the resulting VARX* is unstable. In this case, we select the highest rank that makes the model stable. Since this does not ensure the stability of the global model, we also check the eigenvalues of the global companion matrix $\widehat{\hat{\mathbf{F}}}_{w,b}$. If the global model is unstable, the bootstrap iteration is repeated until stability is achieved.

   To further mitigate the impact of extreme forecasts on the uncertainty measures, we also remove iteration-specific forecasts that are outliers with respect to U.S. GDP, chosen as a representative variable. In particular, global forecasts are discarded whenever the forecasts of U.S. GDP lie more than 3 standard deviations away from their average across iterations.

3 The forecast variance decomposition used to calculate uncertainty spillovers relies on a first-order Taylor series approximation of the variance. To get an intuition, consider that the variance of a nonlinear function $g(X,Y)$ of two random variables X and Y can be approximated as:

$$Var(g(X,Y)) \approx \left(\frac{\partial g(\mu_X,\mu_Y)}{\partial \mu_X}\right)^2 Var(X) + \left(\frac{\partial g(\mu_X,\mu_Y)}{\partial \mu_Y}\right)^2 Var(Y) + 2\left(\frac{\partial g(\mu_X,\mu_Y)}{\partial \mu_X}\right)\left(\frac{\partial g(\mu_X,\mu_Y)}{\partial \mu_Y}\right) Cov(X,Y)$$

where μ_X is the mean of X and μ_Y is the mean of Y. Accordingly, the contribution of X to the variance of $g(X,Y)$ is the sum of two terms: one depends on the variance of X, specifically $(\partial g(\mu_X,\mu_Y)/\partial\mu_X)^2 Var(X)$, i.e., the first term in the formula, and the other depends on the covariance between X and Y, specifically $(\partial g(\mu_X,\mu_Y)/\partial\mu_X)(\partial g(\mu_X,\mu_Y)/\partial\mu_Y)Cov(X,Y)$, i.e., one-half of the third term in the formula. In our spillover analysis, we decompose the variance of GVAR forecasts, which are nonlinear functions of the VARX* model parameters (as a result, in particular, of the inversion of the **G** matrix in (6)).

4 Like Klößner and Sekkel (2014) and Rossi and Sekhposyan (2017), we do not give a causal interpretation to the uncertainty spillovers, as they are not based on structural (orthogonal) shocks. In this respect, we also follow the GVAR literature, which typically uses non-orthogonalized shocks to conduct impulse response analysis, in the form of generalized impulse response functions (GIRFs) and generalized forecast error variance decomposition (GFEVD) (see Pesaran et al. 2004 and Dées et al. 2007a, 2007b).

5 As in Cesa-Bianchi et al. (2014), real GDP, exchange rates and equity indices are transformed to logs, while each interest rate is transformed to $0.25[1+\ln(R_t/100)]$, where R_t is the rate expressed in percentage values on an annual basis.

6 All results are obtained using 1000 bootstrap iterations.

7 The two schemes provide highly correlated results for global uncertainty (the correlation coefficient is 0.75). In the quarters 2020Q2–2020Q4, the GVAR estimated by rolling windows on actual data is explosive for any choice of the cointegration ranks. In this case, to generate the bootstrap samples, we use the model estimates obtained on the window ending in 2019Q4.

8 To apply the methodology by Jurado et al. (2015), we transform the non-stationary variables used in the GVAR by first differencing. Once uncertainty is calculated for each variable, we first average variable-specific uncertainties within each country (with equal weights), then calculate global uncertainty as the PPP GDP-weighted average of uncertainty across countries.

9 The estimated spillovers from all countries to a given country do not exactly sum to 1, because the forecast variance decomposition is based on a linear approximation of a nonlinear function, as explained in endnote 3. However, the discrepancy is in general very small. The sum of the estimated spillovers is 0.98 on average and ranges between 0.93 and 1.04 across countries. In the results reported here, all spillovers are rescaled so that they exactly sum to 1 for each "uncertainty-importing" country.

10 We use the fast algorithm developed by Klößner and Wagner (2014).

11 Cointegration ranks in Tables A1 and A2 are determined using the Johansen (1995) trace test at the 5% level of significance. Estimates are reported for all countries except Brazil, for which the Johansen (1995) test indicates no cointegration relationships. For the U.K. (GBR) and the Latin American aggregate area (LAM), Tables A1 and A2 report results using the cointegration ranks determined over the pre-COVID-19 sample 1979Q2-2019Q4 (2 cointegration relationships for both), instead of the ranks estimated over the full sample 1979Q2-2020Q4 (1 and 3 cointegration relationships, respectively): this adjustment provides more reasonable long-run properties, while having almost no effect on our uncertainty measure (in particular, a rank of 1 for GBR would result in unrealistically large long-run coefficients linking GDP and inflation, while a rank of 3 for LAM would imply that all variables, including GDP, are trend-stationary).

12 Both types of uncertainty measures are highly correlated across countries, implying that the IRFs strongly depend on the specific Cholesky ordering. Still, the analysis is mainly intended to check if country-specific uncertainty shocks generate significant cross-border dynamic spillovers.

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